

# Spatial and temporal rainfall erosivity change throughout the 21st century by statistical downscaling model

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**Abstract:** Global climate change will induce changes in rainfall patterns and increase in rainfall events and consequently increase rainfall erosivity. In this study, simulating future rainfall erosivity was considered under different statistical downscaling model (SDSM) scenarios in the North of Iran. Rainfall erosivity (R-factor) until the end of the 21st century and during the current period were compared under four scenarios. With regard to regression equation between R-factor and daily rainfall, annual rainfall and modified founrier index (MFI), it was found that annual rainfall and R-factor had the highest correlation ( $R^2=0.812$ ) and thus, it was extended for future periods. Annual rainfall erosivity in the Kasilian watershed indicated a high degree of variability from year to year (139 years of study), ranging from 302 to 693 MJ ha<sup>-1</sup>mmh<sup>-1</sup>. Although, in the early 21st century and at the end of it, rainfall erosivity is greater than the mid-21st century, rainfall erosivity will be higher than the current period in all studied periods. Current rainfall erosivity was 388.18 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>, which, under the effect of climate change will be increased 6-31% under the HadCM3 scenario and rainfall mean will increase 2-5%. The results reveal that rainfall with extreme intensity and less duration will occur. The spatial interpolation method indicated that the R-factor will increase towards the highlands, therefore, future rainfall erosivity changes will have significant impacts on soil and water resources in the North of Iran.

**Key-Words:** Erosion, rainfall erosivity, climate change, Iran

## 1 Introduction

The rainfall erosivity, whose concept were developed by Wischmeier and Smith [1], describes an interaction between the kinetic energy of raindrops and the consecutive 30-min maximum rainfall intensity during the storm the soil surface indicating. Rainfall erosivity is one of the key input parameters for (R) RUSLE modeling that was first calculated by Wischmeier and Smith [1]. All factors required for calculating rainfall erosivity are under the effect of rainfall patterns. Any changes in precipitation, whether in amounts of rainfall intensity, rainfall frequency, spatial extent, duration, and timing of extreme weather may directly influence rainfall erosivity and erosion rates [1,2,3].

Global precipitation has changed under climate change [4]. Climate change lead to changes in climate variables such as precipitation, temperatures, windiness and solar radiation [5], which affect rainfall erosivity in a variety of ways. One of the most direct impacts of climate change is the change in the erosive power of rainfall [6].

In order to investigate the effects of climate change and different scenarios on rainfall erosivity, several studies have been conducted which indicate climate change has a direct impact on rainfall

characteristics and it will lead to increase in rainfall erosivity in future [7,8,9].

Research has been conducted to assess future changes in R-factors based on Global Climate Model (GCM) outputs [5]. GCM outputs cannot provide rainfall characteristics which are able to directly estimate rainfall erosivity. Therefore, in many of the studies in the literature, by regression relationship between annual rainfall, monthly rainfall or daily rainfall of GCM outputs and rainfall erosivity, the researchers could simulate rainfall erosivity condition in future [10,11].

Although these models are very useful in the investigation and predictions climate change in future, the current versions of GCMs are according to a large grid scale from 250 to 600 km [12] and unable to resolve important sub-grid scale features Under certain conditions such as clouds and topography [13].

To overcome this problem, downscaling methods have developed as a means of connecting regional-scale atmospheric predictor variables to local-scale surface weather so that the local scale is defined as 0–50 km and the regional scale as 50\*50 km [14]. Among these downscaling models, the Statistical Downscaling Model (SDSM) has been used widely

to generate climate data such a precipitation and temperature throughout the world [13,15,16].

The objectives of this study were to investigate the adaptability of SDSM for downscaling precipitation in the Kasilian watershed and simulate future rainfall erosivity change in the Kasilian watershed.

## 2 Study area and data description

### 2.1. The case-study area

The target area of this study was the region surrounding the Caspian Sea (Fig. 1), located at 53°01' to 53°26' E and 35°01' to 36°32' N containing Shirgah city, Zirab city in Mazandaran Province and it is drained by the Talar River and its tributaries. It has a spatial extent of almost 342.86km<sup>2</sup> and a mean altitude of 1080m. Climate is characterized by extreme wet (summer) and dry (winter) seasons with 95% of its annual rainfall occurring between the months of September and June. Mean annual rainfall varies from 600 mm to 110 mm across the catchment with higher rainfall occurring in the plain areas. The average annual temperatures range from 18°C on the plain areas to 10°C in the mountains. The study area is composed of a variety of land cover types, mainly forest (82.2%), and remainder of the study is 14% rangeland, 2.4% settlement and 1.4% agricultural. The soil in this basin is primarily of podzolic, brown forest and sedimentary types. The Kasilian is sensitive to environmental change. Soil loss in the Kasilian has been caused by both natural factors and human activities and has been a critical issue during the past few decades.

