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Comparative Evaluation of Derived and Previously Published Models for Estimating Annual Runoff in the Mountainous Watersheds of Sulaimani Province

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ABSTRACT

Water availability estimation is critically needed in order to maximize water use for a range of uses. As in other similar regions, the majority of the watersheds in the study area are ungauged, necessitating the use of empirical models to estimate runoff indirectly. The required data for three watersheds were generated before developing a local model and before evaluating a host of empirical models. The watersheds were situated to the east of Sulaimani, Iraqi Kurdistan, and described with particular reference to climate, soil, land use/landcover and, morphometric characteristics. The tested models included: Inglis and De Souza, Khosla, Justin, Lacey, Turc, Indian Irrigation Department, Coutagine, Indian Council of Agricultural Research, and the Soil Conservation Service – Curve Number, as well as a locally derived model. Several performance indicators were used as criteria for ranking the empirical models using the compromise programming index. The analysis of annual rainfall and temperature recorded at the surrounding stations revealed that the Empirical Bayesian Kriging is the best scheme for interpolation in the northeast of the Iraqi Kurdistan Region. Moreover, the results indicated that the annual runoff coefficient was below 6%, and most of the rainfall time series recorded at nearby stations exhibited an insignificant declining trend. Also, a non-linear multivariate model was developed for the study area for predicting annual runoff with annual rainfall, temperature, and length of the main channel as input variables. Furthermore, the analysis of the compromise programming index revealed that the suggested model ranked highest among the assessed models, followed by the Soil Conservation Service – Curve Number and Turc models.

Keywords: Empirical models, spatial interpolation, annual runoff, ungauged watersheds, compromise programming index.

1. Introduction

In spite of a great number of flowmeters (exceeding 60000) being established over the world, and there are also a huge number of not measured watersheds where runoff data are unavailable[1]. The drivers for deriving runoff modeling in such types of watersheds include design applications (dam, culvert, etc), forecasting apps (flood warning), and management applications such as water allocation[2].

A portion of the rainfall turns into runoff that reaches the soil's surface and is absorbed by streams when the intensity of the rainfall surpasses the soil's capacity for infiltration [3]. Recent studies by numerous researchers have shown recently that runoff and soil erosion are related to the amount of precipitation, rainfall intensity, and vegetative cover[4]. The evaluation of rainfall-induced runoff is crucial for the planning and design of water resources[5]. When runoff is collected using water harvesting methods, it becomes a significant source of recharge for groundwater[6]. To describe the runoff process of the hydrological cycle, a variety of rainfall-runoff modeling approaches have been developed, ranging from straightforward empirical equations to complex mechanistic approaches[7]. There are three types of applied models: conceptual models, physically-based models, and black box models. The first category can be thought of as empirical models devoid of output transfer functions and physically based input[8].

Rainfall-induced runoff prediction is a complicated process, and a huge number of empirical models can be found in the literature. Up to the present time, there is a need for simpler empirical models for assessing runoff from ungauged catchments an annual scale. These models can predict runoff close to that postulated by the Soil Conservation Service – Curve Number (SCS-CN) method[9]. Because of its practicability, the SCS-CN became very popular among empirical methods[10]. Empirical models are appropriate for the regions in which they have been developed or for regions with similar characteristics[11].

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Understanding the complex relationship between rainfall and runoff is of vital importance for accurate assessment of the surface runoff from rainfall[12]. They also revealed that non-linear relationships can represent the relationship between precipitation and runoff. Rainfall during a period and the runoff that results is not a straightforward relationship that is influenced by a variety of factors, including catchment and climate-related factors. Indirect estimation of runoff through empirical models is necessary because many watersheds worldwide, such as those in India and other countries, lack gauges[5].

[13]Showed that runoff estimation is a common task in the field of engineering hydrology and that the conversion of rainfall into discharge can be simplified in the form of rain-flow models[8] Highlighted that runoff prediction is crucial because of the non-linear relationship between runoff and rainfall on the one hand and due to the lack of recorded data at many watersheds[9] Revealed that estimation of runoff from the SCS-CN method chiefly depends on Curve Number value, which is closely related to antecedent soil moisture content, catchment slope, type of soil, and land cover/land use. In contrast, the previously published model for estimating annual rainfall did not take into account soil type, antecedent soil moisture, land use/cover, or annual rainfall; instead, it only took into account annual air temperature and annual rainfall.

[14]Evaluated several models for assessing runoff yield in catchments lacking hydrometric stations. They concluded from their investigation that among the applied models, Coutigne, Indian Council of Agricultural Research, Turc, Irrigation Department of India, and Khosla were superior to other models. [15] applied several models for rainfall estimation at the Kuhbazu catchment situated in Yazd, Iran, and noticed that Coutgine and ICAR models offered inaccurate results. In contrast, Justin offered reasonable accuracy in the indicated area. On the other hand,[16] revealed that among nine models for estimating runoff, the Lacey model offered the highest efficiency in the Banadaksadat watershed, Yazd Province, Iran. The main weakness of the empirical models, with the exception of the SCS-CN, is the assessment of runoff on an annual basis[9].

It's interesting to note that models at the regional scale are unable to fully capture the variations and processes; models for runoff estimation at the local scale must be developed.

In light of this, the current study was started with the goal of developing a model for estimating runoff in ungauged watersheds and choosing the best empirical model from previously published models by contrasting estimated and measured runoff values.

2. Methods and Materials

2.1 Description of the Study Area

The study area is situated to the northeast of the Iraqi Kurdistan region- within the administrative border of Halabja and Sulaimani governorate, and encompasses three watersheds, namely, Darashish, Gulp, and Xargillan. They are sandwiched between latitudes of 35° 10′ N - 35° 13′ N and longitudes of 46° 04′ E - 46° 11′ E. Fig.1. Shows the location map for the watersheds and the stations surrounding the study area. Over the entire research region, the altitude ranged from 720 m to 2522 m above mean sea level (amsl). The comprehensive descriptions of the watersheds, specifically pertaining to soil, hydrology, and land cover/land use, were provided by[17]. With no exception and according to the Koppen classification scheme, three watersheds are situated with the Csa class. The database for the estimated runoff by SCS-CN was also provided by[17].

