COMPARISON OF DEVELOPED AND PREVIOUSLY PUBLISHED UNIVARIATE MODELS FOR ESTIMATING EROSIVITY IN A COUNTRY WITH MEDITERRANEAN RAINFALL REGIME

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ABSTRACT

Information on the degree of water erosion is of imperative importance to professionals who are engaged in reducing soil losses via implementing soil conservation measures. Soil Conservation requires the knowledge of the factors controlling soil loss. Rainfall erosivity is one of the major controlling factors inducing water erosion. To achieve this objective, several univariate models were developed to estimate the rainfall erosivity in the upper part of Iraq. The database for models development was based on rainfall data of different time scales obtained from 25 stations distributed across the study region. The explanatory variables encompassed annual rainfall (P), Fournier index (FI), modified Fournier index (MFI) and precipitation concentration index (PCI). Additionally, the performance of a host of previously published univariate models were evaluated. Most of these models were derived for countries with Mediterranean rainfall regimes. It was observed that neither FI nor the PCI approaches were effective in capturing the variability of rainfall erosivity in the study area. Overall, the annual rainfall based models outperformed the Fournier and modified Fournier based models. The results also indicated that among eight developed models, the quadratic and linear forms of annual rainfall based models ranked first and second respectively. Additionally, the test of performance of a host of previously published models revealed they have restricted applications in Iraq.

Keywords: modified Fournier index, precipitation concentration index, models comparison, rainfall erosivity, regression models.

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المقارنة بين النماذج المتطورة والمنشورة سابقًا لتقدير دليل قابليةالمطر على التعرية في مناطق البحر الابيض المتوسط

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المستخلص

تعد البيانات المتعلقة بشدة التعرية المائية ذات أهمية حتمية للمهنيين الذين يساهمون في السيطرة على مفقودات التربة من خلال تنفيذ أجراءات صيانة الترب. تتطلب صيانة الترب معرفة العوامل التي تتحكم في كمية مفقودات التربة. ويعد دليل قابلية المطر على التعرية أحد العوامل الرئيسية الذى يتحكم على كمية مفقودات التربة. و لتحقيق هذه الأهداف ، تم تطوير عدة نماذج أحادية المتغير لتقدير دليل قابلية المطر على التعرية في الجزء الشمالى من العراق. استندت قاعدة بيانات تطوير النماذج على بيانات هطول الأمطار بمقاييس زمنية مختلفة تم الحصول عليها من 25 محطة موزعة في جميع أنحاء منطقة الدراسة. وشملت المتغيرات المستقلة على الأمطار السنوية (P) ، مؤشر(MFI) Fournier، مؤشر Fournier المعدل (MFI) ومؤشر تركيز هطول الأمطار(PCI) . بالإضافة إلى ذلك تم تقويم أداء مجموعة من النماذج أحادية المتغير المنشورة مسبقًا تعود معظمها الى مناطق البحر المتوسط. وقد لوحظ عدم فعالية كل من FI أو PCI في التقاط تباين دليل قابلية المطرعلى التعرية في منطقة الدراسة .وإشارت النتائج الى تفوق النماذج المستندة على الأمطار السنوية على النماذج المعتمدة على مؤشرى فورنيه و فورنية المعدلة. كما أوضحت النتائج أيضًا أنه من بين النماذج المتطورة و المعتمدة على الامطار السنوية أن الصيغة التربيعية والخطية احتلت لا المرتبة الأولى والثانية على التوالي. و علاوة على ذلك اشارت اختبار أداء النماذج المنشورة سابقًا الى تطبيقاتها المقيدة في العراق للتنبؤ بدليل قابلية المطر على التعرية.

كلمات مفتاحية: مؤشر Fournier المعدل، مؤشر تركيز هطول الأمطار، مقارنة النماذج، دليل قابلية التربة على التعرية ،نماذج الانحدار.

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INTRODUCTION

Information on the degree of water erosion is vital to engineers, agriculturists and soil scientists who are engaged in reducing soil losses via implementing soil conservation measures (29). Conservation of these resources is in need of the knowledge of the factors controlling natural resources like soil and water (26); (36).

Rainfall erosivity is one of the major controlling factors inducing water erosion, which is defined as the aggressiveness of the rain to give rise to erosion (20). It is the product of the total storm kinetic energy and maximum 30-minute rainfall intensity (28).

