A new approach for suspended sediment load calculation based on generated flow discharge considering climate change

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ABSTRACT

Use of general circulation models (GCMs) is common for forecasting of hydrometric and meteorological parameters, but the uncertainty of these models is high. This study developed a new approach for calculation of suspended sediment load (SSL) using historical flow discharge data and SSL data of the Idanak hydrometric station on the Marun River (in the southwest of Iran) from 1968 to 2014. This approach derived sediment rating relation by observed data and determined trend of flow discharge time series data by Mann-Kendall nonparametric trend (MK) test and Theil-Sen approach (TSA). Then, the SSL was calculated for a future period based on forecasted flow discharge data by TSA. Also, one hundred annual and monthly flow discharge time series data (for the duration of 40 years) were generated by the Markov chain and the Monte Carlo (MC) methods and it calculated 90% of total prediction uncertainty bounds for flow discharge time series data by Latin Hypercube Sampling (LHS) on Monte Carlo (MC). It is observed that flow discharge and SSL will increase in summer and will reduce in spring. Also, the annual amount of SSL will reduce from 2,811.15 ton/day to 1,341.25 and 962.05 ton/day in the near and far future, respectively.

Key words | flow discharge, suspended sediment loads, the latin hypercube sampling, the Markov chain method, the Monte Carlo method

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HIGHLIGHTS

- Use of data generation methods and trend tests for detection of climatic change.
- Determination of 90% of total prediction uncertainty bounds by LHS on MC.
- Increase of monthly flow discharge and SSL in summer from 2014 to 2094.
- Reduction of monthly flow discharge and SSL in spring from 2054 to 2094 .

INTRODUCTION

The control of erosion, sediment transport, sedimentation and water quality are considered important issues in watershed management, river engineering and design of hydraulic structures. In recent decades, climatic changes, global warming, increasing population growth and human activities have ruined forests, pastures, wetlands and other natural resources. Humans have developed cities and industrial regions; this matter has reduced permeability of watersheds and has increased flow discharge of floods and erosion of watersheds. By increasing sediment yield, water quality will be reduced and the life of aquatic vegetables, animals and fish will be endangered.

Due to a shortage of sediment data and their low quality, generating synthetic data using methods such as the Markov chain and Monte Carlo methods is necessary. These methods are stochastic approaches used for data generation.

This study deals effectively with different methods for generation of flow discharge and SSL time series and evaluation of the ability of these methods to generate the time series for the future.

The performed researches have paid attention to only one aspect of application of these methods; these studies are classified to the categories below:

(a) Generation of flow discharge time series data by the Markov chain method:

Xu *et al.* (2001, 2003); Adib & Mahmoodi (2017) only used the Markov chain method to generate daily, monthly and annual flow discharge time series data in flood or non-flood conditions.

(b) Derivation of sediment rating equation:

Emamgholizadeh & Demneh (2019); Cigizoglu (2004); Cigizoglu & Alp (2006); Cigizoglu & Kisi (2006); Raghuwanshi *et al.* (2006); Zhu *et al.* (2007); Melesse *et al.* (2011); Malik *et al.* (2017); Alp & Cigizoglu (2007) utilized different types of artificial neural network (ANN) for derivation of sediment rating equation and estimation of suspended sediment load (SSL). Also, Adib & Mahmoodi (2017) utilized ANN and the Markov chain method for estimation of the suspended sediment load (SSL). They did not use different data generation methods and total prediction uncertainty bounds and did not evaluate the trend of observed flow discharges. Then, they did not estimate the range of SSL for the future.

(c) Application of MK trend test and TSA estimator to find the trend of flow discharge time series data:

Mostowik *et al.* (2019); Sun *et al.* (2019); Masih *et al.* (2011); Abghari *et al.* (2013); Zamani *et al.* (2017); Adib *et al.* (2017a, 2017b); Tekleab *et al.* (2013) applied the MK trend test and TSA estimator to identify increasing or decreasing trends of flow discharge time series data in different watersheds.

(d) Generation of flow discharge time series data and uncertainty analysis of these values by MC method:

Zhu *et al.* (2018); Zhang *et al.* (2016); Razmkhah (2018); Adib *et al.* (2019) utilized the MC method to generate daily, monthly and annual flow discharge time series and hydrodynamic models to evaluate the effects of uncertainty of parameters on simulated flow discharge. They did not get a relation between their researches and estimation of SSL in the present and the future periods.

The novelty of this study is development of a procedure to detect the effects of climatic change on flow discharge and SSL. The new aspects of this procedure include the following cases.

1. Simultaneous use of the Markov chain and MC methods to generate flow discharge time series and comparison of these methods.
2. This research compares generated flow discharge time series with both observed and predicted flow discharge time series.
3. Use of generated flow discharge time series data by MC method to determine 95% of total prediction uncertainty bounds. Comparison between the uncertainty bounds and the results of the MK test and TSA estimator can show the effects of climatic change.
4. Selection of the best model (the Markov chain or MC methods) and flow discharge time series data (average of 100 monthly and annual generated flow discharge time series data or the driest or the wettest monthly and annual generated flow discharge time series data) for estimation of monthly, seasonal and annual SSL in a historical period (1968–2014), near future (2014–2054) and far future (2054–2094).
5. Using the MK test, TSA estimator and the Latin Hypercube Sampling (LHS) on MC for determination of variations of flow discharge and SSL at the future. These methods use observed data, while the global circulation models (GCMs) and downscaling models utilize various scenarios and their uncertainty is more than those of the applied procedure in this study.