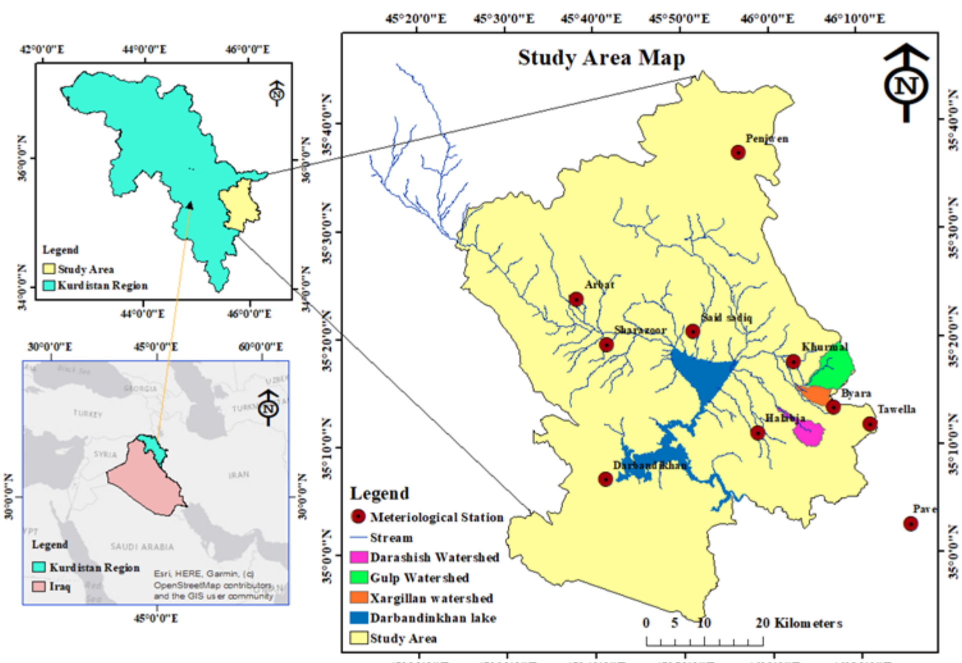

Figure 1: Location map showing the selected watersheds and the stations surrounding the study area.

2.2 Measurement of Direct Runoff

In order to measure runoff following storms over the chosen watersheds in the hydrologic years 2022–2023 and 2021–2022, a suitable section was chosen in close proximity to each watershed outlet. The procedure described by[17] was followed to create the database for the measured rainfall and runoff for the watersheds under study for two consecutive years.

2.3 Generation of Spatial maps for annual rainfall and Annual Temperature over the Study Watersheds and its peripheral area

In a GIS environment, various interpolation methods were assessed using the ArcMap version 10.8 software to predict annual air temperature and rainfall at unsamples locations without data across the three watersheds.

The database for this investigation included annual rainfall and air temperature data from ten stations surrounding the watersheds under study, covering the period from 2000-2001 to 2020-2021. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) analysis revealed that the Empirical Bayesian Kriging (EBK) method ranked first for predicting rainfall and air temperature. Based on EBK, spatial maps were generated for the study area and its surroundings with the main purpose of estimating rainfall and air temperature over the entire area of each watershed for the years 2021- 2022 and 2022-2023.

2.4 Trend Analysis for Annual Rainfall

Mann-Kendall, linear regression, and Spearman rank tests were used to analyze trends in the yearly rainfall over the surrounding areas. Prior to trend analysis, the annual rainfall time series at each of the stations surrounding the investigated area was examined for homogeneity test using the Buishand range test[18], the Standard Normal Homogeneity Test (SNHT)[19], Pettitt test [20], and the Von Neumann Ratio test (VNR)[21], additionally, the time annual rainfall time series were tested for serial autocorrelation following the procedure outlined by[22].

The described method was implemented to validate the effectiveness of the EBK technique in estimating annual rainfall at unsampled locations using leave-one-out cross-validation (LOOCV)[23].

2.5 Calculation of Mean Annual Rainfall and Mean Annual Temperature over the Selected Watershed during the Period of the Study

The average rainfall depth between successive lines and the area between the lines were multiplied to find the mean value of rainfall for each watershed. The sums of the products were then divided by the watershed area:

$$\bar{d} = \frac{a_1 x \bar{d}_1 + a_2 x \bar{d}_2 + \ldots + a_n x \bar{d}_n}{A} \quad [1]$$

Where $a_1, a_2 \ldots a_n$ is the area sandwiched between successive lines (Isohyetes)

$\bar{d}_1, \bar{d}_2 \ldots \bar{d}_n$ *are average depth of rain fall between two sucessive lines*

A= an area of the entire watershed

2.6 Derivation of a Locally Multivariate Non-Linear Regression Model for estimating runoff

The current study also focused on deriving a locally nonlinear model for runoff estimation as a first approximation based on rainfall and some other variables pertinent to climatic and morphometric characteristics using SPSS software, version 24.

2.7 Evaluation of Different Empirical Models for Runoff Estimation

An attempt was also made to estimate runoff in the three selected watersheds using nine empirical models, namely, Inglis and De Souza (IDS), Indian Irrigation Department (DII), Turc relationship (TR), Coutagine relationship (CR), Khosla method (KH), Justin Equation (JE), Indian Council of Agricultural Research (ICAR), Lacey relationship (LR), Soil Conservation Service – Curve Number (SCS-CN) method. The empirical models used in this study are briefly described in Table 1. These models depict the relationship between rainfall and runoff with an additional variable accounting for climatic and watershed characteristics.

Table 1: Specification of empirical mathematical models (EMM), the purpose, mathematical expression, and reference.