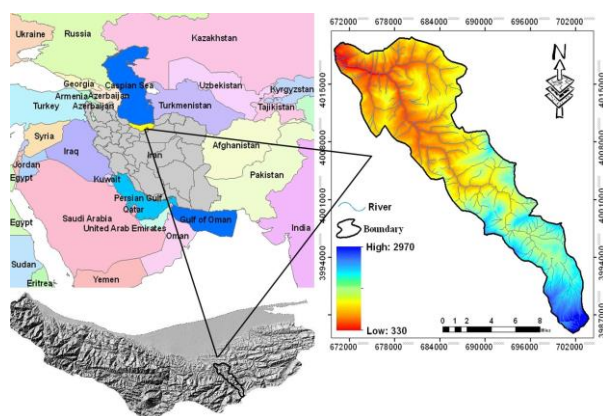


Figure 1: Location, boundary, and watershed in the North of Iran.

### 2.2. Data description

The historical observed daily precipitation data covering 1961–2000 from 6 Iran Water Resource

Management Company (IWRMC) stations were used in this study.

The predictors which are large-scale atmospheric field data are divided into two groups that included observed predictors and modeled predictors. National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis gridded data sets and (GCMs simulated gridded data) from the grid box of the predictor dataset closest to the study area were observed predictors and modeled predictors, respectively.

## 3 Methods

### 3.1. Rainfall erosivity

The rainfall erosivity according to Daily rainfall (EI<sub>30</sub>) in the RUSLE model is obtained through the R-factor quantifying the effect of kinetic energy of a rainfall event and its maximum 30- minute intensity (eq. 1):

$$R = \frac{1}{n} \sum_{i=1}^n [\sum_{k=1}^m KE(I_{30})] \quad (1)$$

Where R is rainfall erosivity (MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>), KE is total kinetic energy of each index (MJ ha<sup>-1</sup>), I<sub>30</sub> is the maximum intensity of 30-minute rainfall (mm h<sup>-1</sup>).

The kinetic energy of each index is calculated through Wischmeier and Smith equation [1] (eq. 2):

$$KE = (11.98 + 8.73 \log_{10} I) \quad (2)$$

There were only a limited number of rainfall register stations in Kasilian watershed and its surrounding that makes the rainfall erosivity calculation difficult. So, in order to overcome this defect, the monthly and annual average rainfall amounts have been used to estimate R-factor by Renard and Freimund [17] equation resulted from Wischmeier studies. Hence, after determining the desired stations, the monthly and annual rainfall was achieved. In the next step, Fournier index and R-factor were obtained for all rain gauge stations in the Kasilian watershed using equation (3).

$$F = \frac{\sum_{i=1}^{12} P_i^2}{\sum_{i=1}^{12} P} \quad (3)$$

Where P<sub>i</sub> is the average rainfall (mm) and p is the annual average rainfall (mm).

Fournier index equation was calculated for the stations with rain gauge. In the next step, there was a relationship between the values resulted from Fournier index and rainfall erosivity index. Finally,

the rainfall erosivity map in Kasilian watershed was prepared using the interpolation method in ArcGIS 10.3 software.

### 3.2. Climate change scenarios

In order to investigate the impact of climate change and different scenarios on rainfall erosivity in future, climate variables such as precipitation and temperature are predicted under the change of local climate at basin scale that are due to modification of the general circulation in the atmosphere. Global Climate Model (GCM) outputs were used. The transformed GCM data for 1961–2099 was directly downloaded from the Internet (<http://ccds-dscc.ec.gc.ca>). Then, the simulation of future rainfall erosivity was calculated based on those climate change scenarios.

### 3.3. Description of SDSM

The Statistical Downscaling Model (SDSM) is developed by Wilby [13], which is an integration of Stochastic Weather Generator (SWG) and Multiple Linear Regression (MLR) for generating future climate scenarios to assess the impact of global climate change. The SDSM modeling of daily precipitation consist of step-wise process: modeling precipitation occurrence followed by modeling of precipitation amounts while precipitation occurs [18]:

$$O_i = \alpha_0 + \sum_{j=1}^n \alpha_j p_{ij} \quad (4)$$

$$R_i^{0.25} = \beta_0 + \sum_{j=1}^n \beta_j p_{ij} + e_i \quad (5)$$

Where  $O_i$  is the daily precipitation occurrence,  $R_i$  is daily precipitation amount,  $p_{ij}$  are predictors,  $n$  is number of predictor,  $\alpha$  and  $\beta$  are model factors and  $e_i$  is modeling error.

