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Estimation of seasonal and annual river flow volume based on temperature and rainfall by multiple linear and Bayesian quantile regressions

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Abstract— Investigation of river flow volume in different conditions as a function of temperature and rainfall variables can be quite effective in understanding the hydrological and hydro-climatic conditions of the watershed. Multiple linear regression models were applied in estimating river flow in several studies due to their straightforwardness and appropriate interpretation of results. In this study, to overcome the limitations of the multiple linear regression model, the Bayesian quantile regression model was used to estimate the river flow volume as a function of rainfall and temperature, and the results were compared. The data and information used for the Qareh-Sou basin in northern Iran are of substantial environmental and socio-economic importance. Five data series, including spring, summer, autumn, winter, and annual series, were created and used for this study. It was found that the Bayesian quantile regression model has considerable flexibility to model the volume of flow for different quantiles, predominantly upper and lower quantiles, and can be used to model high and low flows. With increasing the values of quantiles, a limited decreasing pattern in the effect of rainfall on the volume of flow was identified, which can be due to increasing the effect of other factors in the formation of extreme flows of the river. For summer data in high quantiles, the effect of rainfall on river flow volume shows an increasing pattern. This pattern is different from the other studied series, which may be due to the low base flow in summer. The results confirm that the application of Bayesian quantile regression compared to multiple linear regression leads to much more valuable information on the impact of rainfall and temperature on river flow volume.

Key-words: Qareh-Sou basin, modeling, quantile, extreme events

1. Introduction

One of the critical components of the hydrological cycle is river flow (*Ansarifar et al.*, 2020a). This component can interact with other components such as groundwater (*Ansarifar et al.*, 2020b). Surface water, which is the result of rainfall-runoff responses in a basin, is a potential source that, if properly managed, can meet agricultural (*Steinfeld et al.*, 2020), industrial (*More et al.*, 2020), and environmental (*Karimi et al.*, 2021) demands. The increase in water demand in different regions, especially in arid and semi-arid regions, shows the need for optimal water resources management. Therefore, the estimation of river flow resulting from climatic factors is the basis for studying many different plans to develop and exploit water resources (*Bahrami et al.*, 2019). Estimating river flow in a basin is a complex one, in which human knowledge, understanding, and knowledge of the physical laws governing it are incomplete. Several factors affect the river flow pattern in the basin area (*Salarijazi* and *Ghorbani*, 2019). These factors include topographic features, river morphology, rainfall dynamics, temperature, and human activities. Estimating river flow under the influence of hydroclimatic variables is possible using different approaches (*Mudbhatkal et al.,* 2017). In general, there are two major approaches to modeling river flow. The first approach is knowledge-based, known as modeling, based on the basin area's characteristics and physical laws (*Kavian et al.*, 2020). This approach requires a wide range of different information and data that, in most cases, may not be available (*Bahremand et a*l., 2021). In most parts of the world, especially in developing countries, this approach is limited. The second approach is data-driven, which involves analyzing the data set recorded over a historical period (*Chadalawada et al.*, 2017). There is a need for more limited data and information in this approach than the first approach (*Nourani et al.,* 2019). The use of data-driven models has developed in recent years (*Sezen et al.*, 2019). Although Modeling with a data-driven approach may not be sufficient to interpret the physical processes within the basin, it can accurately estimate the amount of river flow (*Mishra et al.*, 2018: The multiple linear regression model is one of the basic and well-known models in the data-driven approach (*Niedzielski et al.*, 2019). This model has several advantages. The multiple linear regression model is fast and straightforward and leads to specific mathematical equations. Also, by interpreting these equations, we can understand the effect of each of the model inputs on the output (*Cho* and *Lee*, 2018: A multiple linear regression model has been used in meteorology, climatology, hydrology, and water resources due to the stated advantages (*Niu et al.*, 2019: Using data from 33 catchments in Iowa, *Schilling* and *Walter* (2005) used multiple linear regression modes to predict total flow, base-flow, and flood flow. The results of this study indicate a significant effect of rainfall over other input variables of the model. A multiple linear regression model was developed using principal component analysis and discrepancy ratio modified by *Noori et al.* (2010). This study showed that the developed model has better performance than the standard model for predicting river flow. The multiple linear regression model was developed using bootstrap resampling and wavelet analysis, and was evaluated to predict the daily flow of the river. This study indicates that it is substantial that the developed model has better accuracy in estimating the peak flow of river flow in flood conditions than the standard model of multiple linear regression (*Sehgal et al.*, 2014). *Latt* and *Wittenberg* (2014) studied artificial neural networks and stepwise multiple linear regression models to simulate the flow of the Chindwin River in Myanmar. They showed that the multiple linear regression model has good accuracy in predicting river flow, but it is weak in estimating extreme values. The results of a study in India showed that the multiple linear regression model could be used as a suitable option to assemble different hydrological models to predict river runoff (*Kumar et al.,* 2015). Using 14 years of Wainganga River runoff data in India, the efficiency of the multiple linear regression method to simulate river flow using rainfall and temperature data was studied. The study results indicate the appropriate efficiency of the multiple linear regression model in rainfall-runoff modeling and the effect of different inputs on increasing the accuracy of the results (*Patel et al.,* 2016). *Tsakiri et al.* (2018), in their research on river flow modeling in the Mohawk River in New York, concluded that the use of a multiple linear regression model has the advantage that it can lead to a physical interpretation of the river flow time series. He also pointed out that the development of a standard model can significantly improve the model's accuracy. *Popat et al.* (2020) used a multiple linear regression model to predict river flow in the Wernersbach catchment, Germany. In this study, rainfall, runoff, and soil moisture information were used for modeling. The results show that the multiple linear regression model is not accurate enough to predict extreme flows.

