Comparison of different statistical downscaling models and future projection of areal mean precipitation of a river basin under climate change effect

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ABSTRACT

Investigation of the hydrological impacts of climate change at the local scale requires the use of a statistical downscaling technique. In order to use the output of a Global Circulation Model (GCM) model, downscaling technique is used. In this study, statistical downscaling of monthly areal mean precipitation of Göksun River basin in Turkey was carried out using the Group Method of Data Handling (GMDH), Support Vector Machines (SVM) and Gene-expression Programming (GEP) techniques. Large-scale weather factors are used for a basin with monthly areal mean precipitation (Pm) record from 1971 to 2000 for training and testing periods. The R²-value for precipitation in SVM, GEP and GMDH models are 0.62, 0.59, and 0.6 respectively, for testing periods. The results showed that SVM has the best model performance than the other proposed downscaling models, however, AIC values showed the GEP model has the lowest AIC value. The simulated results for CGCM3 A1B and A2 scenarios show a similarity in their average precipitation prediction. Generally, both scenarios anticipate a decrease in the average monthly precipitation during the simulated periods. Therefore, the results of future projections show that the mean precipitation might decrease during the period of 2021–2100.

Key words: artificial intelligence, climate change, GCMs, precipitation, statistical downscaling

HIGHLIGHTS

• An integrated hydrological model for prediction of areal mean precipitation of a river basin under climate change effect is proposed.
• Statistical downscaling and GCM are utilized to estimate the climate change effects on the basin.
• Göksun River basin is used as case-study area with 3 precipitation stations.
• Simulated results anticipate a decrease in the average monthly precipitation during the period of 2021–2100.

1. INTRODUCTION

Climate change and its impact, increasing concentration of ‘greenhouse gases’ in the atmosphere causes to climate changes, have gained serious consideration in hydrology. General circulation models (GCMs) are analytical models representing physical processes in the atmosphere, ocean, ice and land surface, are the primary tools that maintain reasonable accurate climate information at global scale, simulating the response of the global climate system to increasing greenhouse gas concentrations (Tofiq & Guven 2014, 2015).

GCM outputs cannot generate local climate details in the finer spatial resolution due to the uncertainty in the spatial resolution between the GCM and hydrological models (Shahid et al. 2013). Subsequently, downscaling methods have been developed to transform the GCM outputs from coarse spatial resolution to a finer spatial resolution that it can be directly used for forecasting the climate change at the local scale (Hashmi et al. 2011). Based on its working principle, it can be broadly categorized as statistical downscaling and dynamic downscaling. Statistical downscaling is more widely used in hydrology studies because it requires less computational demand while dynamic downscaling requires high computational resources and expertise. Statistical downscaling establishes the empirical relationship between the large-scale climatic parameters such as mean sea level pressure, wind speed, zonal velocity (predictors) and local parameters (predictand) such as temperature, precipitation, and discharge (Chen et al. 2010a, 2010b).

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Statistical downscaling can be roughly divided into four categories: regression methods, weather pattern-based approaches, stochastic weather generators, and limited-area modeling (Wilby & Wigley 1997). A regression method is preferred among these approaches because it is easy to implement and it has low computation requirements. However, when the variable of interest is precipitation, the input-output relationship is often very complex and linear regression-based methods may not work very well. Therefore, a number of non-linear regression based downscaling techniques have been offered and successfully applied (Mpelasoka et al. 2001; Haylock et al. 2006). Scientific literature of the past decade includes predicting the runoff based on precipitation and rainfall-runoff models using statistical downscaling and different GCM scenarios (Schmidli et al. 2007; Yonggang et al. 2007; Chen et al. 2012).

Group Method of Data Handling (GMDH) method was invented by A. G. Ivakhnenko (Ivakhnenko 1971). GMDH is described as a nonparametric (self-organizing) learning algorithm. This means that it makes no prior assumptions about the ‘true’ form of the model that it derives. It is a learning algorithm in the sense that it uses a ‘hill-climbing’ approach and remembers its successes during a systematic trial and error search (Green et al. 1988). It is also called as a ‘polynomial model’ acting the predicted value of the output will be as close as possible to the actual value of output by constructing successive layers with simple polynomial terms such as polynomial, harmonic, square root, inverse polynomial, logarithmic, exponential, rounded polynomial, etc. (Muttil & Liong 2012). These polynomials with two variables can be expressed as:

$$y = p_0 + p_1x_1 + p_2x_2 + p_3x_1^2 + p_4x_2^2 + p_5x_1x_2$$

(1)

where, $p_i$ is the model coefficient, $x_i$ is the base function.