The main procedures of the SDSM for downscaling wet precipitation (predictands) contains four parts: (1) identification of predicts and predictors; (2) model calibration; (3) weather generator; (4) generation of future series of climate variable. In this study, the large-scale predictors for the meteorological prediction signing the SDSM model were used according to NCEP outputs in calibration step, as well as A1B and A2 for CGCM3, A2 and B2 for HadCM3 model for future generation.

A simulation of mean monthly rainfall during the calibration and validation of the SDSM were checked by using the coefficient of correlation (R) and root mean square error (RMSE).

## 4 Result and discussion

Results of the relationship between rainfall erosivity index and Fournier index, daily rainfall and annual rainfall rate based on 598 events show that the best fit between rainfall erosivity and annual precipitation was obtained with a power law equation ( $R^2=0.812$ ) so it can be used for the stations without rain gauge using the obtained equation and based on Table 1, R-factor did not correlate with other factors.

Table 1: Relationship between rainfall erosivity index and Fournier, Daily and annual precipitation.

Rainfall erosivity	Equation	$R^2$
Fournier index	$y = 0.98x + 6.75$	0.25
Daily rainfall	$y = 0.007x + 0.29$	0.34
Annual rainfall	$y = 0.0169x + 1.14$	0.812

### 4.1. Calibration and validation of SDSM

The Statistical Downscaling Model was first calibrated using large-scale predictor variables of the current climate condition derived from the NCEP reanalysis dataset as driving data, and then validated in an independent time period using NCEP data [15].

In order to observed data series for 1961–1990 were divided into two periods, 1961–1980 and 1981–1990, used for model calibration and validation, respectively. The monthly precipitation of the six climatic stations shows in table 2 during the calibration period.

Table 2: Performance assessment of the Statistical Downscaling Model during calibration (1961–1990) for precipitation, in the Kasilian watershed.

Station	$R^2$ (mean)	SE (mean)
Darzikola	0.283	0.387
Sangdeh	0.45	0.236
Rigcheshmeh	0.616	0.204
Shirgah	0.319	0.3
Kaleh	0.68	0.194
Talar	0.55	0.212

To validate the SDSM model, five sets of atmospheric data were used, i.e., from NCEP, as well as scenarios A2 and B2 from HadCM3 model, A1B and A2 for CGCM3.

## 4.2. Change of Future precipitation downscaling scenarios

In this study, the generated of precipitation was divided into basis period (1961-1990) and future period 2020s (2010-2039), 2050s (2040-2069), and 2080s (2070-2099). In fact, the pattern of change under future precipitation scenarios were analyzed using H3A2, H3B2, CGCA1 and CGCA1B data compared to basis period.

The changes of mean precipitation in Kasilian watershed under scenarios H3A2, H3B2, CGCA1 and CGCA1B would present obvious differences in different periods. Furthermore, rainfall changes in future years are under the effect of different scenarios and spatial distribution of stations.

The results indicated rainfall mean in all stations was 833 mm in current period so that for CGCM3 scenarios, rainfall mean is less than the current period. The results showed in the first simulating period, rainfall mean was more than current period which H3A2 and H3B2 scenario, rainfall mean was 8% and 11% more than current period, respectively. However, in the second and third simulating periods and most of the scenarios, the amount of rainfall will decrease compared to current period.

Generally, under H3A2 and H3B2 scenarios, rainfall mean will increase 2% and 5% compared to current period, respectively. However, under CGCM3A1 and CGCM3A1B scenarios, rainfall mean will be 4% and 8% less than current period.

## 4.3. Change of current and Future rainfall erosivity under downscaling scenarios

Figure 2 presents rainfall erosivity and its changes the region during the three future periods under the different scenarios. The range annual R-factors varied between 302 and 693 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup> from site to site during 1961-2099. The smallest R-factors (302 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>) concerns Darzikola station and current period. The maximum value (693 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>) was calculated in Talar station and H3A2 (2020s).

Rainfall erosivity variation in the current period (1961-1990) in the study region was equal to 388 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>, whereas rainfall erosivity in future periods has become much more than current period. Rainfall erosivity variations in 2020s and 2080s were close to each other and in 2050s it will be much less. In fact, it is expected that, in mid 21<sup>st</sup> century, less erosivity will occur than early and late 21<sup>st</sup> century.