The quantile regression model has been considered in meteorology, climatology, and hydrology in recent years (*Nguyen et al.*, 2021). This model has far fewer limitations than the multiple linear regression model (*Hossain et al.,* 2021). *Shiau* and *Chen* (2015) used the quantile regression model to estimate the uncertainty of river sediment load as an appropriate model. *Sa'adi et al.* (2017) used the quantile regression model to estimate changes in the variable probability distribution function of rainfall in Sarawak, Malaysia. They described this method as a suitable tool in this field. In another study, the quantile regression method was used to investigate changes in extreme rainfall in South Korea. Based on the results, the study areas were classified according to the type of changes, and the use of this method was recommended to classify rainfall changes (*Uranchimeg et al.*, 2020). In another study, the quantile regression model was used to predict dissolved oxygen concentrations considering land use and soil cover (*Ahmed* and *Lin,* 2021).

A review of the research using the multiple linear regression model to predict river flow shows that this model has relatively good accuracy for predicting the mean values of river flow. At the same time, it should be developed for extreme flow modeling. The Bayesian quantile regression model has also been developed to be suitable for the modeling of extreme flows. This research investigates the Bayesian quantile regression model in predicting river flow volume in different time scales and compares it with the multiple linear regression model. Moreover, the impacts of inputs and modeling results in different standard and extreme flow conditions are compared and analyzed for better interpretation. The Qareh-Sou River in northern Iran is of significant environmental importance, and in this study, the effect of rainfall and temperature on the volume of this river flow is studied.

2. Materials and methods

2.1. The Qareh-Sou basin

The Qareh-Sou basin, with an area of 1670 square kilometers, forms a significant part of Golestan province in northern Iran. This basin area is limited to the Gorgan-Roud basin from the north and east, the Naka-Roud basin from the south, and the Gorgan Bay basin and the Great Caspian Sea from the west. The Qareh-Sou River discharges into the bay near Qareh-Sou village. The main Qareh-Sou basin area is covered by forest in the south, while in the north, an alluvial plain with agricultural and residential uses forms the basin. The differences in elevation between the southern heights and northern alluvial plain, besides heavy rainfall, have caused very young south-north rivers to flow with severe erosion. After reaching the plain, these rivers leave their primary sediment by forming large-grained alluvial fans. Due to a sudden change of direction, the rivers upstream of this basin discharge most of their sediments in the river after joining the main river of the Qareh-Sou basin. The Qareh-Sou River is vital in supplying agricultural water resources in the region, and therefore, it has socio-economic importance.

Another point is that this river is the leading supplier of freshwater resources for Gorgan Bay. Gorgan Bay is of enormous environmental and ecological importance. Due to the quite effective role of the Qareh-Sou River, any changes in the flow volume of this river can be the source of severe effects on this water body. The data of Siah-Ab and Gorgan hydrometric meteorological stations were used to investigate the effect of rainfall and temperature variables on the flow volume of the river. The location of the studied basin, and the hydrometric and meteorological stations are shown in *Fig. 1*.