It is of vital importance to consider rainfall data series with less than an hourly time resolution for evaluating erosivity (7). By the time, such types of data are scare in Iraq and many other countries of the world. Furthermore, many attempts have been made worldwide to estimate the rainfall erosivity from more readily available rainfall data like daily, monthly and annual rainfall. Prediction of rainfall erosivity from mean annual rainfall and mean monthly rainfall has been broadly cited in the literature (2), but most of these models have restricted application outside the region where they were developed without testing their performance (14).

For the above reasons, the rainfall erosivity has been estimated using annual rainfall or indices based on monthly rainfall data. During a study, Hernando and Romana (14) have selected several estimators for estimating rainfall erosivity: total annual rainfall (P), Fournier Index (F) Modified Fournier Index (MFI) and precipitation concentration index (PCI). Bols (9) developed a relationship relating rainfall erosivity to annual rainfall applicable in Indonesia and Malaysia. Similarly, Torri et al. (30) established developed a linear relationship between R and P applicable in Italy. On the other hand, Renard and Friemund (25) established a power function model relating R to P, which is applicable in the continental US.

Arnoldus (6) observed that the Fournier Index (F) was poorly correlated with R-values for 178 stations in the United States and West Africa. As a consequence, he proposed a modification of this index and obtained significantly higher accuracy of prediction in term of R^2:

$$EI_{30} = 0.302\left(\sum_{j=1}^{m}\frac{p_i^2}{P}\right)^{1.93} \qquad [1]$$

Where: EI_{30} is the R-factor in SI unit, p_i is the mean monthly rainfall in mm for the ith month and P is mean annual rainfall in mm.

Hussein (15) observed that equation [1] approximate the R-value in the low rainfall zone of northern Iraq satisfactorily and was used as a base for preparing the isoerodent map for the indicated region. The present study is an attempt to focus on:

1) Establishment of univariate models to predict rainfall erosivity from monthly and annual rainfall depths.

2) Evaluation of some previously published models for prediction rainfall erosivity from monthly and annual rainfall depths.

MATERIALS AND METHODS

Description of the study area

The study area is located in the upper part of Iraq spanning from 34° 28′ 10″N to 37° 22′ 40″N and from 42° 22′ 15″ E to 46° 20′ 35″ E and has a total area of about 47,000 km^2. It is draining its water into the Tigris River and its tributaries (Khabour, the Greater Zab, the Less Zab, and Sirwan). The elevation ranges from less than 250 m in the wide plains to more than 3600 m at the Iraqi-Turkish and Iraqi-Iranian borders. It abuts Turkey in the north, Iran in the northeast, and Diyala and Tikrit provinces in the south and Syria in the northwest. Fig. 1 shows that the majority of employed stations are within Duhok, Erbil and Sulaimaniyah Provinces. Topography plays a major role in creating disparate microclimates ranging from arid to semiarid. The spatial distribution of rainfall is highly affected by orography. The arid zone receives rainfall less than 250 mm while the semi-wet zone receives 900-1000 mm and over. The area above the timberline is covered with snow in winter for several months. The rainfall has a unimodal distribution. In general, the annual distribution shows a dry season lasting from June to September and a wet season from October to April. There is a surplus of water from mid of

November to about mid of April. On the other hand, there is a water deficit over the remaining period of the year. Maximum occurrences of rainfall take place from November to April, which accounts for more than 90% of the total rainfall in the region. The majority of the study sites fall in Semi-arid to Semi-wet classes according to Emberger scheme (13). On the other hand, most of the study sites fall in Csa (warm temperate rainy climate) to Csb (rainy winters warm temperate summer) according to the scheme proposed by Köppen (18). The UNESCO aridity index (AI), which is based on the ratio of annual precipitation and potential evapotranspiration rates ranges from 0.1 at the lower part to 0.83 at borders. However, most of the sites can be classified as semiarid ($0.2<AI<0.5$) (30). Elsahookie et al. (12) reported similar results.