MATERIALS AND METHODS

The Marun watershed

The Marun Watershed is located in the southern part of the Zagros Mountains, in the southwest of Iran, between 30° 30′

to 31°20′ N and 49°50′ to 51° 10′ E. The area of this watershed is 5,401 km². The maximum and minimum heights of this watershed are 3,400 and 195 meters above sea level (asl). The length of the Marun River is 201.3 km. The Marun River has five main branches and its source is the Zagros Mountains. By connecting the two rivers Marun and Allah, the Jarahi River is formed (Adib & Mahmoodi 2017).

The distance between Idanak hydrometric station (in 50°28′ E and 30° 57′ N) and the Marun Dam is 40 km. Since this station is upstream of the Marun Dam, the flow discharge of the station is not regulated by dam. The height of this station is 610 m (asl) and the area of its watershed is 2,776 km². In this station, the mean annual potential evaporation, temperature and precipitation are 2,742.3 mm, 22.9 °C and 651.45 mm, respectively. In addition, the mean annual flow discharge and SSL are 51.34 m³/s and 2,811.15 ton/day. This station was established in 1968 (the first hydrometric station on the Marun River) (Adib & Mahmoodi 2017). Figure 1 illustrates the location of the Idanak watershed in Iran.

The Markov chain method

The Markov chain method memorizes stochastic characteristics historical data such as mean, variance, skewness coefficient, governing stochastic distribution and so on. In this research, the monthly Markov chain method is applied for generation of synthetic data. The equation used is:

$$Y_{i,j+1} = \overline{Y}_{j+1} + b_j(Y_{i,j} - \overline{Y}_j) + t_{i,j+1}S_{Y_{j+1}}(1 - r_j^2)^{1/2} \qquad (1)$$

$$b_j = r_j \frac{S_{j+1}}{S_j} \qquad (2)$$

In which: *i* is index of year and j is index of month, $Y_{i,j+1}$ is generated data for the *i*th year and month (*j* + *1*)th, $Y_{i,j}$ is generated data for the *i*th year and *j*th month, r_j is the regression coefficient between observed data of the *j*th and (*j* + *1*)th months, S_y is the standard deviation of observed monthly data, $\overline{Y}$ is the mean of observed monthly data, t_{i+1} is a random value that is regarding to the governing probability distribution on data (for normal probability distribution, t_{i+1} is equal to the frequency factor (*k*) of normal probability distribution).
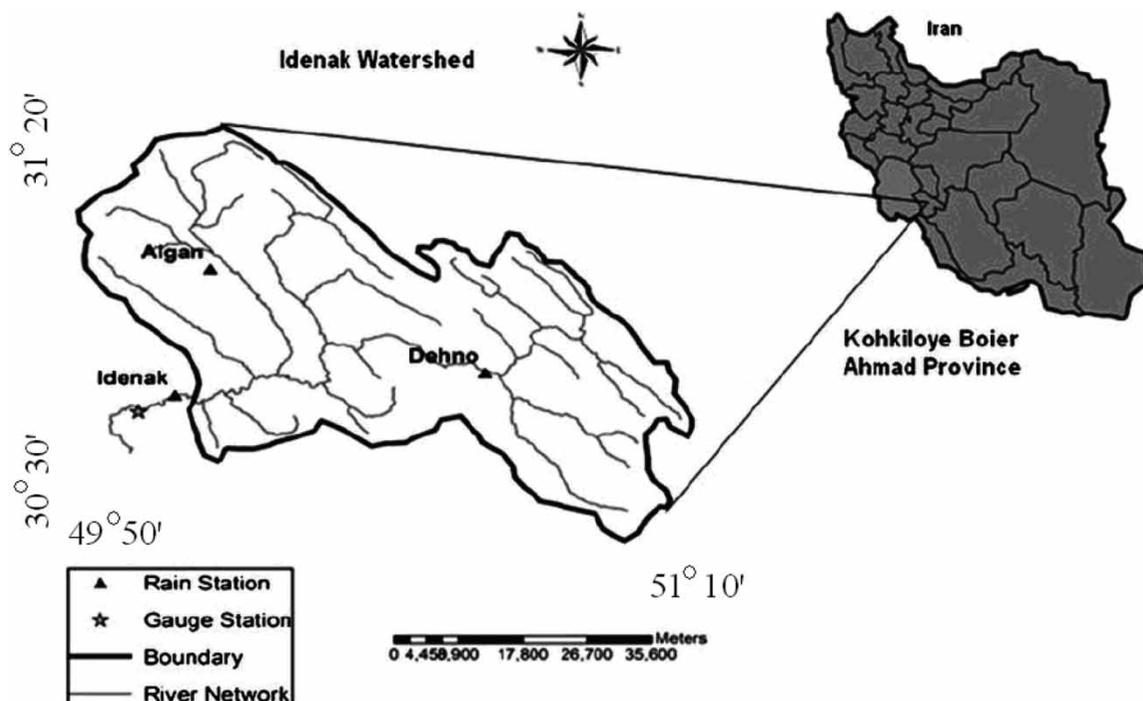

Figure 1 | The location of the Idanak Watershed in Iran (Rezaeian-Zadeh *et al.* 2013).

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The Monte Carlo (MC) method

This research utilized the Monte Carlo (MC) method to generate data. This method generated 4000 monthly flow discharge time series data. For each month and each time series, the number of generated data is 40.