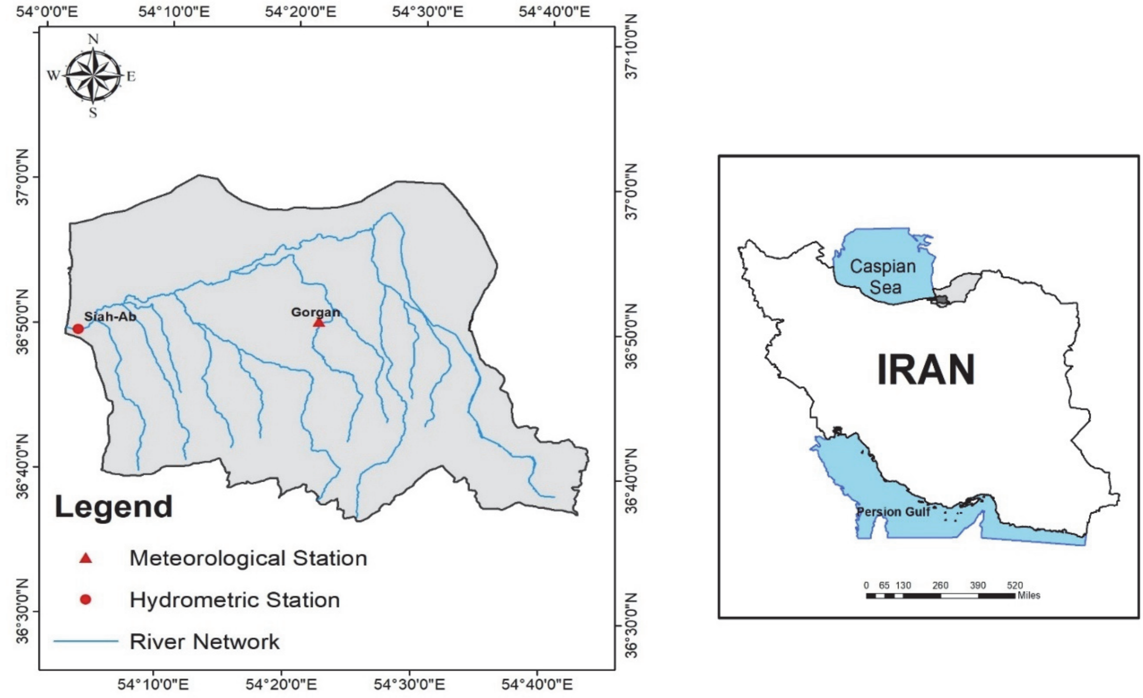

Fig. 1. Location of Gorgan meteorological and Siah-Ab hydrometric stations in the Qareh-Sou basin.

2.2. *The multiple linear regression model*

One of the standard methods in multivariate analysis is the multiple linear regression model (*Kadam et al*., 2019). A linear relationship is established between the independent variable and one or more dependent variables (*Jolánkai* and *Koncsos,* 2018). In the multiple linear regression, the parameters of a linear model are estimated using an objective function and the values of the variables (*Zhang et al*., 2020). In the linear regression, the considered model is a linear relationship between the model parameters (*Ali et al*., 2020). Thus, if we have n observations of x independent variable with p dimension and want to establish a linear relationship with the dependent variable y, we can use the following linear regression model (*Li et al*., 2019):

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i \ , \qquad i = 1, \ldots, n \ , \tag{1}$$

where β is the model parameter. Index i shows the observation number and ε is considered a regression model error. If two independent variables are linearly related to a dependent variable in multiple linear regression, the relationship will form a plane (*Fig. 2*).

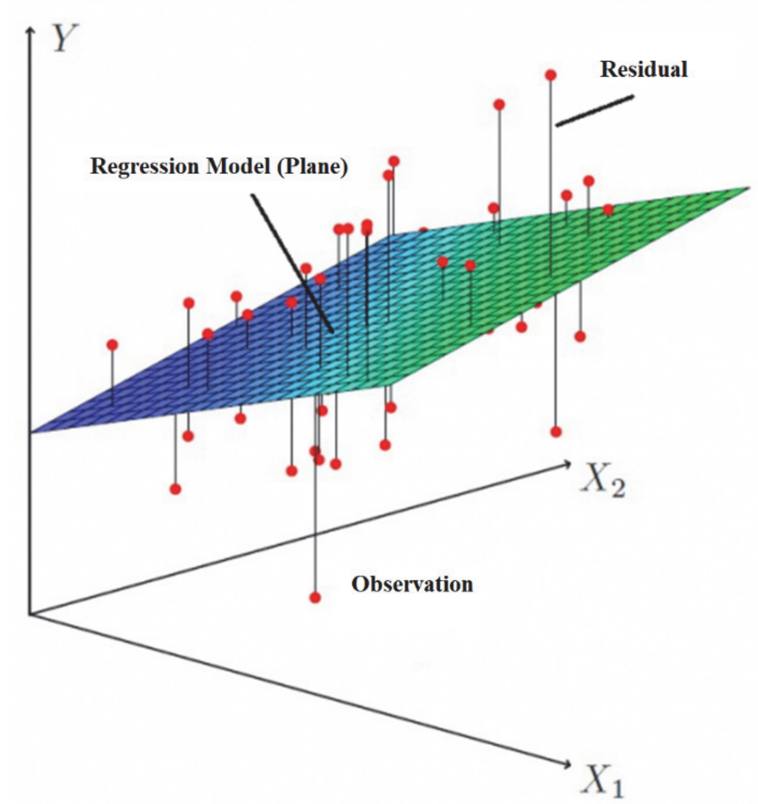

Fig. 2. Multiple linear regression model for two independent variables.