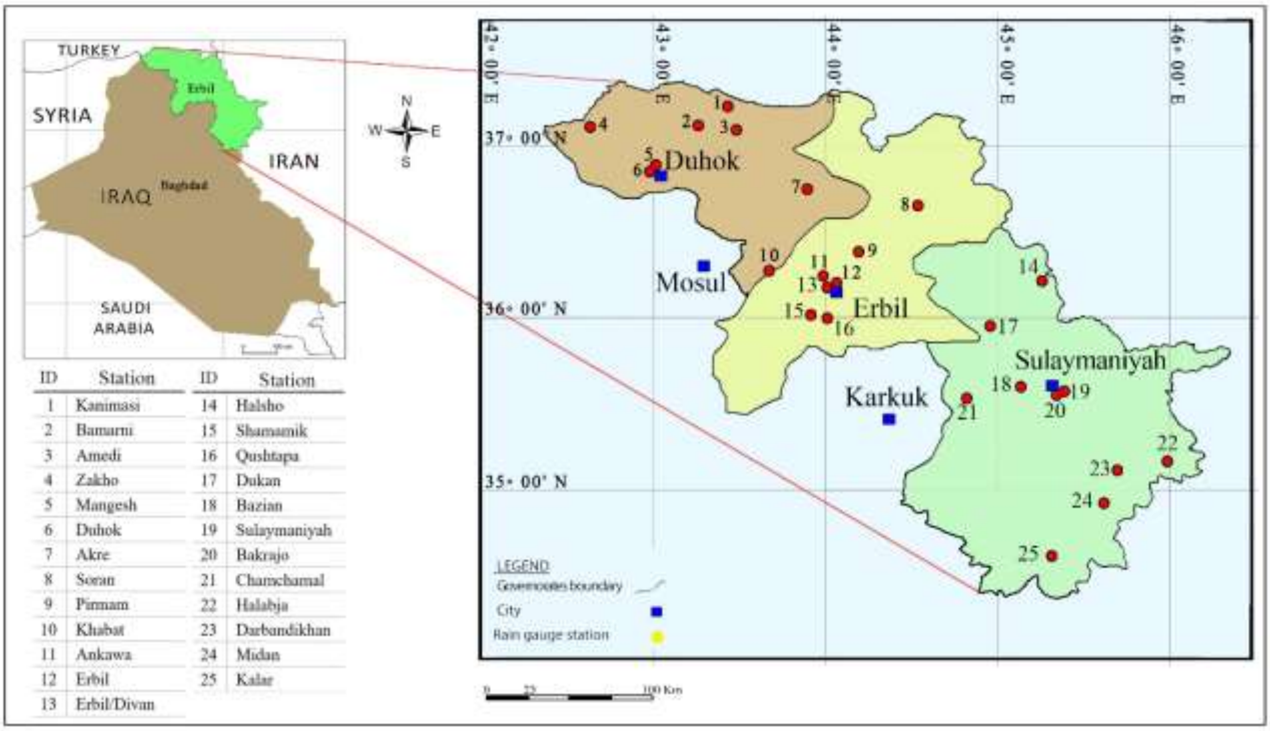

Fig. 1. Location map showing the meteorological stations within the study area.

Database

The first phase of this analysis was dedicated to rainfall data collection. The data set consists of rainfall records during 2000 -2018 at 25 rain gauges located in the study region and its peripheral areas (Fig. 1). It is worth noting that the number of stations in service has changed over the years. About 50% of the data set obtained from pluviographic stations. At these stations, the measuring device was recording rain gauge of the tipping-bucket type that is relatively well distributed over the study region. The available data with 15-minute interval was gathered from electronic rain gauges. The data were checked and filtered to remove spurious data before its release.

Data processing: The unit rainfall energy for a given interval was based on the equation developed by Wischmeier and Smith (34):

$$E_r = 0.119 + 0.0873 \log(i) \qquad [2]$$

When: $i<76$ mmh^{-1}, e_r=the unit rainfall energy (MJha^{-1}mm^{-1}) and i= the rainfall intensity during the time increment (mmh^{-1}).

Subsequently, the unit rainfall erosivity was used to calculate the rainfall erosivity (EI_{30}) for an event j (R_j) according to Panagos et al. (24); Lee and Lin (21):

$$R_j = EI_{30} = \left(\sum_{i=1}^{k} e_r V_r \right) I_{30} \qquad [3]$$

Where: V_r=the rainfall depth (mm) during the rth time interval of the rainfall event that has been subdivided into k segments. I_{30}=the maximum-30 min. rainfall intensity (mmh^{-1}).