The MC method is a mathematical method that generates random data considering probability distribution governing the main time series data. This method calculates quantiles and values of different confidence levels (for example 90% (it ranges from 5% to 95%)) of the whole predicted uncertainty bounds. The predicted uncertainty bounds are determined by probability distribution governing the generated time series data.

Methodology

The procedure of this study includes the following steps:

1. Collection of daily flow discharge and suspended sediment load (SSL) time series data from the Khuzestan Water and Power Authority (KWPA).
2. Evaluation of homogeneity of flow discharge time series data by run test and stationary of flow discharge time series data by the Augmented Dickey-Fuller test (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin test (KPSS), detection of change points of flow discharge time series data by the Pettitt's test, the trend analysis by the Mann-Kendal test (MK) and calculation of the trend line slope by the Theil–Sen's approach (TSA) estimator.
3. Prediction of monthly and annual flow discharge in the future based on monthly and annual observed flow discharges and calculated slope of trend line by TSA estimator.
4. Generation of flow discharge time series data by the Markov chain and Monte Carlo (MC) methods.
5. Determination of average, driest and wettest generated flow discharge time series data by two methods.
6. Extraction of sediment rating relation and determination of monthly and annual SSL in the future based on monthly and annual generated flow discharges by TSA estimator.
7. Determination of monthly and annual SSL related to average, driest and wettest generated flow discharge time series data by the Markov chain and MC methods.
8. Selection of SSL related to the model (the Markov chain or MC methods) and flow discharge time series data (average of 100 monthly and annual generated flow discharge time series data or the driest or the wettest monthly and annual generated flow discharge time series data) that has the most compliance with observed and predicted SSL.
9. Determination of 90% of total prediction uncertainty bounds for flow discharge time series data by the LHS on MC and its relationship to occurrence of climatic change.

Figure 2 illustrates the flowchart of research methodology.

The performance criteria

In order to evaluate the performance of the models, the following criteria are applied:

Root mean square error (m^3/s):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{pre}^i - Q_{obs}^i)^2} \tag{3}$$

where: Q_{pre} is the predicted flow discharge and Q_{obs} is the observed flow discharge.

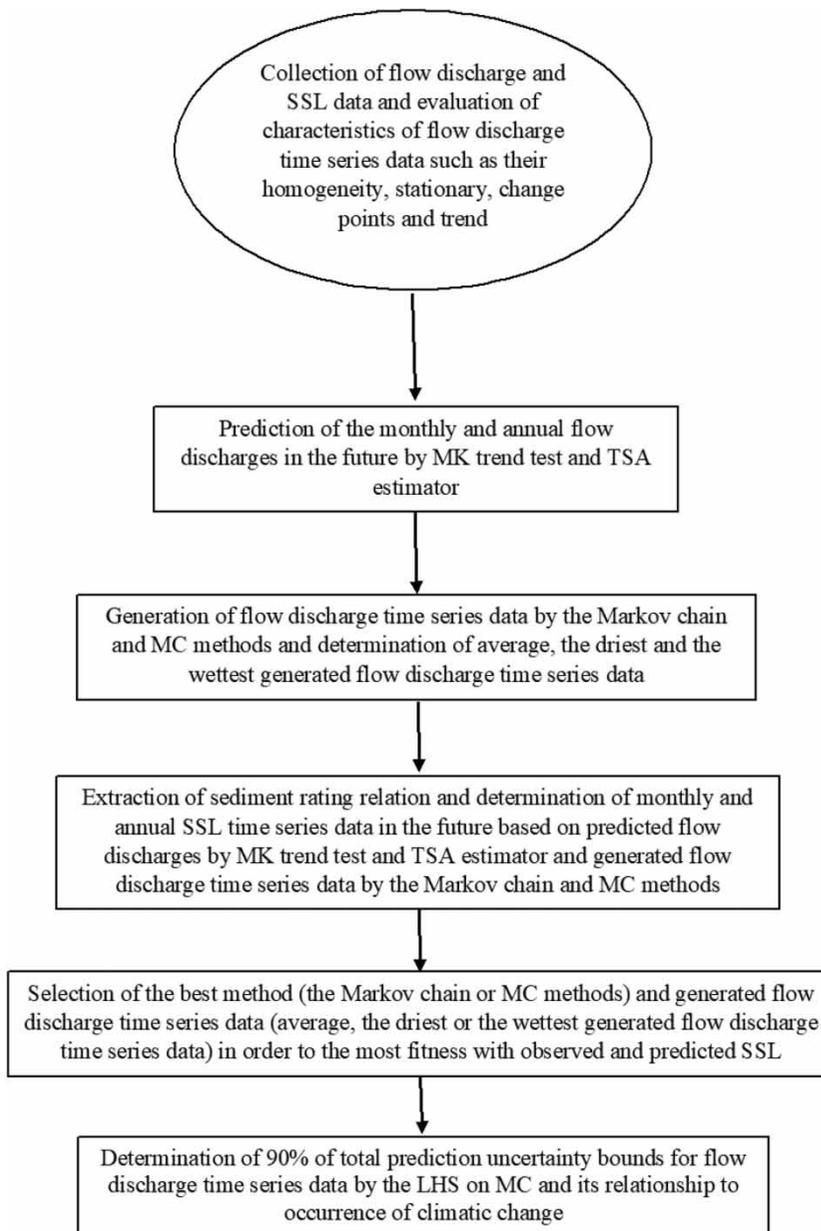The Nash–Sutcliffe model efficiency coefficient is defined as follows:

$$E_{NS} = 1 - \frac{\sum_{i=1}^{N}(Q_{pre}^i - Q_{obs}^i)^2}{\sum_{i=1}^{N}(Q_{obs}^i - \overline{Q_{obs}})^2} \tag{4}$$

For an ideal model, the *RMSE* should be close to zero and E_{NS} should be close to one.