2.3. The Bayesian quantile regression model

Research on changes in hydrological and hydroclimatic variables has been mainly based on models that examine the median or average changes (*Hu et al.,* 2020; *Ali et al*., 2019). An important point to note is that in hydrological and hydroclimatic events, the upper and lower quantile, which can represent extreme events, are extremely important (*MacLeod et al*., 2021). Simultaneously, it should be considered that conventional models in this field do not have good performance (*Shiau* and *Huang*, 2015). The study of changes in hydrological and hydroclimatic variables in the upper tail of the probability distribution function is of great importance for studies related to risk and uncertainty in design related to hydrology, climatology, meteorology, and the environment (*Shiau* and *Chen*, 2015). The Bayesian quantile regression model can be a suitable and practical tool to study the upper and lower quantiles (*Uranchimeg et al*., 2020). Estimating the changes in the upper and lower quantiles can be used to study wet and dry seasons and extreme floods, which shows the importance of this type of analysis (*Kalisa et al.*, 2021). In the quantile regression, the values of conditional quantiles of dependent variables estimate for changes in independent variables (*Wan* and *Liew*, 2020). Therefore, the quantile regression model is entirely different from the known model of linear regression and multiple linear regression that examines the conditional mean changes of the dependent variable (*Bogner et al.,* 2017). The Bayesian regression has been developed to overcome the limitations of quantile regression. More information on quantile regression and Bayesian quantile regression are available from sources such as *Acharya et al.* (2020), *He et al.* (2021), and *Shin et al.* (2021). The following function is minimized in the quantile regression model to estimate regression lines for different quantiles (*Wang et al.,* 2018):

$$\hat{\beta}_\tau = argmin \sum_{i=1}^{n} \rho_\tau \quad (y_i - x_i^T \beta)^2 \quad , \tag{2}$$

where $\hat{\beta}_\tau$ is τth quantile regression line. The $\rho_\tau(x) = x(\tau - I(x < 0))$ is also considered a loss function, and i is defined as an indicator function. The maximization of a regression likelihood function generated by asymmetric Laplace densities, presented by *Yu* and *Zhang* (2005), is the same as the minimization of the previous equation:

$$f(x|\mu, \delta, \tau) = \frac{\tau(1-\tau)}{\sigma} \exp[-\sigma = \rho_\tau \left(\frac{x-\mu}{\sigma}\right)] \quad , \tag{3}$$

The Bayesian inference can estimate the studied parameter's entire posterior probability distribution function, including parameter uncertainty, based on this inference (*Yang*, 2019). In this study, a Bayesian quantile regression model was used to investigate the relationship between the river flow volume as a dependent variable and the rainfall and temperature as independent variables. The calculations were performed using the "bayesQR" package (*Benoit* and *Van den Poel*, 2017) developed in the R environment.

3. Results and discussion

The data were divided into five series: annual, spring, summer, autumn, and winter. The reason of division is that the relationship between rainfall and temperature with the volume of river flow experience changes in different seasons. According to the generated series, the relationship between hydroclimatic variables and river flow volume was investigated using multiple linear regression and Bayesian quantile regression models, as reported below.

Examination of the slope values of Bayesian quantile regression lines in the annual data shows that the relationship between the annual rainfall and annual flow volume with the slope range (7–156) is direct, which increases with increasing the values of quantiles (*Fig. 3*). In the upper quantiles, this incremental pattern disappears, which may be because a set of other factors can also have significant effects on the annual extreme flows. The annual temperature effect on the annual flow volume with a slope range of ((-3) –15) is also direct in some quantiles and indirect in others. The maximum effect of temperature on the annual flow volume is in the upper quantiles. Comparing the effect of rainfall and temperature on the annual flow volume confirms that rainfall has greater effect than temperature, so that with increasing the values of quantiles, the difference between the effect of rainfall and temperature increases.