GMDH model automatically selects the most accurate input variables and the optimal network structure in order to minimize the difference between the structure output and desired output. GMDH is therefore generalizable and can be adapted to the complexity of non-linear systems with a relatively simple and numerically stable network (Assaleh et al. 2013). The advantage of GMDH algorithm is reasonable for the system that has large input dataset. There are a lot of applications of the GMDH in environmental, ecological, and the social systems (Duffy & Franklin 1975; Josef & Petr 2011). GMDH has become a popular method used in water resources studies and was successfully applied in the prediction of hydro meteorological variables (Saburo et al. 1976; Muttil & Liong 2012; Zahirae et al. 2017).

Gene Expression Programing (GEP) is a new variant of genetic programming (GP) that was progressed by Ferreira (Ferreira 2001). GEP is a genotype/phenotype system that evolves computer programs of different sizes and shapes (the phenotype) encoded in linear chromosomes of fixed length (the genotype). GEP is an evolutionary algorithm, uses symbolic regression to fit the data to get an optimum form of mathematical function. The GEP has determined automatically the state and regression method that has been obtained from statistical learning theories. The regression version of the SVM framework follows the principle of Structural Risk Reduction (SRM), which is proven to be superior to the traditional empirical risk reduction (ERM) principle used by traditional modeling techniques (Vapnik 1999). The traditional ERM concentrates on minimizing training data error, whereas SRM minimizes the upper limit of expected risk, hence providing SVM with the ability to generalize and this is the essential aim of statistical learning (Vapnik 1999). There are four fundamental advantages of SVM. Firstly, it has a regularization parameter, which makes the user thinking about escaping over-fitting. Secondly, SVM is decided by a convex optimization problem for which there are accurate methods (e.g., SMO). Thirdly, it is estimated to bound on the test error rate, and there is a significant body of theory behind it which suggests it should be a good idea. Final and main advantage of SVM is that it utilizes the kernel trick (function) to construct expert knowledge about the investigated phenomenon so that the model complexity together with estimation error is concurrently minimized (Karimi et al. 2017). SVM has been used during the last decade for rainfall-runoff modeling. Many SVM-based models related to the field of hydrology have been investigated (Raghavendra & Deka 2014).
They concluded that the regression models were ineffective compared to SVM models in many cases as analyzed in the literature. The statistical downscaling of daily precipitation using SVM and multivariate analysis have been investigated. The SVM model results are compared with statistical downscaling model (SDSM) and found that the statistical performance of SVM model is better than SDSM in predicting daily precipitation (Chen et al. 2010a, 2010b). Daneshfaraz et al. (2021a, 2021b) investigated the application of SVM for predicting hydraulic parameters of a vertical drop equipped with horizontal screens and the results showed that the application of SVM performs high \( R^2 \) value. (0.991 for testing and training modes). Daneshfaraz et al. (2021a, 2021b) also examined the application of the SVM for estimating vertical drop hydraulic parameters in the presence of dual horizontal screens. The results show that this method can accurately predict the hydraulic performance of the systems.

GMDH, GEP and SVM techniques are applied separately and results are compared. On the contrary, inclusive multiple modelling (IMM) strategy can be used to decrease residual errors. Sadeghfam et al. (2021) investigated hydrological impact of climate change in terms of downscaling of monthly precipitation by producing an inclusive multiple modelling (IMM) approach. IMM strategies handle multiple models at two levels. The model at Level 2 merges outputs of those at Level 1 and produces Level 2 results, which enhance compared with those at the Level 1 models in terms of dispersion of residual errors. In this way, IMM maintains a more defensible modelling approach for application in the projection stage.