RESULTS

Flow discharge data

Daily flow discharge and suspended sediment load (SSL) time series data during 1968–2014 were derived from data

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Figure 2 │ The flowchart of research methodology.

sets collected from the Khuzestan Water and Power Authority (KWPA). These time series have no missing data. Then, the daily flow discharges and SSLs were converted to monthly flow discharges and SSLs by averaging daily data for each month. Annual data were also calculated in the same way.

The homogeneity of the monthly and annual flow discharge time series data was illustrated by the run test. The run test showed that the *p*-value of these annual and monthly (from January to December) time series was less than 0.05 and $|Z|$ of the normal probability distribution was more than 1.96. Thus, these time series were found to be homogeneous at a significance level of 5%.

The Augmented Dickey-Fuller test (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin test (KPSS) showed the stationary of flow discharge time series data at a significance

level of 5%. The absolute value of statistic of the ADF test was more than 2.86 for different annual and monthly (from January to December) flow discharge time series data. Also, the absolute value of statistic of the KPSS test was less than 0.463 for different annual and monthly flow discharge time series data.

The Pettitt's test illustrated that time series data (both annual and monthly flow discharge time series data) have no change points (p-value ≥ 0.05) at a significance level of 5%.

On the one hand, the results of the MK test showed that monthly flow discharge time series data had a significant trend at a significance level of 1% in October, April, May, August and September and on the other hand revealed a considerable trend at a significance level of 5% in February and July. The p-value of these time series was less than 0.05 and 0.01, respectively, and their statistic ($|Z|$) was greater than 1.96 and 2.576. Also, the slopes of trend lines for

these time series were calculated by the TSA estimator (Figure 3).

Based on the calculated slope of trend lines by the TSA estimator for different months, the predicted mean values of monthly and annual flow discharges were predicted and illustrated in Figure 4 for the next 40 years and 80 years.

Figures 3 and 4 illustrate a decreasing trend in winter and spring (due to decreasing precipitation) and an increasing trend in summer and autumn due to increasing temperature and snow melting.

Using the Markov chain and MC methods, 100 monthly and annual flow discharge time series data were generated. It is worth noting that those were 40-year time series data. The average of 100 generated time series, the driest and the wettest time series generated by two methods are depicted in Figures 5 and 6. These figures show comparison between the mean of monthly and annual observed flow discharge time series data (during 1968–2014) and the driest,
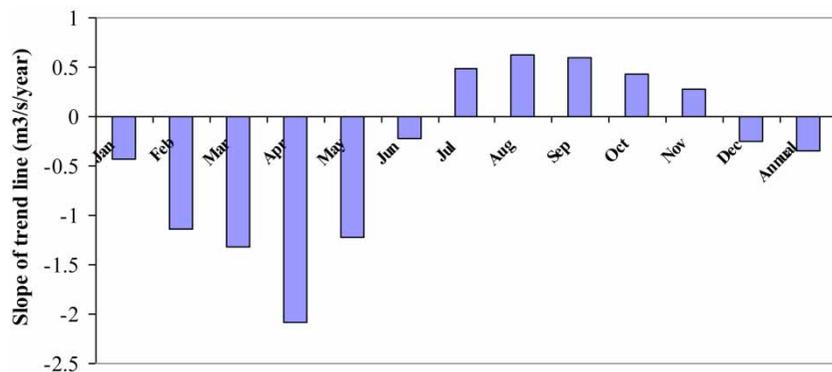