However, Zhang et al. [11] have announced the most rainfall erosivity in China will take place according to A2 and A1B scenarios. The results

indicated rainfall erosivity mean in all scenarios and the first simulating period was 466.78 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup> which shows 28% increase in rainfall erosivity in this period.

This condition shows 9% and 21 % increase for the second and third simulating periods, respectively. However, rainfall mean in H3A2 (8%) and H3B2 (11%) was more than current period. In other words, a little change in rainfall will lead to great change in rainfall erosivity. Also, Plangoen and Babel [19] in Thailand have announced 2% and 7% increase in rainfall in 2011-2040 and 2071-2099 will lead to 5% and 14% increase in rainfall erosivity. It seems that the change of rainfall pattern was one of the most important effects of climate change so that the rainfall with extreme intensity and less duration has occurred and consequently, rainfall erosivity will increase in future.

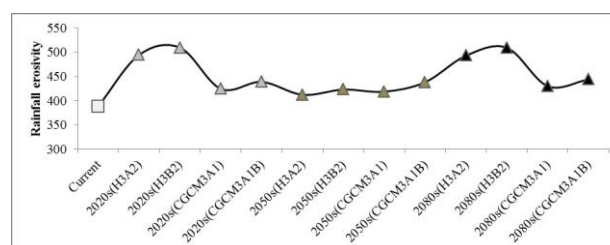


Figure 2: Comparison of rainfall erosivity in current and future periods under climate change scenarios

## 4.4. Spatial distribution of rainfall erosivity in current and future period

The spatial rainfall erosivity in current and future periods under different climate change scenarios is presented in figure 3.

Overall, the R-factors gradually increased from the south east to the north west of the watershed. The values were less than 277 MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup> in Current period and more than MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup> in future period and H3B2 (2020s) scenario. This condition is completely related to rainfall in the region so that the amount of rainfall increases from Highland toward plain areas.

The result of rainfall erosivity zoning in future climate indicates the R-factors of the Kasilian for each of the three future periods increased when compared to the current period. Nearing et al. [4], have been confirmed the trend of increase rainfall erosivity.

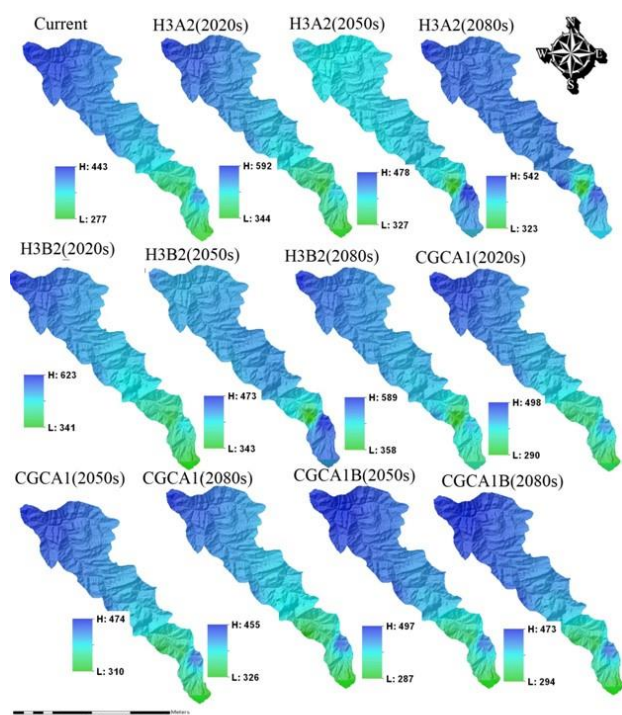


Figure 3: Spatial distribution for rainfall erosivity in current period (1961-1990) and future periods (2010-2039, 2040-2069 and 2070-2099)

## 5 Conclusion

In this study, it was assessed the expected impacts of future climate change on rainfall erosivity in the Kasilian watershed. According to the obtained results, rainfall erosivity will increase in future climate. These changes have rather close relationship with the rainfall in the region so that rainfall means under scenarios H3B2 and H3A2 and for all periods will increase 2% and 5% in comparison to current period, respectively. Despite little increase in rainfall, rainfall erosivity value will increase to a rather great extent. That is, rainfalls with more intensity and less duration will occur in future climate. As far as spatial erosivity changes are concerned, the results of this study indicate rainfall erosivity will move to highlands in future climate. With regard to decrease in land cover density in highlands, it is expected that soil erosion hazard will increase since with an increase of 1% in the rainfall erosivity, soil erosion rates increase by 0.8 to 1 percent.

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