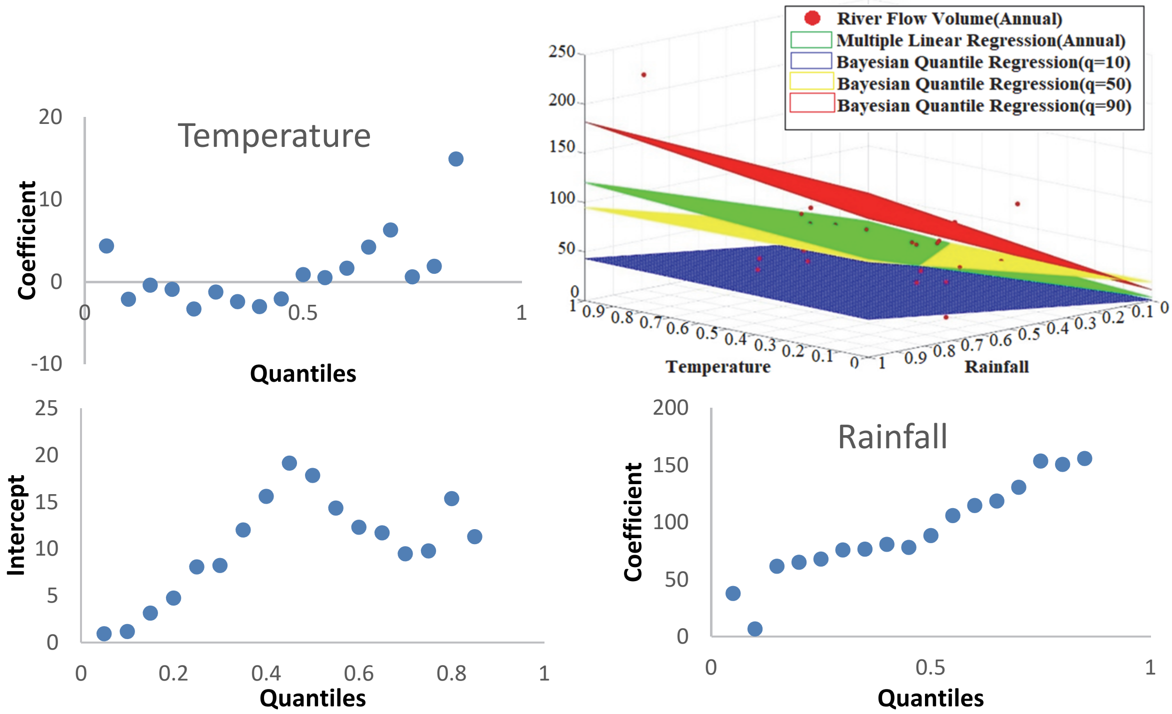

Fig. 3. Results of Bayesian quantile and multiple linear regression models for the annual series.

The slope obtained from the multiple linear regression method for rainfall and temperature is 97 and 20. In the Bayesian quantile regression model, there is a negative slope for temperature in some quantiles. In contrast, in multiple linear regression, there is a positive slope sign. The slope value obtained in the multiple linear regression model for rainfall is in the range of slopes obtained in the Bayesian quantile regression model. For temperature, the slope value obtained in the multiple linear regression method is outside the slope range obtained in the Bayesian quantile regression model.

The slope of Bayesian quantile regression lines in the spring data for the rainfall variable is in the range of ((-5) –4), indicating that the relationship between the spring rainfall and spring flow volume is direct in some quantiles and indirect in others (*Fig. 4*). A remarkable effect of spring rainfall on spring flow volume is detectable in the upper quantiles. The slope value associated with different quantiles for the temperature variable is in the range ((-28) – (- 3)), which means that the relationships between the spring temperature and spring flow volume in all quantiles are indirect. The remarkable effect of spring temperature on the volume of spring flow is in the middle quantile, while in the upper and lower quantiles, this effect is significantly reduced. In spring, the effect of temperature on runoff volume is more than the effect rainfall. The most remarkable difference between the magnitude of the effects of these two variables can be seen in the middle quantiles. The slope obtained from the multiple linear regression model for temperature and rainfall is estimated to be -18 and -17, respectively. Therefore, it can be seen that in the Bayesian quantile regression model, in some quantiles, rainfall has a positive slope, but in multiple linear regression, the slope sign is negative. The value of the slope obtained in the multiple linear regression method for rainfall is outside the range of the slopes obtained in the Bayesian quantile regression model, while for temperature, there is the opposite behavior.