In this study, GMDH, GEP and SVM methods are applied to develop the areal mean precipitation downscaling models and to find the future change pattern for precipitation. Finally, a multiple linear regression model is analyzed for comparison. The novelty of the paper contains the application of three different downscaling techniques (GEP, GMDH, and SVM), comparison of those techniques according to statistical indicators and projection of downscaling techniques under under GCM A1B and A2 emission scenarios.

2. STUDY AREA AND DATA USED

The study area is Göksun River basin which is the sub-basin of Ceyhan River basin. This basin area is located 100 km from Kahramanmaraş city on the boundary of Göksun region on the eastern Mediterranean. Figure 1 shows the Digital Elevation Model (DEM) of Göksun River Basin. This basin surrounds an area of 2,307 km\(^2\), and its elevation ranges from 1,170 m to 2,800 m a.s.l. There are three local precipitation gauge stations near the study area. Summary of the rainfall data used in this study for each station is given in Table 1.

The mean precipitation data of these three stations are converted to the first dataset (predictand set) used in this study, areal mean precipitation (PM) of the basin, which are calculated by using the Thiessen Polygons method. Figure 2 shows thiessen polygons of the basin and location of precipitation gauge stations. Colorful lines represent each thiessen polygon lines to find fraction of each station in order to determine areal mean precipitation. The center of the basin is located at Lat 38° 6’ Long 36° 48’. The second dataset is the large-scale predictor variables data for grid box (Box_11X_14Y) representing the study area, obtained from the Canadian Global Climate Model (CGCM) which is available at the website (www.cccsm.ec.gc.ca/index.php). Each grid cell stands for a mesh surrounding the corresponding model grid points. The dimension of each grid cell is approximately 3.75° latitude and 3.75° longitude (Gaussian grid). This process takes place by input decimal latitude and longitudinal coordinate of any location, and in this study coordinate of the centroid of the basin is used. The CGCM3 variables are used as predictors in this study, in as much as they are broadly used in several climate changes and downscaling studies. Table 2 utilizes the description of CGCM3 variables which contains 26 variable data sets. This data set consist of 26 variables for each scenario (Toﬁq & Guven 2014, 2015; Singh et al. 2015).

Figure 3 shows the location of Göksun basin and precipitation stations. Figure 4 shows Turkey map with centroid of Göksun basin.

3. METHODOLOGY

3.1. Selection of the most effective predictors

Predictor selection is one of the most critical steps in the climate downscaling process. In this study, the correlation between the predictors and predictands were evaluated. To improve the correlation with predictor variables and predictands, the predictands were modified based on some normalization methods. These modifications are: taking natural logarithm (Ln), min-max normalization (Mn) which normalizes the data to the range from 0 to 1, and standardization of (Stand) the predictand variables. To select the most effective predictors and to see the linear relationship between inputs and outputs, correlation
analysis was employed by Pearson rank correlation coefficient method. Results illustrated that most large-scale weather factors were statically correlated with local precipitation under the confidence level of 99%. Factors with a higher correlation coefficient were selected as the predictors for downscaling models. The set of the predictors are divided into three categories according to the value of the correlation coefficient (R) between the predictand and the predictors. These categories are: R > 0.3, R > 0.4 and R > 0.5. Predictors with a correlation of R > 0.5 were used for natural logarithm normalization of predictor and predictand variables. The highest correlating GCM variables, R > 0.5 (10 in this case) were selected and presented in Table 3.

The input correlation bigger than 0.5 were Mean sea level pressure (V1), 1,000 hPa Meridional velocity (V4), 1,000 hPa Divergence (V7), 850 hPa Wind speed (V15), 850 hPa Meridional velocity (V16), 850 hPa Meridional velocity (V17), 850

**Figure 1** | Digital Elevation Model (DEM) of Göksun River Basin.

**Table 1** | Statistical summary of the data used in this study for each station

| Item                      | Afsin  | Göksun  | Elbistan |
|---------------------------|--------|---------|----------|
| Mean Annual Rainfall (mm) | 426.50 | 597.20  | 385.88   |
| Mean Monthly Rainfall (mm)| 35.54  | 49.77   | 32.16    |
| Maximum Annual Rainfall (mm)| 560.30  | 869.40  | 548.50   |
| Minimum Annual Rainfall (mm)| 273.80  | 354.20  | 247.40   |
| Maximum Daily Rainfall (mm)| 65.50  | 85.40   | 46.10    |
| Duration of Data (year)    | 41     | 42      | 42       |
| Number of Data set (days)  | 14,965 | 15,330  | 15,330   |

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hPa Vorticity (V18), 850 hPa Geopotential (V19), 850 hPa Wind direction (V20), 1,000 hPa Specific humidity (V25), Screen air temperature (2 m) (V26).