Figure 3 | The calculated slopes of trend lines by TSA estimator for different flow discharge time series data.
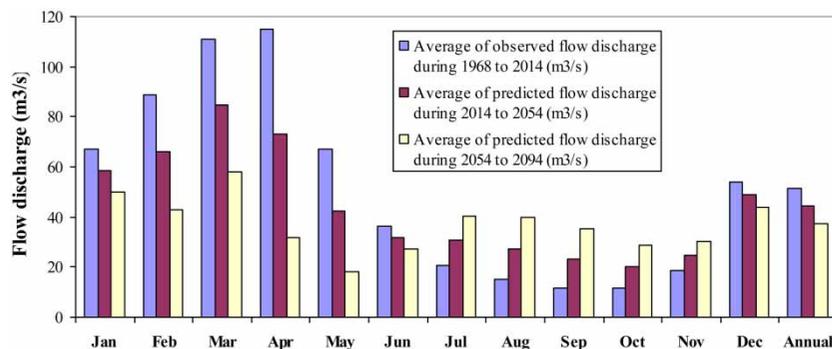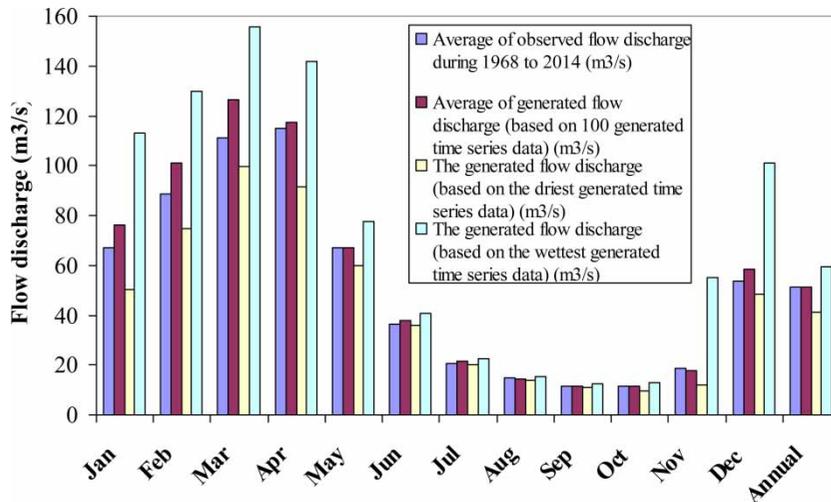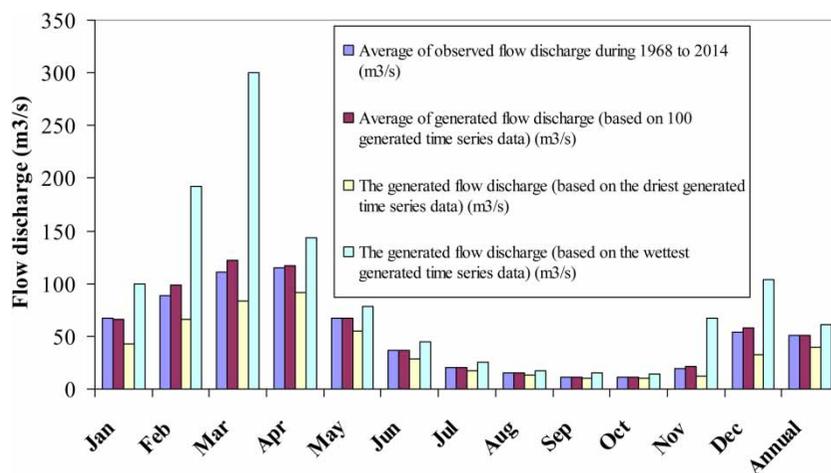

Figure 4 | The observed and predicted mean values of monthly and annual flow discharges by the TSA estimator in the near and far future.

Figure 5 │ Comparison between the observed and generated (by the Markov chain method) flow discharge time series data.

Figure 6 │ Comparison between the observed and generated (by the MC method) flow discharge time series data.

wettest and average of different monthly and annual flow discharge time series data generated by the Markov chain and MC methods.

The performance criteria, namely RMSE and EN_S, show fitness between generated and observed time series data. The performance criteria of two methods are shown in Figure 7. This figure compares the observed flow discharge time series data and average of 100 flow discharge time series data generated by two methods.

Figure 7 illustrates that in most of the months, the flow discharge time series data generated by the Markov chain method have better fitness than the MC. Figures 5 and 6

show that in winter, the average of 100 flow discharge time series data generated by the MC method is more compatible with observed values, while in other seasons, the results of two methods are almost identical.

In order to determine 90% of total prediction uncertainty bounds for flow discharge time series data by the LHS on MC method, 4000 flow discharge data were generated by MC method for each month. Results of this procedure are presented in Figure 8.

Figures 4 and 8 illustrate that the mean of monthly observed flow discharges are in 90% total prediction uncertainty bounds. In the near future (2014–2054), it was
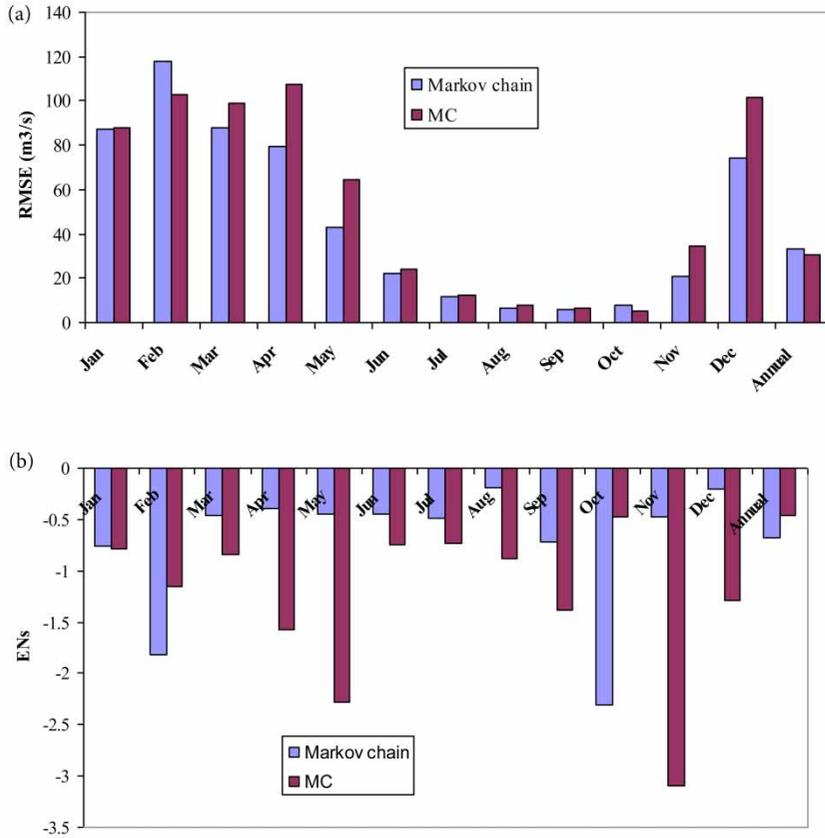
Figure 7 | The calculated performance criteria for the Markov chain and MC methods a)RMSE b) EN_S.
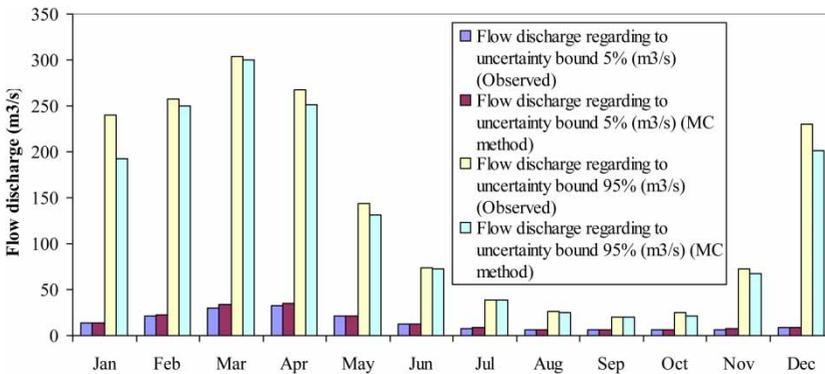