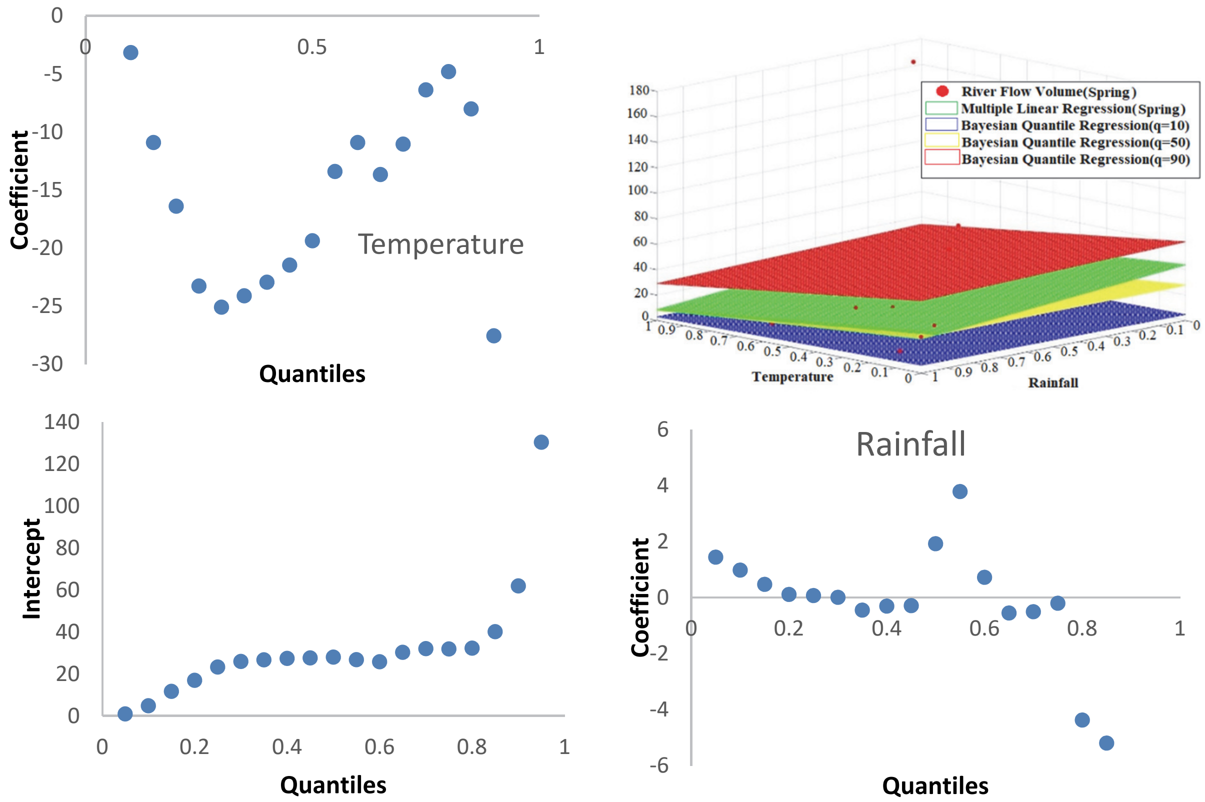

Fig. 4. Results of Bayesian quantile and multiple linear regression models for the spring series

Summer data show that the slope value for the temperature variable is in the range (0–9). Therefore, it can be said that the relationships between the temperature and flow volume in all quantiles are direct (*Fig. 5*). In general, with increasing the values of quantiles, the magnitude of the effect of temperature also increases, and experience a decrease only in the last quantile. This result is because in upper quantiles, the influence of other factors on flow volume increases. For the rainfall variable, the slope value was in the range (0–46), and with increasing the quantile value, the slope magnitude increases significantly. This result is due to the predominant effect of rainfall on the volume of flow in summer, because in this season, according to the river conditions, the river flow in most conditions is the base flow. In the lower and middle quantiles, the effect of temperature is greater than that of rainfall, although this difference is not remarkable. In upper quantiles, the magnitude of the effect of rainfall is dramatic compared to temperature increases, which is different from the other studied series. The value of the slope calculated for temperature and rainfall using multiple linear regression model is 7 and 9, respectively, which in terms of sign and the values are consistent with the results of the Bayesian quantile regression model.

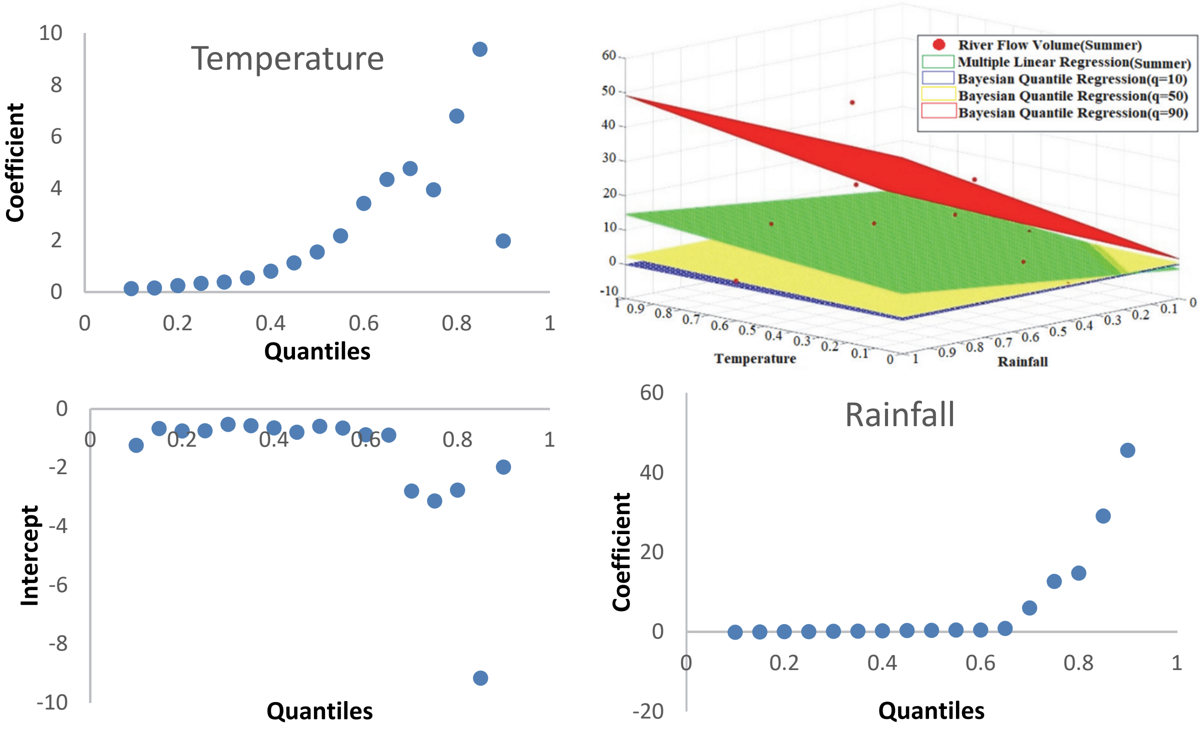

Fig. 5. Results of Bayesian quantile and multiple linear regression models for the summer series.