3.2. Downscaling using GMDH, GEP and SVM techniques

There are several steps to solve a problem using the GMDH and GEP programs (Mpelasoka et al. 2001; Haylock et al. 2006).

There are four crucial steps to get the solution to the problem in GEP. In this study, the first critical step is to determine a set of function. A set of functions (+, -, *, /, power, Ln) were selected from the set of functions in the GEP program. The second critical step for GEP program is to determine the chromosome structure which includes the number of genes per chromosome and the size of the gene. The best model results were obtained by using four genes (4 genes) per chromosome for each GEP model. The third critical step is to select the linking function. In this study, the linking function was selected as ‘+’ (addition). The final critical step is the fitness measure. In this study, the root relative squared error (RRSE) of the training set is employed as a fitness function.

The GEP model also developed an equation, given in Equation (2), for the calibration process to generate the validation process and to predict the future projections. The definition of each variable is given in Table 3.

\[
\text{LnP}_M = \left( \frac{V1 \times \left( \frac{V26}{V15} + \frac{V4}{V20} \right)}{V18} \right) + 2.4824 + \left( \frac{(V1 - (V26 + 2.4924)) \times V26}{V18} \right) + (0.0365 \times (27.383 - V26))
\]

Figure 2 | Thiessen polygons of the basin and location of precipitation gauge stations.

The main step is to determine the set of network parameters in order to obtain a solution from GMDH model. In this study, the maximum network layer is set to fifteen (15), the maximum polynomial order is twelve (12), and the convergence tolerance factor 0.001 is used for GMDH model. Network layer connection is selected as the previous layer and original input...
variables. The number of neurons per layer is fixed as fifteen (15) neurons. The final main step is to decide suitable functions that will be used in the GMDH network. We got the best results by using Linear 1, 2, and 3 variables and Quadratic 1, and 2 variables.

Epsilon Support Vector Regression (SVR) was used to predict monthly mean precipitation for SVM model. Radial basis function was used as a kernel function. Parameter optimization search control is chosen to get optimal parameter for SVM models. Then grid search and pattern search is done. The SVM model has three parameters which are C, \( \gamma \), and \( \varepsilon \).

Table 4 shows parameters, which are acquired via the SVM to predict the monthly areal mean precipitation.

The statistical measures used to evaluate the accuracy performance of GMDH, GEP and SVM models and linear regression models which are the coefficient of determination \( (R^2) \), the root mean square error \( (RMSE) \) and the mean absolute errors \( (MAE) \).

4. RESULTS AND DISCUSSION

Large-scale weather factors (26 input sets) were used as predictors which were obtained from the Third Generation Coupled Global Circulation Model (CGCM3). The areal mean precipitation of the basin \( (P_M) \) was used as predictand (output). All data sets are based on a monthly time scale. Both data sets were divided into two subsets (calibration and validation). The first one is the calibration period ranging between 1971 and 1990. The second one is the validation period.
ranging between 1991 and 2000. GMDH, GEP, and SVM downscaling techniques were utilized to predict the downscaled PM of the basin. Furthermore, the prediction results of downscaling techniques were compared with each other to examine the best model performance. Also, Multiple Linear Regression was used for comparison of the proposed nonlinear models with a linear model.

The statistical results of the best model of monthly areal mean precipitation PM in Göksun River Basin for validation period are shown in Table 5. It is seen in Table 4 that the simulated mean monthly areal mean precipitation by SVM, GEP, GMDH models, and LR are lower than the observed mean PM numerically 10, 10.9, 11.6, and 14.5 mm respectively. It means the means were underestimated by all models. But, the SVM model yielded better results than the other models to simulate the mean PM. The SVM and GMDH models perform well in predicting the minimum PM while LR performs poorly to simulate the minimum PM. Moreover, there is a significant difference in the maximum value of simulated PM compared to observed data. GMDH model records the minimum difference of 9% for maximum PM, and the SVM model records the maximum difference of 41% for maximum PM. Like the mean, all models underestimated the standard deviation, but the SVM model has the minimum underestimating difference of 36% among the all models.