The annual rainfall erosivity over a given year (Ry) was obtained by summing the rainfall erosivity over the year in question:

$$R_y = \sum_{j=1}^{m} R_j \qquad [4]$$

The average annual rainfall was obtained according to the equation proposed by Wischmeier and Smith (35):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{m_j}(EI_{30})_k \qquad [5]$$

Where: n=the number of years recorded, m_j=the number of erosive events during a given year j, and k=an index of a single event with its corresponding erosivity (EI_{30}).

For the sake of comparison, the above procedure was repeated for calculating the annual rainfall erosivity of the different stations after replacing the equation [2] by the equation proposed by Brown and Foster (10):

$$e_r = 0.29\left[1 - 0.72e^{-0.05i_r}\right] \qquad [6]$$

Where: I_r=the rainfall intensity during the time increment (mmh^{-1}), and e_r=the unit rainfall energy ($MJha^{-1}mm^{-1}$).

The pluvial regime of study area was assessed after calculating the precipitation concentration index (PCI) for each station according to the following equation (23):

$$PCI_{annual}(\%) = \frac{\sum_{i=1}^{n} p_i^2}{\left(\sum_{i=1}^{n} p_i\right)^2} \qquad [7]$$

Development of univariate models.

Univariate linear and nonlinear predictive models were developed for predicting annual rainfall erosivity using linear and non-linear least squares techniques. The input variables included annual rainfall, Fournier index (F), modified Fournier index (MFI) and precipitation concentration index (PCI).

Assessment of the models

Additionally, a host of statistical indices was selected to evaluate adequately the model's performance. The indicators encompassed: mean biased error (MBE), mean absolute percentage error (MAPE), root mean square error (RMSE), coefficient of variation (CV), coefficient of agreement (d), coefficient of residual mass (CRM), and symmetric mean percentage of error (SMAPE) (4); (19); (1).

In addition, the models that offered the highest performance were cross-validated using K-fold methods after subdividing the whole data was into six groups. The proposed model was fitted to 4 folds and validated using the remaining fold. This process was repeated until every fold served as a as a test set. Additionally, about of 8 percent of the was considered as unseen data used for testing the performance of the proposed model.

Evaluation of some common models for predicting rainfall erosivity

Besides developing univariate models for predicting rainfall erosivity, the performances of thirteen common univariate models that previously published were evaluated for predicting rainfall erosivity. Most of these models were derived for countries with Mediterranean rainfall regimes. The evaluation was conducted in terms of some indicators like R^2, mean absolute error (MAE) and mean absolute percent error (MAPE) and the coefficient of residual mass (CRM).

RESULTS AND DISCUSSION

General behavior of rainfall and erosivity indices in the study area

It was observed that both the monthly and annual rainfalls are characterized by high spatial and temporal variation across the study area. For, instance it was observed that the annual rainfall in the study area varied from 120.4 to1048.0 mm, with a high coefficient of variability (35.7%). Furthermore, the annual rainfall exhibited an increasing trend from west to east, and from south to north, which is related to the increase in the altitude in the same directions; the highest values occurred near the Iraqi-Iranian and Iraqi-Turkish borders. Calculation of rainfall seasonality index indicated that 48% and 32% of the existing stations within the study area showed markedly seasonal and seasonal distribution. The rest of the station (20%) showed rather seasonal. The results also revealed that of the modified Fournier index ranges from as low as 25.5 at Shamamik station during the hydrologic year of 2008-2009 to as high 227.0 mm at Darbandikhan station during the hydrologic year of 2015-2016. It was also observed that more than 80% of MFI values were less than 104 mm. This implies that the majority of the data fell in the moderate, low and very low classes of rainfall erosivity index (8). The measured rainfall erosivity in the context of USLE and RUSLE ranged from 16.6 to 112.3 and from 12.7 to 87.0 metric $ton.mha^{-1}yr^{-1}cmh^{-1}$ (hereinafter referred to metric unit) respectively. To convert this values from metric unit to $MJmmha^{-1}h^{-1}yr^{-1}$, multiply the former by 9.81. With no exception, the rainfall erosivity of all the station falls within the low erosivity class based on the scheme proposed by Carvalho (11) (R<2452 $MJmmha^{-1}h^{-1}yr^{-1}$).