Figure 8 | 90% total prediction uncertainty bounds for the observed and flow discharge time series data generated by MC method.

observed that the mean of monthly flow discharges is more than the uncertainty bound 95% in August and September while in the far future (2054–2094), it was observed that the mean of monthly flow discharges is more than the uncertainty bound 95% in July, August, September and October and less than the uncertainty bound 5% in April and May.

This fact can indicate the effects of climatic change on flow discharge in the Idanak Watershed. Since the applied methods to generate synthetic data, such as the Markov chain and MC methods, utilize characteristics of the observed time series data, they cannot show effects of climatic change. In other words, the uncertainties considered

by the LHS on MC method do not include effects of climatic change.

Suspended sediment load (SSL) data

In order to establish a regression relation between input (flow discharges) versus (SSL), the following exponential relation, called the sediment rating relation, is presented.

$$Q_S = 0.9766Q_W^{1.9063} \quad R^2 = 0.73 \tag{5}$$

In which SSL (ton/day) and flow discharge (m³/s) are denoted by Q_S and Q_W, respectively. Since scattering of data is very high, the value of R is relatively low for the sediment rating relation.

The SSL related to the average of 100 generated flow discharge time series data, the driest and the wettest flow discharge time series data generated by two methods are illustrated in Figures 9 and 10. These figures compare the mean of monthly and annual observed SSL time series data (during 1968–2014) and the SSL related to the driest, wettest and average of different monthly and annual flow discharge time series data generated by two methods.

Figures 9 and 10 show that the SSLs related to flow discharge time series data generated by MC method have more compliance with the observed SSL time series data compared to the Markov chain method. Also, the SSLs related to the generated flow discharge time series data (based on the driest generated time series data) have more compliance with observed SSL time series data compared to wettest generated time series data.

Based on the calculated slope of trend lines by the TSA estimator for different months, the predicted mean values of monthly and annual SSLs in the next 40 years and 80 years are provided in Figure 11. The observed and predicted mean values of seasonal SSls are illustrated in Figure 12 too.
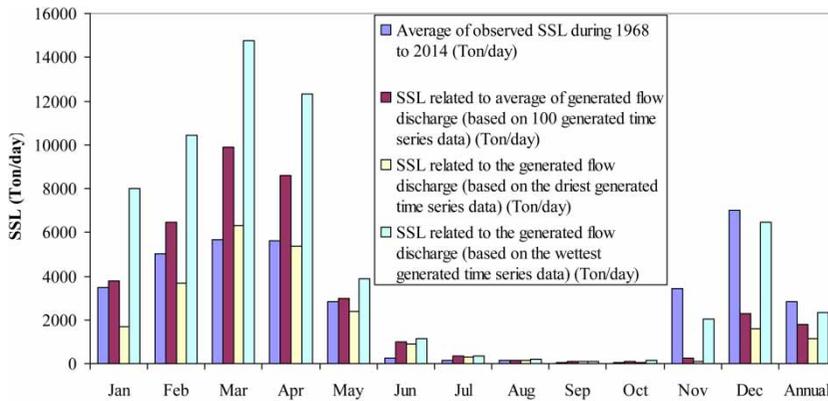