#.	EMM	Mathematical Expression	Reference
1	**Inglis and De Souza (IDS)**	$R = \frac{(P-17.8) \times P}{254}$ Where P is annual precipitation (cm), and R is annual runoff (cm)	[24],[11]
2	**Indian Irrigation Department (DII)**	$R = P - (1.17 \times P^{0.86})$ Where, P is annual precipitation (cm), and R is annual runoff (cm)	[25]
3	**Turc relationship (TR)**	$R = P - D$ $D = \frac{P}{\sqrt{0.9 + (\frac{P}{LT})^2}}$ $LT = 300 + 25 \times T + 0.05 \times T^2$ Where P is annual precipitation (mm), R is annual runoff (mm), T is the mean annual temperature (°C), and D is annual flow shortage	[16]
4	**Coutagine relationship (CR)**	$D = P - \lambda P^2$ $R = P - D = \lambda P^2$ D: The shortage of annual follow (m) P: Mean annual precipitation (m)	[26]

		R: Mean annual runoff (m) λ: The following comes from the relationship, the recommended the following equation: $$\lambda = \frac{1}{0.8 + 1.14T}$$ T: Mean annual temperature (c). The P must be between the $\frac{1}{2\lambda}$and $\frac{1}{8\lambda}$	
5	**Khosla method (KH)**	$$R = P - \frac{T}{3.74}$$ Where R: mean annual runoff in a watershed (cm) P: Mean annual precipitation in a watershed (cm) T: Mean annual temperature in watershed (c).	[27], [16]
6	**Justin Equation (JE)**	$R = \frac{0.284 \times S^{0.155} \times P^2}{1.8 \times T + 32}$, $S = \frac{H_{max} - H_{min}}{\sqrt{A}}$ Where: R: Runoff height (cm) P: Mean annual precipitation (cm) T: Mean annual temperature (c) S: Mean slope of the watershed H: Elevations A: is the watershed area (km^2)	[27]
7	**Indian Council of Agricultural Research (ICAR)**	$$R = \frac{1.115 \times P^{1.44}}{T^{1.34} \times A^{0.0613}}$$ Where: R: annual runoff (cm), P: annual precipitation (cm), T: Mean annual temperature (c), and A: The area of the watershed (km^2)	[26]
8	**Lacey relationship (LR)**	$$R = \frac{P}{1 + \frac{304.8\,(F_Z)}{P}}$$ Where: Fz: Parameter of rainfall duration and physiographic properties taken from table (not shown here), P: Mean annual precipitation (cm), R: Mean annual runoff (cm)	[11], [27]
9	**SCS-CN model**	$$Q = \frac{(P - 0.2S)^2}{P + 0.8S}$$ Q = is direct runoff (mm), P precipitation (mm), S is watershed potential retention.	[28]

The estimated results were compared with the measured runoff values at suitable sections close to the outlet of the watersheds. The TOPISIS was used for ranking the empirical models based on five statistical metrics, namely, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), Coefficient of Agreement (d), and Nash-Sutcliffe efficiency (NSE).

Additionally, the compromise programming index (CPI) was employed to integrate the results of the performance indicator (statistical metrics) and to rank the empirical models at each watershed. The CPI was calculated according to;

$$CPI = \left[\sum_{j=1}^{n} \alpha_j \left|x_j - x^*_j\right|^p\right]^{\frac{1}{p}} \quad [2]$$

Where xj= considered the point, x^*_j= ideal point, α_j = weight of the criterion j, and p= a parameter reflecting regulation distances between x_j and x^*_j, In this study, the empirical models were evaluated by comparing their estimates with the non-linear regression model derived by the authors during this investigation. It is commendable to mention that the data from the three watersheds were merged into one location due to limited data availability. This means that the frequency of each model was one. The ranking procedure can be outlined as follows::

1. The empirical models were ranked based on CPI value. The model with the lowest CPI is given the first rank.

2. The weight of a given rank was taken as the inverse of the rank.

3. The overall score S for each model was obtained by summing the product of the frequency of occurrence of a given rank and its corresponding weight or

$$S = F_1 W_1 + F_2 W_2 + \ldots F_n W_n \quad [3]$$

Here $F_1 = F_2 = F_n = 1$

4. The final ranking was based on the overall score of each model. The above procedure was implemented for three values of p (p=1, 2, and ∞).

During the two consecutive years of 2021–2022 and 2022–2023 for each watershed, the overall runoff coefficient was also calculated by dividing the measured annual runoff by the annual rainfall.

3. Results and Discussion

3.1. Morphometric Characteristics of the Study Watersheds

Table 2 shows a few selected meteorological features of the watersheds. It is obvious from Table 2 that the total areas are 20.30, 37.76, and 13.85 km^2 for Darashish, Gulp, and Xargillan watersheds, respectively. All the three watersheds fell within Milli-watershed (10 to 100 km²)[29]. These watersheds are located in the steeply sloping mountainous region northeast of Iraqi Kurdistan. The average slope ranges from a minimum of 21.57% at Xargillan to a maximum of 45.91% at Gulp. The average annual rainfall of Halabja, the nearest meteorological station to the watersheds, amounts to 645.52 mm. Based on annual rainfall and annual temperature, they fell in Csa according to the scheme proposed by Koppen. Based on the circularity ratio, all the watersheds fell in the medium class of circularity ($0.4 < Rc < 0.6$), while they are within the elongated class based on the elongation ratio ($0.5 < Re < 0.7$)[30]. All of the land in the three watersheds is used for grazing without exception. Based on the drainage density, the Darashish were classified as coarse ($1.24 < Dd < 2.49$), whereas the two remaining watersheds ($2.49 < Dd < 3.73$) belonged to the moderate class. On the other hand, their stream frequency ($5 < Fs < 10$) placed them in the moderate class[31]. Further, the length of the main channel ranges from as low as 4.22 km in Xargillan to as high as 7.89 km in Darashish. It was also shown that the bifurcation ratio is less than 3 therefore they fell with the theoretical basin ($Rb < 3$) according to[32].

Table 2: Database covering climatic and watershed characteristics for the study watersheds during the period of the study.