In autumn, the slope for rainfall is in the range (6–25), which means that the relationship between the rainfall and flow volume is direct in all quantiles, and a remarkable amount of impact is observed in the upper quantile (*Fig. 6*). It is important to note that the increasing trend of the rainfall-related slope disappears in the upper quantiles, which may be due to the significant impact of other variables on autumn flow volume. The slope range for temperature in this season is (1–4), which means that in autumn, the relationship between the temperature and flow volume is generally similar to the relationship between the rainfall and flow volume, with the difference that the intensity of the impact of rainfall is far greater than that of the temperature. The differences between the magnitudes of rainfall and temperature in the middle and upper quantiles are far more significant than in the lower quantiles. In a multiple linear regression model, the slopes for temperature and rainfall are 7 and 20, respectively. The linear regression model's slope sign in autumn is similar to the Bayesian quantile regression model results. It should be noted that the slope values for temperature and rainfall in the multiple linear regression model are outside and inside the range obtained from the Bayesian quantile regression method, respectively.

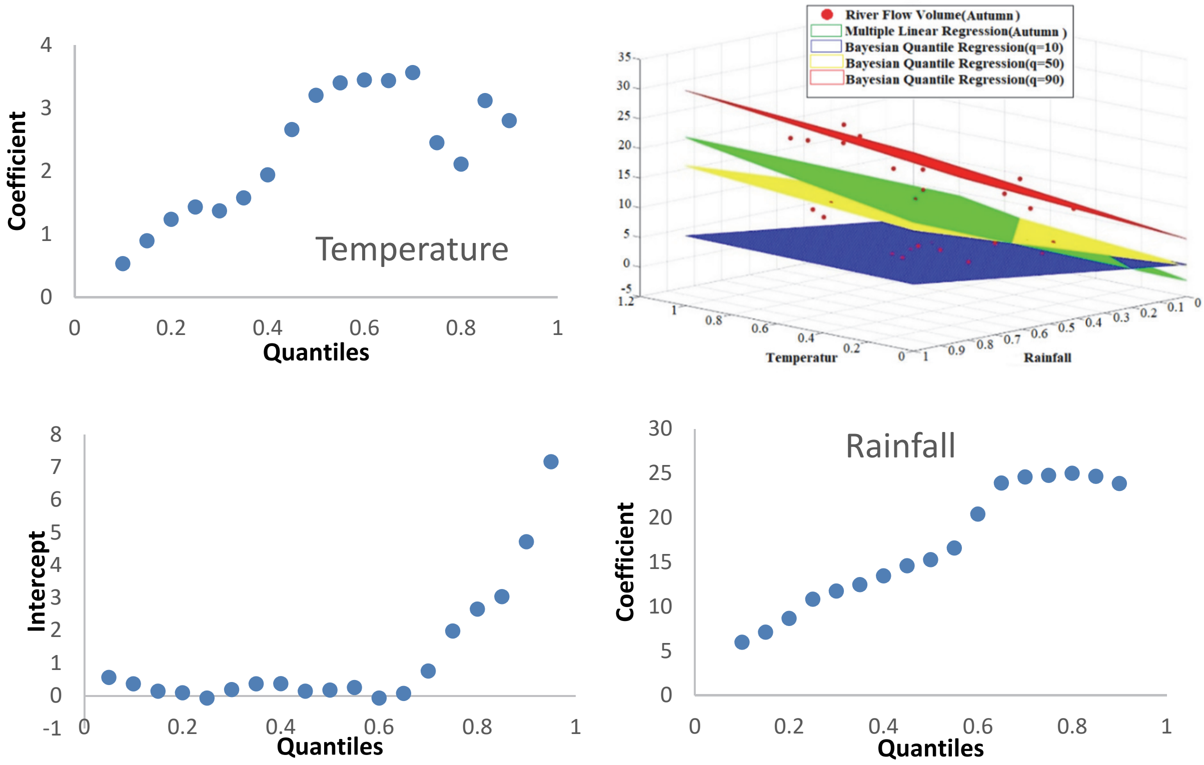

Fig. 6. Results of Bayesian quantile and multiple linear regression models for the autumn series.

Examination of winter data reveals that the values of slopes for rainfall are in the range (9–41), and in other words, the effect of rainfall on flow volume is direct (*Fig. 7*). However, the magnitude of this effect in the middle quantiles is significantly higher than that of the upper and lower quantiles in this respect, and it behaves almost like spring. The values obtained for the temperature slopes are also in the range ((-12) –0). The effects of temperature on flow volume are direct in the lower quantiles and indirect in the upper quantiles. The intensity of this effect increases with increasing the values of quantiles. Comparison between the magnitude of the effect of rainfall and temperature on the volume of winter flow shows that rainfall has more effect than the temperature, and the critical point is that the most significant difference between the magnitude of the effect of these two variables occurred in the middle quantiles, which behave similarly to spring data. The slope obtained from the multiple linear regression model for temperature and rainfall in winter is -8 and 28, respectively. Comparison of these values with the range of values recorded in the Bayesian quantile regression model indicates a quantitative agreement between the results of these two models.