As seen by the values of statistical indicators given in Table 4, the SVM model has a lesser MAE (22.26 mm) and RMSE (32.36 mm) than the other proposed models. The MAE is approximately 8%, 8.8% and 19.5% for the GEP, GMDH, and LR models, respectively, greater than that of the SVM. The RMSE is approximately 5.5%, 7.5%, and 19.5% for the GEP, GMDH, and LR models, respectively, greater than that of the SVM.

Figure 5 represents the scatter plot of the observed PM versus the predicted ones of the Göksun River Basin for GMDH, GEP, SVM and Linear Regression for validation period. The SVM ($R^2 = 0.62$) and GMDH ($R^2 = 0.61$) model have the almost same coefficient of determination ($R^2$) and GEP model's $R^2$ (0.59) is close to these two models. However, the SVM model has the highest $R^2$ while the linear regression model has the lowest $R^2$ (0.53).
**Table 4** | Parameters of SVM model

| c  | γ  | ε  |
|----|----|----|
| 9.03 | 3.39 | 0.01 |
The linear equations comprising the relation between the observed and the predicted PM for the four models (GMDH, GEP, SVM, LR) were obtained to be:

\[ y = 0.780x + 0.905 \] \hspace{1cm} \text{(GMDH model)} \hspace{1cm} (2)  \\
\[ y = 0.827x + 0.717 \] \hspace{1cm} \text{(GEP model)} \hspace{1cm} (3)  \\
\[ y = 0.738x + 1.036 \] \hspace{1cm} \text{(SVM model)} \hspace{1cm} (4)  \\
\[ y = 0.893x + 0.568 \] \hspace{1cm} \text{(LR model)} \hspace{1cm} (5)  

where \( y \) represents the observed PM and \( x \) represents the predicted PM.

**Table 5** | Comparison of statistical results of observed and simulated PM during the validation period (1991–2000)

| Data            | Mean (mm) | Std. Deviation (mm) | MAE (mm) | RMSE (mm) | \( R^2 \) |
|-----------------|-----------|---------------------|----------|-----------|---------|
| Observed        | 45.94     | 40.53               | -        | -         | -       |
| GMDH Model      | 34.37     | 25.25               | 24.23    | 34.14     | 0.61    |
| GEP Model       | 35.07     | 25.59               | 24.05    | 34.78     | 0.59    |
| SVM Model       | 35.94     | 25.94               | 22.26    | 32.36     | 0.62    |
| Linear Regression | 31.43  | 25.86               | 26.60    | 38.67     | 0.53    |

**Figure 5** | Scatter plot of the observed PM versus the predicted ones of the Göksun River Basin for GMDH, GEP, SVM and LR for the validation period.
Some of the predicted PM values of the proposed downscaling models were observed to be negative values. Under this situation, those negative values were adjusted to zero. The percentage of negative values over the total number of monthly areal mean precipitations were 3.32% in the GMDH, 2.49% in the GEP, 0.83% in the SVM, and 10% in linear regression models. Linear regression has the biggest percentage correction of negative values adjusted to zero, while GMDH, GEP, and SVM needed less correction. These corrections affect the statistical properties of models and cause the tendency to right of predicted value when the observed value is equal to 0.

Also, the Akaike Information Criterion (AIC) values of each proposed models were calculated and given in Table 5. AIC, introduced by Akaike (1974), is employed to evaluate the generalization capacity of the proposed models.

\[ AIC = N \times \ln(MSE) + 2k \]  

where \( N \) is the number of data, \( MSE \) is the mean square error, and \( k \) is the number of fitting parameters. AIC is used to evaluate the exchange between calibration performance and network size. The aim is to get smaller AIC to acquire a network with the best generalization. The number of data used in the validation period is 120. It can be seen that AIC increases when the number of the fitting parameter (k) increases. Table 6 indicates that the SVM model has the lowest MSE value (1047.3 mm²), however SVM model has the biggest AIC value (3,078) because of having high number of fitting parameter. Consequently, the lowest AIC (860) with k (4) values of the GEP model presents its best robustness and the generalization capacity.