Watershed	Year	P	T	S	A	Q	DH	Rn	F_f	Rb	Rc	Re	Dd	Fs	La	I_f
Darashish	2021-2022	494.95	18.61	39.97	20.30	10.99	1008	2.256	0.22	1.74	0.55	0.53	2.23	5.81	7.88	14.07
	2022-2023	634.58	17.71													
Gulp	2021-2022	517.41	18.32	45.91	37.76	11.67	1796	4.674	0.44	1.83	0.57	0.75	2.61	6.59	5.10	17.16
	2022-2023	658.31	17.71													
Xargillan	2021-2022	497.79	18.90	21.57	13.85	10.44	851	2.288	0.25	1.66	0.46	0.57	2.68	9.53	4.22	25.61
	2022-2023	635.32	18.28													

P: Annual rainfall (mm), **T**: Annual Temperature(ºC), **S**: Average slope(m/m), **A**: Area(km^2), **Q**: annual runoff (mm), **DH**: Difference in elevation (m), **Rb**: Bifurcation ratio (-), **Rn**: Ruggedness number =R x Dd(-), **F_f**: Form factor(-), **Rc**: Circularity ratio(-), **Re**: Elongation ratio(-), **Dd**: Drainage density(km^{-1}), **Fs**: Stream frequency(km^{-2}), **La**: Length of mainstream (km), **I_f**: Infiltration number =Dd x Fs(km^{-3}).

3.2 Preliminary Tests

Before being used to create the database needed for estimating the runoff using a set of empirical models, the annual rainfall time series of the stations surrounding the study area were put through homogeneity and autocorrelation tests. Four commonly used tests, namely Pettitt, SNHT, Buishand, and VNR, were used for examining the homogeneity of rainfall time series at 10 stations for a period of 16-23 years, and the results are displayed in Table 3. As can be noticed, all the rainfall time series, with one exception, fell into the useful class. This suggests that the recorded data is suitable for further analysis.

Furthermore, Table 4's results show that 90% of the time series under investigation have lag-1 autocorrelation coefficients that fall between the lower and upper bounds of the range, suggesting that the data are not serially correlated. By contrasting the calculated t-values with the critical ones, this conclusion can be verified. As the calculated t-values are less than the tabulated values, the null hypothesis cannot be rejected. In other words, the applied data are not serially correlated. This means that the Mann-Kendall test, a non-parametric method, can be used to detect trends without requiring additional techniques like modified Mann-Kendall for such analysis. Likewise, the outcomes showed that there is no autocorrelation and homogeneity in the temperature time series at various stations. Table 5 displays the results, which showed that 80% of the time series that were recorded showed a decreasing trend. However, at 70% of the time series, the decrease was not statistically significant. Among all the stations, only the Penjwen station exhibited a significant decreasing trend, symbolized by DT. Conversely, two stations showed non-negative trends, which were not significant at ($P>0.050$). Sen's slope results as a non-parametric test revealed that the rate of decrease in annual rainfall varies from as low as 3.056 mm year^{-1} at Khurmal to as high as 28.956 mm year^{-1} at Penjwen. Unlike this trend, the rate of increase in annual rainfall ranged from 0.25 mm year^{-1} at Arbat station to 7.00 mm year^{-1} at Tawella station during the period from 2000 to 2023. Further, it was noticed that the results of the Spearman rank test for detecting trends in annual rainfall are comparable to those of the Mann-Kendall test (not shown here because of limited space).

Table 3: Homogeneity tests for the annual rainfall time series were recorded at stations surrounding the study area using the four commonly used homogeneity tests.

#	Station	N	Pettitt's test			SNHT			Buishand's test			VNR test			Classification
			K_N	P-value	K_N -critical	To	P-value	T-critical	Q	P-value	Q-critical	N	P-value	N-critical	
1	Halabja	23	56	0.28	72	4.91	0.19	7.16	4.58	0.21	1.45	1.48	0.10	1.34	Useful
2	Penjwen	23	80	0.04	72	7.17	0.04	7.16	5.82	0.05	1.45	1.09	0.01	1.34	Suspect
3	Saidsadq	23	50	0.40	72	4.02	0.39	7.16	3.31	0.55	1.45	1.57	0.14	1.34	Useful
4	Byara	22	48	0.38	67	2.66	0.65	7.09	3.02	0.65	1.44	1.76	0.29	1.32	Useful
5	Darbandikhan	23	48	0.45	72	3.62	0.40	7.16	3.14	0.63	1.45	1.58	0.15	1.32	Useful
6	Tawella	16	24	0.56	46	3.22	0.42	5.56	2.45	0.67	1.15	1.79	0.34	1.04	Useful
7	Khurmal	23	40	0.65	72	3.14	0.52	7.16	2.92	0.72	1.45	1.70	0.24	1.34	Useful
8	Arbat	22	45	0.45	67	3.33	0.48	7.09	4.31	0.23	1.44	1.38	0.07	1.34	Useful
9	Sharazor	22	39	0.62	67	2.26	0.73	7.09	2.68	0.76	1.44	1.67	0.21	1.32	Useful
10	Pave	23	68	0.24	72	3.34	0.50	7.16	3.20	0.60	1.45	1.97	0.47	1.34	Useful

Table 4: Lag 1 autocorrelation in annual rainfall time series recorded at the stations surrounding the study area.

#	station	Correlation coefficient	$\frac{-1-1.96\sqrt{n-2}}{n-1}$	$\frac{-1+1.96\sqrt{n-2}}{n-1}$	$t_{cal} = \lvert\rho_i\rvert\sqrt{\frac{n-2}{1-\rho_i^2}}$	t- table
1	Halabja	0.23	-0.44	0.35	1.08	2.07
2	Penjwen	0.42	-0.43	0.34	2.56	2.07
3	Saidsadq	0.19	-0.43	0.34	0.97	2.07
4	Byara	0.09	-0.42	0.33	0.46	2.08
5	Darbandikhan	0.17	-0.43	0.34	0.89	2.07
6	Tawella	0.023	-0.362	0.275	0.089	2.14
7	Khurmal	0.093	-0.434	0.347	0.447	2.07
8	Arbat	0.302	-0.425	0.338	1.618	2.08
9	Sharazor	0.159	-0.425	0.338	0.777	2.08
10	Pave	-0.019	-0.434	0.347	0.087	2.07
Note ; ρi = r = correlation coefficient						

Table 5: Mann- Kendall test results for detecting trends in annual rainfall time series recorded at the stations surrounding the study area during the period from 2000 to 2023.