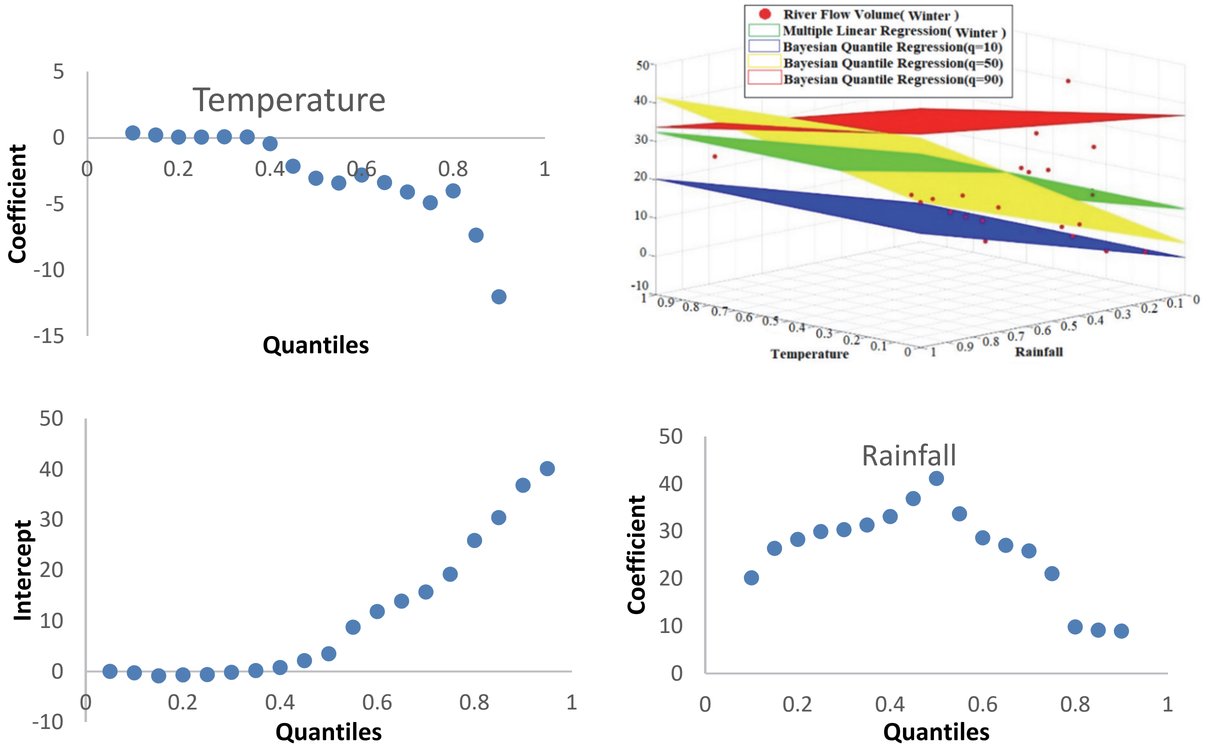

Fig. 7. Results of Bayesian quantile and multiple linear regression models for the winter series.

A comparison between the multiple linear regression and Bayesian quantile regression results was presented in the section above. Investigating these results indicates that the behavior between the flow volume and temperature and rainfall variables in different quantiles may be quite different. This difference can be seen in the magnitude of the slope value and in the slope sign of the regression lines. This issue is fundamental in hydrological estimates, because it shows that the value of rainfall and temperature variables varies in different quantiles on the volume of flow, and this difference is significant in some cases.

4. Conclusion

The volume of river flow is significantly affected by hydroclimatic factors such as rainfall and temperature. The multiple linear regression model is a well-known model in hydrological and climatological studies used to investigate the effect of independent variables on dependent variables, but this model has its limitations. In this study, multiple linear regression and Bayesian quantile regression models were used to investigate the effect of rainfall and temperature on river flow volume. Data belonging to the Qareh-Sou basin area in northern Iran were used in five (annual, spring, summer, autumn, and winter) series for this study. According to the results of the calculations, the following can be considered a general conclusion of this research.

Comparison between the magnitude of the effect of rainfall and temperature in different series indicates that in spring, the effect of temperature on flow volume is greater than the effect of rainfall, while in the annual, autumn, winter, and summer series, the effect of rainfall on flow volume is much greater than that of the temperature .The effect of rainfall and temperature variables on flow volume in different quantiles in terms of value and sign can significantly change. The results obtained from the multiple linear regression model differ from the results obtained from the application of Bayesian quantile regression for the quantile 0.5 in value and in some cases in the sign, which means that the only application of multiple linear regression models alone can lead to erroneous analysis. The differences between the plane fitted by multiple linear regression with the planes fitted by Bayesian quantile regression in the upper and lower quantiles are enormous. Therefore, the multiple linear regression model has many limitations in studies related to extreme river flows. In the annual, autumn, winter, and spring series, with increasing the values of quantiles, the effect of rainfall on flow volume decreases, which may be because of extreme flows. Other variables such as previous soil moisture, soil cover, and land use are influential. In summer, a different pattern is seen so that with increasing the values of quantiles, the effect of rainfall on flow volume increases. This result may be since river flow in summer is generally of the base-flow type, and therefore, the amount of rainfall has a significant effect on flow volume in upper quantiles.

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