Calibration of the developed univariate models

It is noteworthy that each of the study input variables like annual rainfall (P), modified Fournier index (MFI), Fournier index (FI) and precipitation concentration index (PCI) exhibited lower correlation coefficient with the rainfall erosivity in the context of RUSSEL compared to that in the context of USLE. Furthermore, it was shown that the precipitation concentration index was poorly correlated with the rainfall erosivity in the context of both USLE and RUSSLE; therefore, neither RUSLE nor PCI results are presented hereafter. Among the annual precipitation, based Model 3 has the first rank followed by Model 1 and 2 in term R^2 (Table 1). The quadratic formula describes the R-P relationship better than the simple linear and power function formulas. Additionally, it was observed from Table (1) that among the MFI based models, Model 6 offered the highest performance and Model 4 the next highest. By contrast, The Fournier based models (Model 7 and 8) offered the lowest performance in term R^2 compared with all the presented models in Table 1. The linear form of FI based model offered higher performance compared to power form of the FI based models. This implies that the FI approach was not effective in capturing the variability of rainfall erosivity in the study area.

Test of performance of the developed univariate models

Judging from the root mean square error (RMSE), the results elucidated that Model 1 and 8 offered the least and highest values for RMSE (14.14 versus 25.85) and the RMSE for the remaining models fell between these two extremes. Smaller RMSE values from a given approach indicate the closeness of the modeled values to the observed ones (16).

Table 1. Some derived models for estimating rainfall erosivity ($MJmmha^{-1}h^{-1}yr^{-1}$) from annual rainfall or modified Fournier index during the current study.

Model ID	Formula	Regressor	R^2
1	$R=0.164P-12$	P=Annual rainfall (mm)	0.797
2	$R=0.015P^{1.34}$	P=Annual rainfall (mm)	0.795
3	$R=0.00001P^2+0.153P-9.467$	P=Annual rainfall (mm)	0.798
4	$R=0.616MFI+12.14$	MFI=Modified Fournier Index (mm)	0.602
5	$R=0.676MFI^{1.016}$	MFI=Modified Fournier Index (mm)	0.567
6	$R=-0.0005MFI^2+0.727MFI+7.295$	MFI=Modified Fournier Index (mm)	0.603
7	$R=0.682FI+39.17$	FI=Fournier Index (mm)	0.355
8	$R=11.88FI^{0.456}$	FI=Fournier Index (mm)	0.252

Based on the classification scheme proposed by Wilding (33) the coefficient of variability of the predicted and observed rainfall erosivity for Model 1 through 3 are moderate (15%<CV<30%). According to this scheme, the rest of the models fell in the high class (CV>30%) indicating that the predicted R-values from model 4 through 8 were highly dispersed from the observed values. Model 3 displayed the lowest value for CV (21.95%) followed by model 1 and 2. The index of Agreement (d>0.86) suggests that model 1 through 6 are calibrated well enough to simulate the rainfall erosivity in the context of USLE. The reverse of this statement may be true for Model 7 and 8. The positive values of the coefficient of residual mass (CRM) and mean biased error (MBE) for the P and MFI based models indicated that these models tended to slightly underestimate the annual rainfall erosivity in the context of USLE. Positive and negative values for CRM are indication of underestimation and overestimation of the observed values (3). Based on the obtained values the mean absolute percent error (MAPE), the results disclosed that the P based models fell in the "forecasts potentially good" class (10%<MAPE<20%), while all forms of MFI models fell in the "forecasts potentially reasonable" class (20%<MAPE<30%). According to the scheme proposed by Lewis (22), the proposed models (3 and 1) are categorized under "Potentially good" class (MAPE< 20%). Judging from the performance indicators (R^2; MAE, MAPE, SMAPE) shown in Table 2, the conducted analysis obviously showed that Model 3 ranked first among all the developed models during this study. On the other hand, it can be observed that Model 1 the MFI provided the best results in terms of the rest of the indicators (MBE, RMSE, CV, d and CRM) are considered, it can be inferred that Model 1 scored best. It is commendable to indicate that the linear and power forms of the Fournier index based models produced an unacceptable match with the measured value of rainfall erosivity (Table 2). These models include Model 7 and 8. They provided the poorest results in terms of R^2 and the other performance indicators. Therefore, they were not recommended to be used as predictive models for estimating rainfall erosivity in the study area.