#	Station	S	S var.	Sen's. slope	Z-value	Type of trend		p-value
1	Halabja	-55	1433.67	-13.52	-1.42	No trend	NT	0.156
2	Penjwen	-107	1433.67	-28.95	-2.80	Decreasing trend	DT	0.005
3	Saidsadq	-25	1433.67	-3.98	-0.63	No trend	NT	0.53
4	Byara	-19	1257.67	-5.43	-0.50	no trend	NT	0.61
5	Darbandikhan	-57	1433.67	-9.28	-1.47	no trend	NT	0.14
6	Tawella	16	493.34	7.00	0.67	no trend	NT	0.50
7	Khurmal	-13	1433.67	-3.05	-0.31	no trend	NT	0.75

8	**Arbat**	1	1257.67	0.25	0.00	no trend	NT	1.00
9	**Sharazor**	-25	1257.67	-3.05	-0.67	no trend	NT	0.50
10	**Pave**	-29	1433.67	-5.21	-0.73	no trend	NT	0.46
If Z<-1.96 Decreasing Trend (DT), if Z >1.96 Increasing Trend (IT), if Z between (-1.96 t0 1.96), it means no trend (NT).								

3.3 Prediction of Annual Rainfall and Temperature by Different Interpolation Schemes

Table 6 showed, for the study station surrounding the watersheds under investigation, the measured annual rainfall and those predicted by a variety of interpolation schemes, including deterministic and geostatistical methods. In order to assess how predictable the schemes in Table 6 are, a host of performance indicators such as MAE, MPE, RMSE, d, and NSE have been used, and the results are presented in Table 7. As can be seen in Table, the EBK offered the lowest value of 60.00, 7.98. 101.44 For MAE, MAP, and RMSE respectively, and the highest value of 0.58 for d. In contrast, the Global polynomial interpolation (GPI) scheme offered the highest values of 94.01, 13.62, and 118.88 for MAE, MAP, and RMSE, respectively. On the other hand, the GPI offered the lowest value of 0.49 for d. According to most criteria, it can be concluded that the EBK scheme is the most prominent among the schemes under investigation. To further confirm the above results, a multicriterion decision analysis was performed using TOPSIS with five criteria (MAE, MAP and RMSE, d and NSE) and eight alternatives (8 interpolation schemes). The results of this analysis indicated that the EBK had the first rank, followed by Local polynomial interpolation (LPI) and Inverse distance weighted (IDW). Unlike this result,[33] observed that the LPI method was the best interpolator for generating continuous surfaces for rainfall over the Erbil Plain.

Similarly, it was noticed that the EBK offered the maximum performance for air temperature prediction (not shown here).

Table 6: Measured annual rainfall at the stations surrounding the study area and their estimated values by using different interpolation schemes.

#	Station	Measured annual rainfall (mm)	Estimated rainfall (mm)							
			IDW	GPI	RBF	LPI	OK	UK	EBK	DK
1	**Halabja**	645.52	647.10	629.24	626.26	629.17	593.54	593.54	601.07	648.36
2	**Penjwen**	924.98	608.03	580.17	604.17	544.63	547.19	547.19	573.08	611.60
3	**Saidsadq**	566.63	623.60	664.65	628.16	642.91	582.26	582.26	610.10	652.58
4	**Byara**	686.27	679.16	714.81	682.37	687.99	677.87	677.87	679.70	655.67
5	**Darbandikhan**	566.38	618.62	387.12	629.28	479.34	713.82	713.82	534.13	629.09
6	**Tawella**	722.69	674.46	728.80	709.14	707.26	701.96	701.96	718.49	653.14
7	**Khurmal**	616.50	664.75	725.97	666.53	700.33	656.32	656.32	670.35	660.85
8	**Arbat**	551.57	585.49	597.37	611.10	574.05	619.35	619.35	594.10	641.19
9	**Sharazor**	553.86	583.98	581.03	555.75	561.39	514.50	514.50	538.40	637.80
10	**Pave**	735.64	673.37	651.03	698.85	718.13	891.05	891.05	741.00	654.16
Inverse distance weighted (IDW), Global polynomial interpolation (GPI), Radial basis function (RBF), Local polynomial interpolation (LPI), Ordinary Kriging (OK), Universal Kriging (UK), Empirical Bayesian kriging (EBK), Diffusion Kernel(DK).										

Table 7: Evaluation of different interpolation schemes for the spatial distribution of annual rainfall recorded at the stations surrounding the study area using some selected performance indicators.

Method/ Criteria	IDW	GPI	RBF	LPI	OK	UK	EBK	DK
MAE	65.76	94.01	63.02	70.85	92.43	92.43	60.00	86.44
MAPE	8.93	13.62	8.63	9.62	12.87	12.87	7.98	12.43
RMSE	94.89	118.88	95.52	113.1	123.9	123.9	101.44	103.40
d	0.45	0.49	0.48	0.52	0.49	0.49	0.58	0.16
NSE	0.04	-0.49	0.03	-0.35	-0.62	-0.62	-0.08	-0.12

2.4 Spatial Distribution of Annual Rainfall and Annual Temperature over the study area

Based on the average annual rainfall from 2001 to 2021, 2021–2022, and 2022–2023, the spatial distributions of annual rainfall were created in a GIS environment. The results are shown in Fig. 2. It is praiseworthy to indicate that the continuous surfaces for rainfall an annual scale were generated using the EBK method as the best interpolation method in the area under study. It is obvious from Figs. 2 that average annual rainfall tended to significantly decrease from Penjwen station.