Figure 6 displays the simulated averaged monthly mean precipitation, PM of GMDH, GEP, SVM, and LR models and the observed data during the validation period. It is clear that the SVM model has slightly underestimated the PM for each month. In January, the LR model overestimated the PM while other models underestimated. In February, the LR model and the GEP model overestimated the PM while other models underestimated the PM. In July and October, the GMDH model overestimated the PM while other models underestimated the PM.

In March, April, May, Jun, August, September, and October all models underestimated the PM. In April, May, and June SVM predicted the best averaged mean precipitation compared to the observed data. The mean underestimating percentage

| Model   | MSE (mm²) | k     | AIC    |
|---------|-----------|-------|--------|
| GMDH    | 1,165.7   | 490   | 1,827  |
| GEP     | 1,209.7   | 4     | 860    |
| SVM     | 1,047.3   | 1,122 | 3,078  |
| LR      | 1,495.1   | 11    | 899    |

Table 6 | AIC values of proposed models during validation (1991–2000)

Figure 6 | Observed and predicted averaged monthly PM for the validation period 1991–2000 by all models.
in April which are 33%, 38%, and 41.8% for the GMDH, GEP, and LR model, respectively, smaller than that of the SVM model as shown in Figure 3. In March, September, November, and December the GEP model performs best in predicting $P_M$. The mean underestimated percentage in March which are 7.5%, 10.4%, and 16.2% for the GMDH model, the LR and SVM model, respectively, smaller than that of the GEP model. In July and October, the GMDH model performs best in predicting $P_M$. The mean underestimating percentage in October which are 3%, 21.4%, and 34.6% for the SVM model, the GEP model, and linear regression model, respectively, smaller than that of the GMDH model. In January, February, July, and August, the LR model performs best in predicting $P_M$. In February, SVM and GMDH models predicted the same amount of $P_M$.

Consequently, the SVM model outperformed over the other models in the validation period with the highest coefficient of determination ($R^2$) and least RMSE and MAE values. However, GEP has the lower AIC values than the other models.

5. FUTURE PROJECTION OF $P_M$ UNDER DIFFERENT EMISSION SCENARIOS AND DIFFERENT DOWNSCALING MODELS

The downscaling performance of the GCM scale simulated under both GCM A1B and A2 emission scenarios for $P_M$ for the study area has been explored and analyzed. These scenarios are defined by IPCC (2007). A1B scenario describes the future of the world with very rapid economic growth, a world population that peaks in the middle of the century and then declined, and the rapid introduction of new and more efficient technologies and technological focus is balanced between all energy sources. A2 scenario describes a very diverse world, with a growing global population and regional economic growth. This scenario is more disconnected and slower than in the other scenarios. It also represents a high emissions scenario and illustrates the worst case scenario (Andersen et al. 2006).

CGCM3A2 and CGCM3A1B variables were utilized to predict the pattern of future change for the period of 2021–2100 for the $P_M$ in the study area. The downscaled results from both scenarios (A1B and A2) were divided into four time periods with 20 years range, namely: 2020s (2021–2040), 2040s (2041–2060), 2060s (2061–2080), and 2080s (2081–2100), and compared with the baseline period (1971–2000) to examine the future change in $P_M$ for the basin area.

Figure 7 displays the projection of averaged monthly $P_M$ change under CGCM3A1B scenario for different time periods by the SVM model. From Figure 7, it is clear that the SVM model projected the amount of precipitation for each different time periods will be decreased compared to baseline $P_M$. A noticeable decrease occurs in May and it projected a decrease in the averaged monthly $P_M$ of about 18%, 31%, 35.5%, and 48.2% for the 2020s, 2040s, 2060s, and 2080s, respectively, under the A1B scenario. From Figure 7, it is observed that a constant decrease in $P_M$ occurs during the four periods (2020s, 2040s, 2060s, and 2080s) for the May, Jun, August, and September. From November to April, it is observed that a constant decrease in PM does not occur during the four periods (2020s, 2040s, 2060s, and 2080s). In April, there is a increase in $P_M$ period of from 2040 to 2060 s. In February, it is observed that there is a noticeable increase in $P_M$ after 2080s.