Table 2. The indicators used for examining the performance of the employed univariate models during the study.

Model ID	Performance indicator								
	R^2	MBE	MAE	RMSE	CV	d	CRM	MAPE	SMAPE
1	0.797	0.105	11.291	14.137	21.960	0.941	0.0016	18.568	19.608
2	0.795	6.352	11.619	15.601	24.234	0.930	0.0987	19.107	20.523
3	0.797	0.233	11.257	14.132	21.953	0.941	0.0036	18.512	19.639
4	0.602	0.109	15.613	19.846	30.829	0.865	0.0017	25.675	27.985
5	0.567	2.862	16.509	20.651	32.079	0.877	0.0445	27.149	29.131
6	0.603	-0.077	15.605	19.819	30.786	0.866	-0.0012	24.239	27.913
7	0.355	-0.084	19.924	25.151	39.069	0.716	-0.0013	32.765	34.181
8	0.252	5.936	20.143	25.846	40.149	0.706	0.0922	33.124	34.954

On the whole, it appears from the above analysis that the best candidates for predicting rainfall erosivity are Model 3 and 1.

The annual rainfall based models provided better results in terms of RMSE and MAPE values compared to Fournier based models. However, Model 3 topped the other models in capturing the variability of rainfall erosivity. The non-parametric Wilcoxon test indicted no significant difference between the observed and the predictive values from Model 1 and 3. To further investigate the degree of agreement between the observed and predicted values, the predicted values from each of model 1, 3, 4 and 6 were plotted versus the observed values of rainfall erosivity in relation to line 1:1. It can also be noticed from Fig. 1, annual rainfall based model (1 and 3) offered a narrower scatter compared with the modified Fournier based models (4 and 6). The plot of the bias from Models 1, 3, 4 and 6 versus the estimated values of rainfall erosivity revealed that the residuals had no a systematic distribution (Fig. 2). This implies that these models are appropriate for estimating rainfall erosivity. Additionally, Kolmogorov-Smirnov proved that the residuals yielded by the indicated models are normally distributed . The proposed models were tested for their effectiveness on some unseen data. To achieve this goal, some data (a sample with a size of 7) was kept aside. This implies that a portion of the data was not used to train the models, but used for the validation process. The results indicated that both models 1 and 3 provided reasonable accuracy in term of MAPE. The values of this indicator for models 3 and 1 were 18.512% and 18.568% respectively. Additionally, cross validation for these two models using K-fold method after portioning the training data into six folds supported the validity of these two models. The mean absolute percent was below 20%.