Figure 9 | Comparison between the observed and generated (by the Markov chain method) SSL time series data.
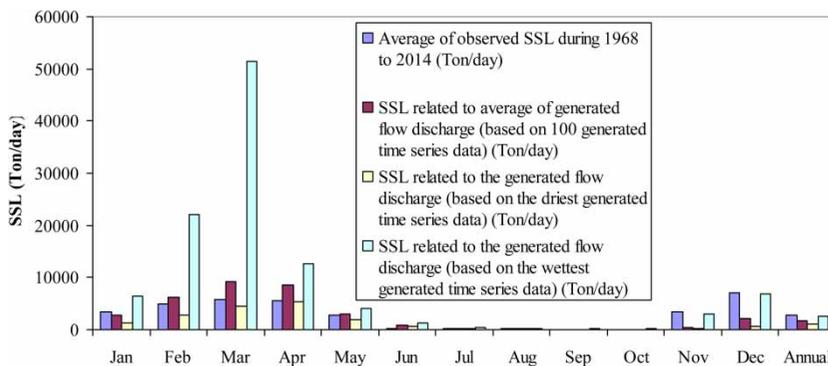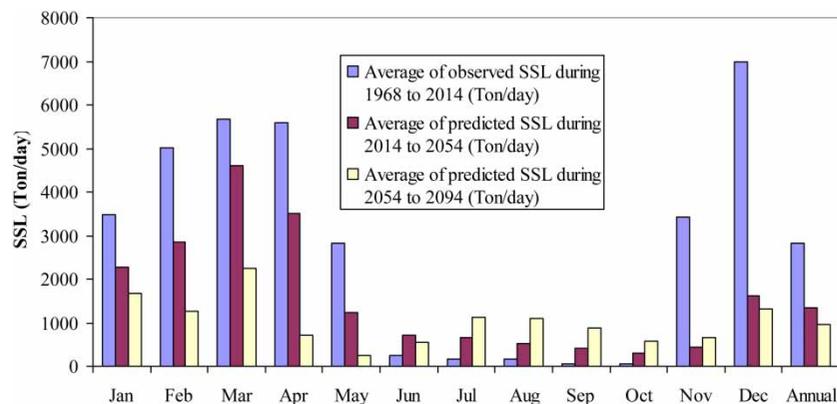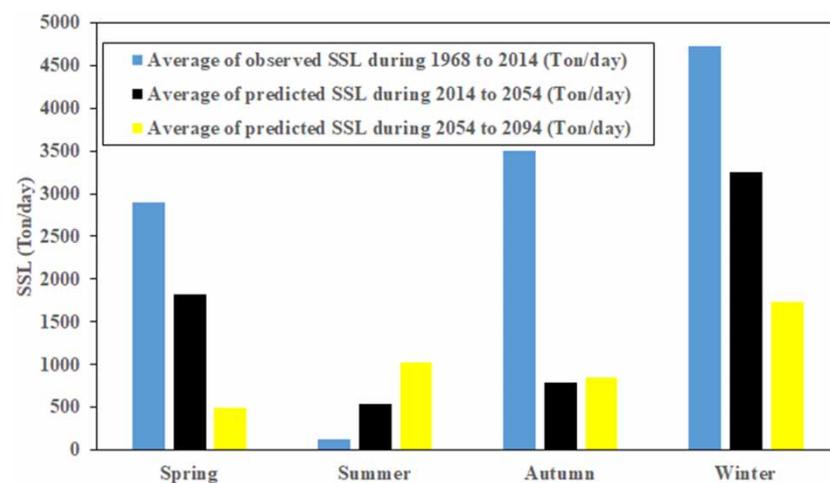

Figure 10 | Comparison between the observed and generated (by the MC method) SSL time series data.

Figure 11 | The observed and predicted (by the TSA estimator) mean values of monthly and annual SSLs.

Figure 12 | The observed and predicted (by the TSA estimator) mean values of seasonal SSLs.

By comparison between SSL related to the driest, wettest and average of different monthly and annual flow discharge time series data generated by the Markov chain and MC methods and average of observed SSL during 1968–2014 and predicted SSL in the near and far future, the results given in Tables 1 and 2 were obtained. These tables show the best method (The Markov chain or MC methods) and generated flow discharge time series data (the driest, wettest or average of 100 generated flow discharge time series data) for compliance with observed SSL and predicted SSL in the near and far future.

DISCUSSION

According to the applied tests, Pettitt's test, run test, ADF and KPSS, the results illustrated homogeneity and stationarity of monthly and annual flow discharge time series data and proved that these time series data have no change point. Therefore, the trend of these time series data can be determined by the MK trend test.

The MK test showed a significant trend, especially in spring and summer. While, the TSA estimator showed a decreasing trend in winter and spring and an increasing trend in summer and autumn and the annual flow discharge

Table 1 | The best method and generated flow discharge time series data for prediction of monthly SSL

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Observed (1968–2014)	Markov-Avg	MC-Avg	Markov-Driest	MC-Driest	MC-Avg	MC-Driest	MC-Driest	Markov-Driest	MC-Driest	Markov-Driest	MC-Wettest	MC-Wettest
Near future (2014–2054)	Markov-Driest	MC-Driest	MC-Driest	Markov-Driest	MC-Driest	MC-Driest	MC-Wettest	MC-Wettest	MC-Wettest	MC-Wettest	MC-Avg	Markov-Driest
Far future (2054–2094)	Markov-Driest	MC-Driest	MC-Driest	Markov-Driest	MC-Driest	MC-Driest	MC-Wettest	MC-Wettest	MC-Wettest	MC-Wettest	MC-Avg	Markov-Driest

time series data showed a decreasing trend. The maximum reduction and increase in flow discharge will occur in April and August, respectively. The climatic change and global warming will reduce precipitation and increase temperature. The flow discharge of the Marun River is dependent on precipitation in winter and spring, while it is dependent on snowmelt and temperature in summer and autumn. Occurrence of droughts will reduce long-term mean of flow discharge in this river.

The average of 100 time series generated by the Markov chain method had better compliance with observed flow discharge time series data in most of the months, since the Markov chain method utilizes the main characteristics of observed time series data to generate time series. These characteristics include mean, variance, and probability distribution governing the observed time series data.

The LHS was used to determine 90% of total prediction uncertainty bounds for monthly and annual flow discharge time series data. This method showed that average of monthly and annual observed flow discharges time series data are in 90% total prediction uncertainty bounds. Also, the average of monthly and annual flow discharges time series data generated by the Markov chain and MC methods are in the 90% total prediction uncertainty bounds. This matter was also seen for the driest and wettest monthly and annual flow discharges time series data generated by the Markov chain and MC methods.