Figure 8 shows the projection of averaged monthly $P_M$ change under CGCM3A2 scenario for different time periods by the SVM model. From Figure 8, it is clear that the SVM model projected the amount of precipitation for each different time
periods will be decreased when compared with baseline mean precipitation. However, in April the projected mean precipitation is so close to the observed baseline mean precipitation. A noticeable decrease occurs in May and it projected a decrease in the averaged monthly $P_M$ of about 27.3%, 51.3%, 37.3%, and 59.1% for the 2020s, 2040s, 2060s, and 2080s, respectively, under the A2 scenario. In Figure 8, it is observed that a constant decrease in $P_M$ does not occur during the four periods (2020s, 2040s, 2060s, and 2080s). It is seen that a tendency to decrease in $P_M$ occurs from May to October. It is observed that there is a noticeable increase in $P_M$ after 2080s from January to April.

The changes in max precipitation predicted by both scenarios are different from each other in magnitude, but almost similar in their patterns as seen in Figure 7 and 8. Both scenarios show an average annual decrement with respect to the baseline period (1971–2000) in these figures. Under the A1B scenario, the SVM model predicts a decrease in the averaged annual $P_M$ by 24.7%, 28%, 30.7, and 32.5% for the 2020s, 2040s, 2060s, and 2080s, respectively. It also projects a decrease in the averaged annual $P_M$ of about 27.5%, 32.3%, 33.1, and 31.1% for the 2020s, 2040s, 2060s, and 2080s, respectively, under the A2 scenario.

Figure 9 displays the projection of averaged monthly $P_M$ change under CGCM3A1B scenario for different time periods by the GMDH model.

Figure 10 displays the projection of averaged monthly $P_M$ change under CGCM3A2 scenario for different time periods by the GMDH model.

Figure 11 displays the projection of averaged monthly $P_M$ change under CGCM3A1B scenario for different time periods by the GEP model.

Figure 12 displays the projection of averaged monthly $P_M$ change under CGCM3A2 scenario for different time periods by the GEP model.

Figure 9 | The projection of averaged monthly $P_M$ change under CGCM3A1B scenario for different time periods by the GMDH model.
Figures 13 and 14 represent the projected annual PM under A1B and A2 scenarios for different time periods by the proposed downscaled models. Figure 6 shows that GMDH model forecasted the lowest annual precipitation, and SVM model projected the highest one. Hollow symbols in Figure 13 and 14 represent the mean annual precipitation downscaled by the models in the baseline period 1971–2000. Figure 14 exhibits that GMDH model projected the highest annual precipitation, and the SVM projected the lowest from 2021–2049 to 2055–2084 periods while SVM model projected the highest annual precipitation, and the GMDH projected the lowest from 2055–2084 to 2070–2099 periods.
The purpose of this study is to evaluate performance of the different artificial intelligence techniques in the statistical downscaling process. GMDH and GEP select the most accurate predictor variables automatically, while SVM uses the whole input set. Statistical downscaling of precipitation is highly difficult, as the relation between the GCM variables and the local variables are often complicated. In this study, statistical downscaling of areal mean precipitation of a basin is carried out by using GMDH, GEP and SVM techniques comparing the results of linear regression. Consequently, results show that the SVM
model outperformed over the other models in the validation period with the highest coefficient of determination ($R^2$) and the least RMSE and MAE values. However, GEP has the lower AIC values than the other models. This proves the highest generalization capacity of the GEP model.

The downscaling performance of these techniques under both GCM A1B and A2 emission scenarios for the areal mean precipitation of the study area was also analyzed. For future projection of different scenarios, all methods perform similar manner in their mean precipitation. Likewise, both scenarios forecast a decrease in the average monthly precipitation for future projection. On account of the results of future projections have simulated that the precipitation might decrease during the period of 2021–2100.

The outcomes of this study are believed to be guide for decision makers in governmental agencies and also a reference for the hydrologists who deal with estimation of water resources of river basins.

**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

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