The fact that the EBK outperformed other interpolation schemes in temperature prediction is also praiseworthy. Accordingly, the distribution of average temperature from 2001 to 2021 and distribution for the years 2021-2022 and 2022-2023 were generated and displayed in Fig.3. Upon preparation of the required maps, the annual rainfall and annual temperature were determined for the three watersheds and the years 2021-2022 and 2022-2023 using isohyetal method or by using equation (1).

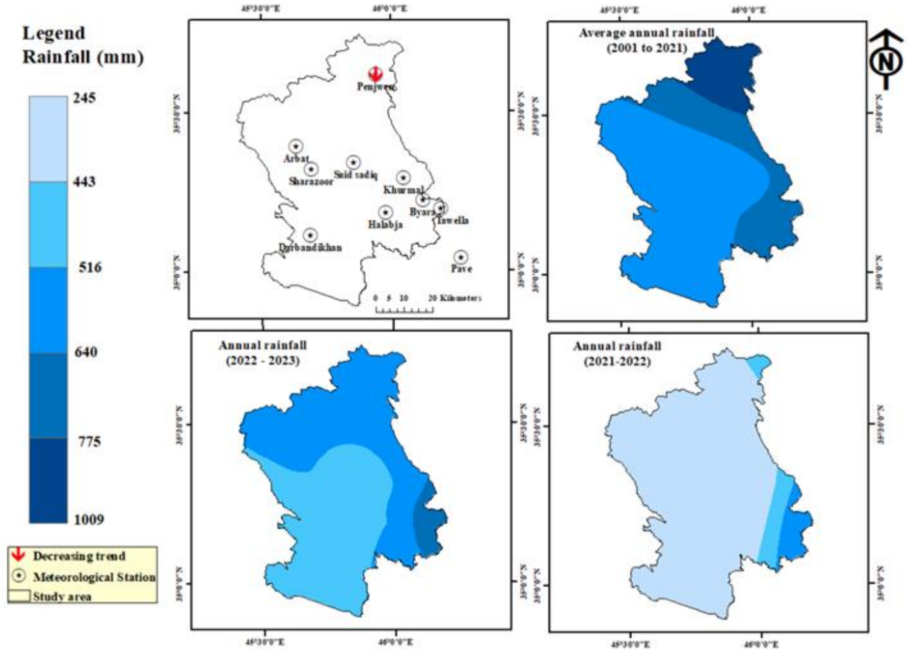

Figure 2: Spatial distribution of annual rainfall over the watersheds and the surrounding area using Empirical Bayesian Kriging scheme.

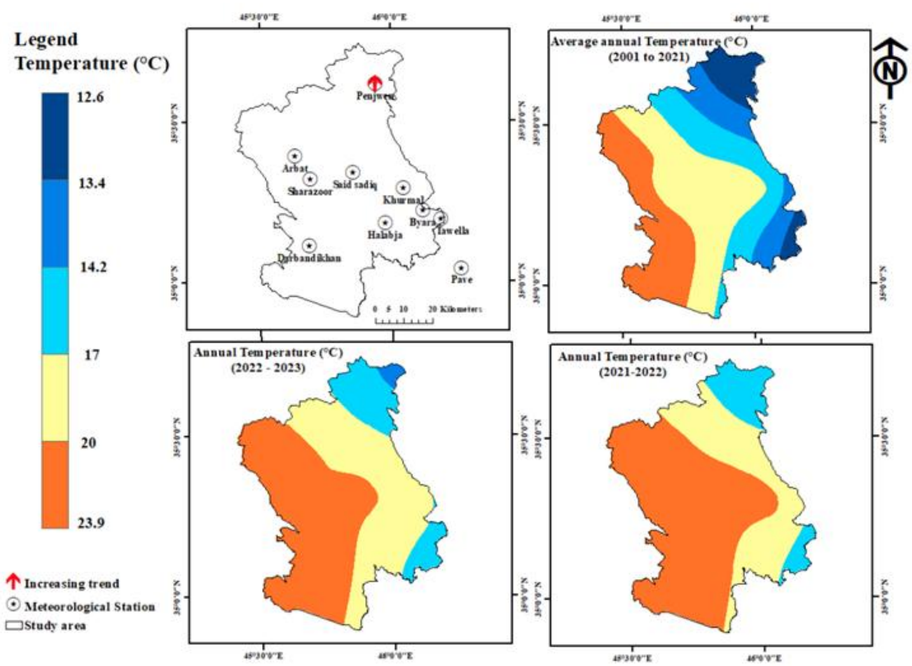

Figure 3: Spatial distribution of annual temperature over the watersheds and the surrounding area using Empirical Bayesian Kriging scheme.

2.5 Derivation of a Multivariate Model for Runoff Estimation from Limited Data

Additionally, an effort was made to develop a multivariate non-linear model to forecast runoff using temperature, rainfall, and other specific watershed characteristics as climatic variables. Many trials were made using a single, two, three, and more than three input variables using linear and non-linear least square methods. It appeared from many trials (not shown here) that a nonlinear model with three input variables was superior to other models. Table 8 presents the parameters and coefficient of determination (r^2) for the proposed multivariate non-linear model. Notably, this model explains over 99% of the variation in runoff by considering changes in rainfall, temperature, and main channel length. Among these factors, rainfall emerges as the most influential predictor for predicting runoff. On the contrary,[11] observed that the simple linear model with rainfall as an input variable was the most effective method for runoff calculation for the lower Mahi Basin. In this model, the rainfall explained more than 93% of the variation in runoff.

One of the drawbacks of this model may be overfitting, i.e., it is good for training data but not accurate for the test data due to the fact the model was built based on limited data from 3 watersheds for only two years of measurement. Therefore, it is recommended to revise this model when expanding the database in the future.

2.6 Annual Runoff Coefficient

Fig.4 presents the measured annual rainfall, annual runoff, and the computed annual runoff coefficient for the three watersheds during the hydrologic years of 2021-2022 and 2022-2023. The annual runoff coefficient is expressed as the ratio of annual watershed runoff to annual rainfall[34]. It is evident from Fig.4 that the runoff coefficient varied from as low as 2.22 % at the Darashish watershed during 2021-2022 to as high as 5.39 % at the Gulp watershed during 2022-2023. It is also evident from Fig.4 that among the three watersheds, Gulp has the strongest capacity for runoff generation compared to the remaining watersheds. Further, the runoff coefficient at a given watershed during the year 2022 -2023 has higher values compared to those of the year 2021-2022.