Comparison between predicted flow discharges in the near and far future, by the TSA estimator method, and 90% of total prediction uncertainty bounds, however, revealed a different truth. In the near future, it was observed that the mean of monthly flow discharges are more than uncertainty bound 95% in August and September while in the far future, the mean of monthly flow discharges are more than uncertainty bound 95% in July, August, September and October and are less than uncertainty bound 5% in April and May. In summer, flow discharge will be significantly increased while in spring, it will be considerably decreased. In other words, the LHS on MC method can not consider uncertainty developed by climatic change because this method only utilizes observed data to generate data.

Observed flow discharges and SSLs data were used to derive sediment rating relation. Due to the high scatter of SSL data, the correlation coefficient of the obtained

Table 2 │ The best method and generated flow discharge time series data for prediction of annual and seasonal SSL

Season	Spring	Summer	Autumn	Winter	Annual
Observed (1968–2014)	Markov-Driest	MC-Driest	MC-Wettest	Markov-Driest	MC-Wettest
Near future (2014–2054)	MC-Driest	MC-Wettest	Markov-Driest	MC-Driest	Markov-Driest
Far future (2054–2094)	MC-Driest	MC-Wettest	Markov-Driest	MC-Driest	MC-Driest

equation was relatively low. It was found that the SSL related to flow discharge time series data generated by the MC method had more compliance with monthly and annual observed SSL data (except January, March, August and October). Also, the average of 100 generated flow discharge time series data had more compliance with monthly observed SSL data in January, February and May. The wettest generated flow discharge time series data had more compliance with monthly (November and December) and annual observed SSL data. For other months, the driest generated flow discharge time series data had more compliance with monthly observed SSL data; this is due to the type of precipitation that occurs in different months. Most rain showers occur in November and December while most ordinary rainfall occurs in January, February and May. In other months, little precipitation occurs. It is worth noting that the rain showers are the main factor of transportation of SSL during the year.

In the future, the value of SSL will be reduced in winter and spring (due to reduction of flow discharge) and will be increased in summer and autumn (due to increase in flow discharge). Since most SSL transportation occurs in winter and spring, the annual value of SSL will be decreased in the future (especially in the far future).

The SSL related to the flow discharge time series data generated by the MC method had more compliance with monthly, seasonal and annual predicted SSL data in the near and far future. The Markov chain method stores main characteristics of observed time series data, therefore it can not state a good fitness with predicted time series data in the future.

With respect to reduction of monthly flow discharge from December to June in future, SSL related to the driest generated flow discharge time series data had more compliance with monthly predicted SSL data in the near and far future. Due to increasing monthly flow discharge from July

to October in future, SSL related to the wettest generated flow discharge time series data had more compliance with monthly predicted SSL data in the near and far future. In November, the variation of monthly flow discharge in future was relatively low, therefore SSL related to the average of 100 generated flow discharge time series data had more compliance with monthly predicted SSL data in the near and far future. Since the Markov chain method stores characteristics of observed flow discharge time series data, it is considered the superior method in this month.

Considering reduction of annual and seasonal flow discharge in spring and winter in future, SSL related to the driest generated flow discharge time series data had more compliance with annual and seasonal predicted SSL data in the near and far future. Due to increasing seasonal flow discharge in summer in future, SSL related to the wettest generated flow discharge time series data had more compliance with seasonal predicted SSL data in the near and far future. In autumn, the variation of seasonal flow discharge in future was less than the other seasons; therefore, the Markov chain method, which stores characteristics of observed flow discharge time series data, was considered a robust method in this season. On the other hand, due to decreasing precipitation and flow discharge in December, SSL related to the driest generated flow discharge time series data had more compliance with seasonal predicted SSL data in the near and far future in autumn.

CONCLUSIONS

Sediment yield in rivers can cause several problems for hydraulic structures such as pumps, sluices and so on. The climatic change and global warming will change hydrological and meteorological parameters such as precipitation, temperature and flow discharge in future. These changes

can affect the amount of SSL in rivers. The GCMs and downscaling models can show the amount of precipitation and temperature in the near and far future. Rainfall-runoff models or methods used for generating synthetic data can be applied to determine flow discharge in future. This research utilized two methods, Markov chain and MC, to generate flow discharge time series data. Based on generated data and sediment rating relation, the amount of SSL was calculated for the near and far future.

The MK test showed a decreasing trend in flow discharge in winter and spring, an increasing trend in flow discharge in summer and autumn and a decreasing trend in annual flow discharge. Also, the LHS on MC method illustrated that the Markov chain and MC methods cannot consider uncertainties regarding climatic change in the future.

This study proved that the MC method is a superior method to generate flow discharge data in most months. The data generated by this method have more compliance with predicted SSL in the near and far future. The wettest generated time series in months must be considered when flow discharge will increase and the driest generated time series in months when flow discharge will decrease to predict SSL in future. The annual value of SSL will reduce from 2,811.15 ton/day to 1,341.25 and 962.05 ton/day in the near and far future, respectively. The greatest reduction and increase in monthly value of SSL will occur in December and July, respectively. Adib & Mahmoodi (2017) illustrated that the amount of SSL will increase in the future for flood conditions at the Idanak Station. This fact shows that climatic change can increase the probability of occurrence of extreme conditions such as severe floods and droughts in the future.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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