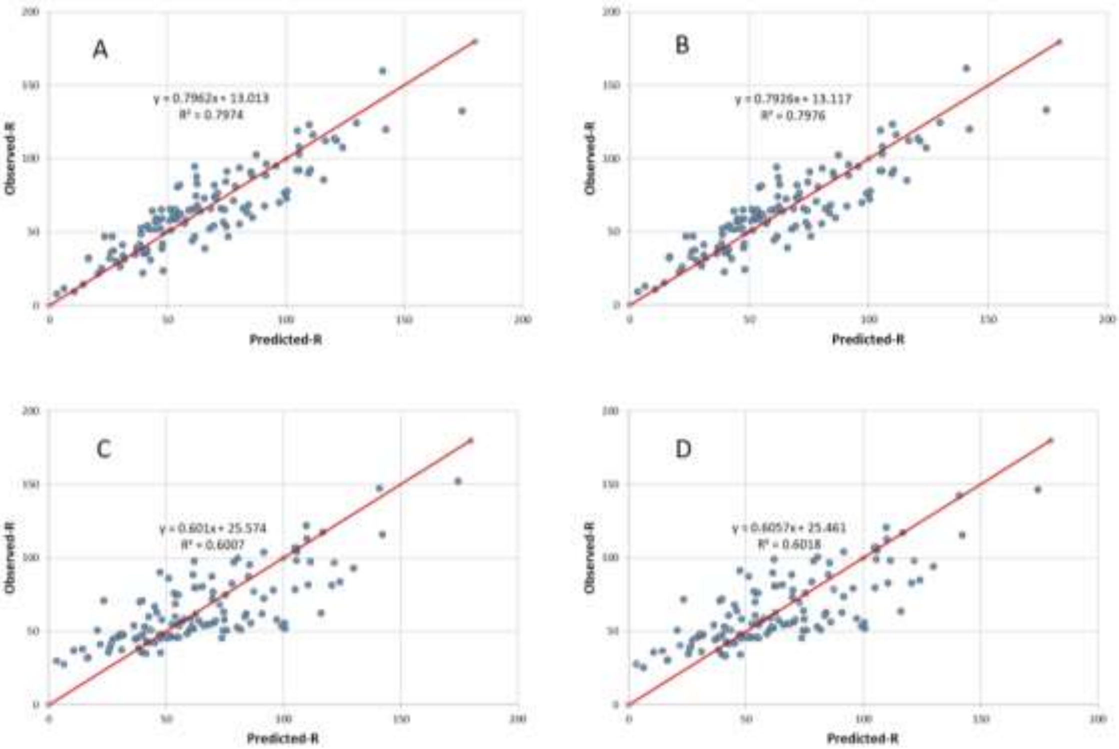

Fig. 2. Plot of observed-R versus predicted-R values from models: A= Model 1, B= Model 3, C= Model 4 and D= Model 6 in relation to the line 1:1.

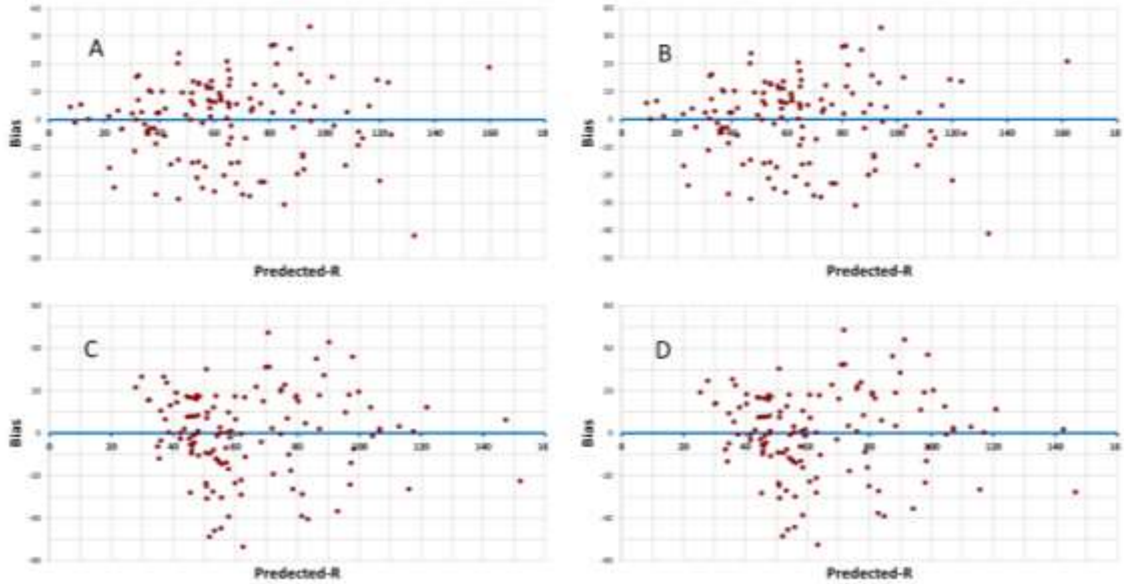

Fig. 3. Plot of bias versus predicted-R from some selected models: A= Model 1, B= Model 3, C= Model 4 and D= Model 6

Test of performance of popular models derived outside the study area for estimating rainfall erosivity

Table 3 enlists a host of the most widely used models for estimating the rainfall erosivity based on monthly and annual rainfall outside the country. With one exception, all the presented models derived outside the country offered unreasonable accuracy in term of their match with the measured values of rainfall erosivity. This is also true for the models that were derived under the Mediterranean rainfall Regime including countries like Morocco, Jordan, Turkey, Iran, and Italy. However, a number of statistical indices were applied to assess the goodness-of-fit of investigated models. In this part of the study, the fitting accuracy of different models was determined by using the mean absolute error (MAE), mean absolute percent error (MAPE) and the coefficient of the residual mass (CRM). The mean absolute percent of error varied from a minimum of 46.61% for Arnoldus (6) model to as high as 386.72% for the Renard and Friedmund (25)-F model. No model offered a MAPE of less than 30%. This implies that none of these models forecasts potentially reasonable results (22).