Variations in rainfall characteristics and antecedent soil moisture conditions may have contributed to variations in the runoff coefficient over, for the data collection years. Overall, the watershed produced relatively low values for runoff coefficient. The low annual rainfall and elevated temperature during the previous years may be responsible for the low capacity of the watersheds for producing runoff water. However, this parameter is a strong predictor of runoff generation at the catchment and regional scales and is important for hydrological research and hydrologic structure design[35].

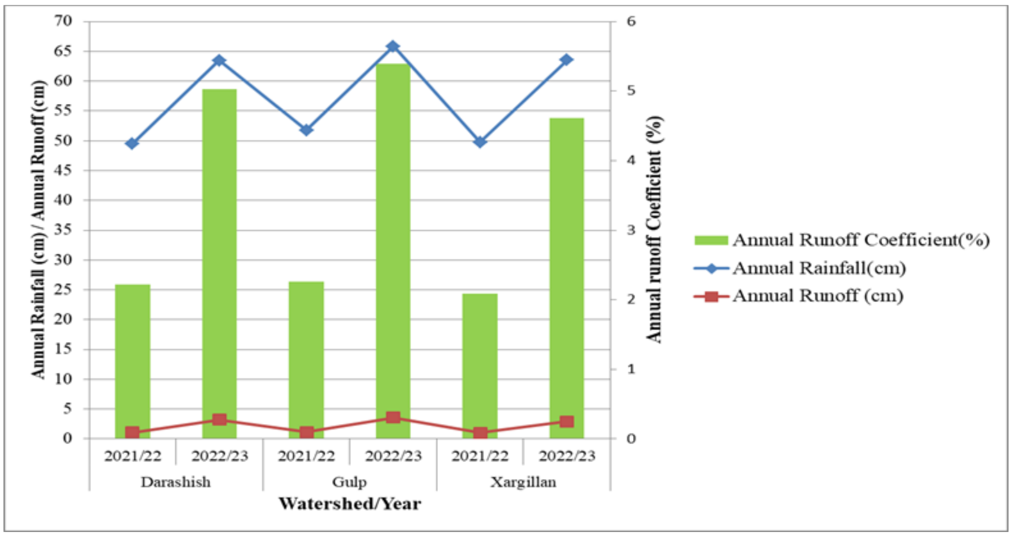

Figure 4: Measured annual rainfall, runoff, and the computed annual runoff coefficient.

Table 8: Parameters of the proposed multivariate non-linear model for predicting annual runoff over the study area.

Type of Model	$Q= \mathbf{a}\, R^{\mathbf{b}}\, T^{\mathbf{c}}\, La^{\mathbf{d}}$				
A multivariate non- linear model	**a**	**b**	**c**	**d**	R^2
	3.959×10^{-10}	4.235	-0.851	0.11	0.99
Q= Estimated annual runoff (mm), R = Annual rainfall (mm), T= Annual air temperature (ºC), La = length of the main channel(km), **a, b, c,** and **d** are fitting parameters.					

3.7 Estimation of Annual Runoff by Different Empirical Models

3.7.1 Comparison of measured and estimated runoff values

Table 9 Shows the measured and estimated runoff values by a host of empirical models in the study watershed during the hydrologic years of 2021-2022 and 2022-2023. Close examination of Table 9 revealed that the proposed model offered the best match with measured values followed by the SCS-CN and Turc. This outcome is consistent with the discovery of [36] , who found that among five different techniques, a locally derived linear model was superior to the other methods and followed by the SCS-CN method for runoff estimation in the northwest of India. In contrast, the remaining models, particularly Khosla, Indian Irrigation Department, Justin, and Lacey's models, offered the poorest results. Unlike this finding, (Golshan and Ebrahimi,

2014) considered the Lacey equation as the most precise method for runoff estimation over the watersheds of Qazvin province. Similarly,[37] considered Inglis and De Souza as the best method after the Lacy method to estimate runoff from the BanadakSadat watershed, Yazd Province, Iran.

Table 9: Estimated annual runoff by different empirical models in the study area.

Watershed	year	Annual rainfall (mm)	Ave. annual rainfall (cm)	Runoff (cm)										
				Inglis and De Souza	Indian Irrigation Department	Turc relationship	Coutagine relationship	Khosla method	Justin Equation	Indian Council of Agricultural Research	Lacey relationship	SCS-CN method	Proposed model	Measured
Darashish	2021-2022	494.95	49.49	6.18	15.96	2.45	7.19	44.52	24.57	5.08	10.83	2.46	1.06	1.10
	2022-2023	634.58	63.45	11.41	21.93	7.51	12.28	58.72	41.41	7.76	16.76	0.80	3.18	3.19
Gulp	2021-2022	517.41	51.74	6.91	16.90	3.19	7.96	46.84	28.21	5.32	11.71	2.96	1.24	1.17
	2022-2023	658.31	65.83	12.45	22.97	8.70	13.33	61.15	46.72	8.00	17.86	0.47	3.58	3.55
Xargillan	2021-2022	497.79	49.77	6.27	16.08	2.34	7.19	44.73	24.74	5.14	6.99	2.55	1.00	1.04
	2022-2023	635.32	63.53	11.44	21.96	6.88	12.02	58.64	40.99	7.63	10.96	1.00	2.90	2.93

3.7.2. Evaluation of the Models by Some Selected Performance Indicators

Table 10 presents the results of using multiple performance indicators to accurately assess the predictability of applied models. Judging from MAE, MAPE, and RMSE, it can be noticed that the proposed model offered the lowest values for these indicators and the SCS-CN and the Turc the second and third lowest values for the indicators as mentioned above. Additionally, it can be observed the proposed model offered the highest value for d and NSE. The best model is the one with the lowest amount of MAE, MAPE, RMSE, and optimum NSE, and d[5].

Table 10: Performance indicators for evaluating the empirical models.

#	Model	Performance indicators				
		MAE	MAPE	RMSE	d	NSE
1	**Inglis and De Souza (IDS)**	6.94	375.68	4.84	0.28	-43.02
2	**Indian Irrigation Department (IID)**	17.13	987.68	11.71	0.12	-256.44
3	**Turc relationship (TR)**	3.01	139.53	2.29	0.51	-8.88
4	**Coutagine relationship (CR)**	7.83	432.73	5.42	0.25	-54.07
5	**Khosla method (KH)**	50.27	2886.29	34.40	0.04	-2217.64
6	**Justin Equation (JE)**	32.27	1739.84	22.56	0.07	-953.25
7	**Indian Council of Agricultural Research (ICAR)**	4.32	256.66	2.94	0.39	-15.25
8	**Lacey relationship (LR)**	10.35	576.97	7.31	0.20	-99.19
9	**SCS-CN method**	2.01	108.21	1.42	0.00	-2.784
10	**Proposed model**	0.03	2.51	0.02	1.00	0.99

3.7.3 Test of Significance Using Paired t-Test

The results of the paired t-test also revealed the runoff depth obtained by the proposed model, and the SCS-CN model did not differ significantly at $P \leq 0.05$ from the measured values. In contrast, the runoff depth predicted by the remaining models differed significantly from the measured values (Table 11). These findings support the usefulness of the suggested SCS-CN models as stand-ins for runoff estimation at ungauged watersheds.

Table 11: T-test results for comparing the estimated runoff by empirical models and the measured values at the outlet of the watersheds during 2021-2022 and 2022-2023.

#	Model	Acronym	t-value	DF	P
1	**Inglis and De Souza**	IDS	-9.58	5	0.000
2	**Indian Irrigation Department**	IID	-19.60	5	0.000
3	**Turc relationship**	TR	-4.44	5	0.003
4	**Coutagine relationship**	CR	-11.50	5	0.000
5	**Khosla method**	KH	-18.46	5	0.000
6	**Justin Equation**	JE	-9.24	5	0.000
7	**Indian Council of Agricultural Research**	ICAR	-36.70	5	0.000
8	**Lacey relationship**	LR	-7.92	5	0.001
9	**SCS-CN method**	SCS-CN	0.5	5	0.63
10	**Proposed model**	PM	0.18	5	0.86
$t_{0.025, 5} = 2.571$					

3.7.4 Ranking of the Empirical Models by Using Compromise Programming Analysis

To further confirm the results, the employed empirical models were ranked after the determination of the compromise programming index (CPI) under different values of the parameter p and by using the measured values as reference values. The analysis was done by using the same performance indicators mentioned in this section. Initially, ranking was based on CPI values, and the three watersheds were treated separately due to limited data, so the frequency of the analysis became 1. The final ranking was based on the displayed overall weight in the last column of Table 12.

The proposed model gained the first rank, while SCS-CN and Turc models acquired the second and third ranks, respectively, irrespective of the p-value. The models that produced the best performance are those that produced the lowest values for runoff. In a similar study,[12] noticed that the SCS-CN method and the formula derived by the Dept. of Irrigation have produced very low values of runoff yield. On the other hand,[9] found the Inglis and De Souza model yielded annual runoff values close to the SCS-CN model.

The above analysis also suggests that while the proposed model appears to be the most suitable option, it's important to note that the SCS-CN method can effectively forecast runoff in other ungauged watersheds within the mountainous regions of Iraqi Kurdistan, provided relevant rainfall event data is accessible. Additionally, since the suggested model was constructed with limited data, it should be employed cautiously. Once the database is expanded, the model can be refined to be more universally applicable, and its reliability can be thoroughly examined using test data.

Table 12: Ranking the empirical models for estimating annual runoff using CPI.

#	Model	CPI			Rank based on CPI			Frequency(F)*			Calculated overall Weight(W)**		
		P=1	P=2	P=∞	P=1	P=2	P=∞	P=1	P=2	P=∞	P=1	P=2	P=∞
1	**IDS**	429.63	375.85	373.17	4	4	4	1	1	1	0.25	0.25	0.25
2	**IID**	1272.29	1018.5	985.16	7	7	7	1	1	1	0.14	0.14	0.14
3	**TR**	152.64	137.42	137.01	2	2	2	1	1	1	0.50	0.50	0.50
4	**CR**	499.21	433.83	430.21	5	5	5	1	1	1	0.20	0.20	0.20
5	**KH**	5187.98	3639	2904.07	9	9	9	1	1	1	0.11	0.11	0.11
6	**JE**	2747.28	1982.5	1737.76	8	8	8	1	1	1	0.13	0.13	0.13
7	**ICAR**	278.22	254.72	254.14	3	3	3	1	1	1	0.33	0.33	0.33
8	**LR**	693.06	583.27	574.46	6	6	6	1	1	1	0.17	0.17	0.17
9	**SCS-CN**	113.84	105.79	105.69	1	1	1	1	1	1	1.00	1.00	1.00
* All three watersheds were combined as one site; therefore, the frequency becomes 1. ** Calculated overall weight = F1 Wr1+F2 Wr2+….+FnWrn, where F is frequency of the method and Wr = inverse of rank of CPI													

Conclusions

This study concludes that there are no gauged stations or meteorological data available in any of the watersheds within the study area or its environs. In this situation, Empirical Bayesian Kriging can be employed to generate continuous surfaces for rainfall and temperature. The area under investigation is generally experiencing drought, and the yearly rainfall is trending lower. The annual runoff coefficient constitutes a small portion of annual rainfall. Among evaluated empirical models, the proposed model and SCS-CN offered the highest and second highest performance, respectively, for estimating annual runoff. The proposed model is in need of cross-validation after expanding the database for its input variables.

Authors contribution

The authors equally participated in various aspects of this project, including its implementation, research design, result analysis, and manuscript writing.

Conflict of interests

None

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