Table 3. Some statistical indices used for testing the performance of previously published models for predicting R-values

Model ID	Authors	Formula	Regressor	MAE	MAPE	CRM	Remarks
1	Arnoldus (1977)	$R=0.302MF^{1.93}$	MFI=Modified Fournier Index	45.447	70.591	0.2940	Morocco
2	Arnoldus (1980)	$R=4.17MF-1.52$	MFI=Modified Fournier Index	30.004	46.605	0.5339	Morocco
3	Renard and Freidmund (1994)-F	$R=0.7397MF^{1.847}$	MFI=Modified Fournier Index	248.969	386.718	-2.8674	U.S.
4	Renard and Freidmund (1994)-P	$R=0.0483P^{1.61}$	P=Annual precipitation(mm)	38.190	59.319	0.4068	Continental U.S.
5	Ferrari et al (2005)-linear	$R=4.0412P-965.53$	P=Annual precipitation(mm)	39.894	61.967	0.3803	Italy
6	Ferrari et al (2005)-power	$R=0.092MF^{1.4969}$	MFI=Modified Fournier Index	31.890	49.533	0.5046	Italy
7	Wischmeier and Smith (1978)	$R=\sum_{i=1}^{12} 1.735\times 10^{1.5\log(MF)-0.8188}$	MFI=Modified Fournier Index	88.627	137.663	-0.3767	U.S.
8	Bols (1978)	$R=\frac{2.5P^2}{100(0.073P-0.73)}$	P=Annual precipitation(mm)	48.116	74.738	0.2526	Indonesia
9	Hussein (1988)	$R=0.0033\sum_{i=1}^{n} p_i^2$	P=Annual precipitation(mm)	49.542	76.952	0.2304	Iraq
10	Torri et al (2006)	$R=3.08P-944$	P=Annual precipitation(mm)	77.921	121.032	-0.2104	Italy
11	Eltaif et al (2010)	$R=23.61\,e^{0.0048P}$	P=Annual precipitation(mm)	35.661	55.392	0.4460	Jordan
12	Zare et al (2017)	$R=1.34FI^2-37.4FI+286.4$	FI=Fournier Index	154.674	240.252	-1.4027	Iran
13	Irvem et al (2007)	$R=0.215MF^{2.3421}$	MFI=Modified Fournier Index	35.836	55.664	0.4433	Turkey

The performance indicators listed in Table 3, also confirms the poor predictability of all the models listed in Table 3 for estimating the rainfall erosivity. It can be inferred from the presented data that Table 3, that with no exception all models have restricted application for estimating the rainfall erosivity in the study area indicating that there are other factors other than the intensity that affecting the variability of rainfall erosivity. Albeit the derivation of Model 9 was based on average monthly and annual rainfall for 49 meteorological stations across Iraq (15), the mean absolute percent error was about 77%. The main reason for this inconsistency is due to the fact the estimated rainfall erosivity values from Arnoldus model (5) were considered as reference values instead of using observed rainfall erosivity values. Furthermore, employed data belonged to the period of record from 1941 to 1980. The subsequent substantial change in the rainfall characteristics may another reason for this disparity. As the annual rainfall data is undoubtedly the simplest, most reliable and more readily available, the use of annual rainfall based models are preferred over other developed models during this study. Rosewell (27) reported that the simple relation between R and P can be used to indicate the sensitivity of soil loss to rainfall fluctuation. In view of the above analysis, it is recommended to use Model 3 and 1 a for estimating rainfall erosivity in the region under study.In can be concluded from above results that the annual rainfall univariate based models provided better results than the modified Fournier index and Fournier index based models for estimating rainfall erosivity. Test of performance of a host previously published univariate models derived outside the country revealed that all these models have restricted application in Iraq.

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