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Assessing Precipitation Trend: a Case Study of Kabul, Afghanistan

Homayoon Raoufi[1], Sayeed Nabi Attayee[2]
[1]Department of Plant Protection, Agriculture faculty, University of Kunduz, Afghanistan
[2]Department of Environment, University of Tehran, Iran
Corresponding Author: Homayoon Raoufi; Email: h.abdullah1400@gmail.com

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ABSTRACT

Climate change is one of the most important issues on a global scale, and it has exerted a significant impact on environmental security and livelihoods, both directly and indirectly. In this study, the precipitation trend is assessed by comparing predictand and predictor data from 1990 to 2020. Predictand data were obtained from local organization data sets, and predictor data were taken from the General Circulation Models. Tow models, statistical downscaling model (SDSM), and Long Ashton Research Station Weather Generator (LARS-WG) are applied to downscale and project the future rainfall condition (2025-2100) under RCP2.6, RCP4.5 and RCP8.5. The performance of the two models was checked by using measured indicators (R, R^2, MAE, RMSE, and NRMSE). The non-parametric Mann-Kendall test was used to determine the precipitation trend. The results revealed that the precipitation trend is decreasing in the reference period. In the future, it would decrease under RCP2.6 and RCP8.5 except for RCP4.5 by SDSM and RCP4.5 and RCP8.5 except RCP2.6 by LARS-WG. The values of Monthly changes in precipitation (%) under RCP2.6, RCP4.5, and RCP8.5 are 0.3 to 2.7%, 0.4 to 2.7%, and 0.4 to 2.8% in December, August, March, and April, respectively. Seasonal changes in precipitation under RCPs ranged from 4.87 to 4.89% in spring, 0.01% in summer, 2.43 to 1.76% in autumn, and 4.35 to 4.63% in winter. The change in precipitation during the spring season is decreasing, whereas it is increasing in the autumn.

INTRODUCTION

All biological systems, including humans, can be affected by biotic variables like temperature, rainfall, atmospheric pressure, humidity, and wind speed, which results in a reduction in agricultural production (Panda and Sahu, 2019). Climate change has an extreme impact on food security, altering resource availability and the hydrological cycle (Javadinejad et al., 2021; Jha et al., 2021). Many studies have determined that climate changes occur and affect natural systems (e.g., biological, ecological, and hydrological systems), but their impacts are not uniform around the world (Saddique et al., 2021), whereas some regions are more susceptible (Munawar et al., 2022). Among the biotic variables, temperature and rainfall are the most important parameters, and these variables control the ecological systems and environmental conditions for food production (Singh et al., 2013; Kumar and Gautam, 2014). An increase in temperature and a decrease in rainfall affect hydrological systems (water resources and hydrological cycles) directly and indirectly over a long period (Pal and Mishra, 2017; Khan et al., 2021). Water resources and the hydrological cycle are the most important parameters of natural systems, agricultural production, and all socioeconomic (Gajbhiye et al., 2016). Over the past few decades, there has been an increase in the frequency and magnitude of extreme climate events, such as floods and droughts.

Due to the dependence of the majority of Afghanistan's population on the availability of natural resources, directly or indirectly, for their livelihoods, the impacts of climate change are very serious and cause great economic loss (UNDP, 2017). People's lives, safety, and property are at risk due to the increasing frequency of extreme occurrences including heat waves, floods, and droughts. These occurrences pose a serious threat to the nation's food security, stability, and economic foundations. Because more intense extreme rainfall events are occurring more frequently and lasting longer, there are more hydro-meteorological disasters (Chen et al., 2022). In Afghanistan and other regions without improved agricultural production systems, precipitation plays a crucial role in agricultural production.

Understanding the climatic situation and parameters requires analyzing climatic parameters like precipitation. Local agencies including the Ministry of Agriculture, Irrigation, and Livestock (MAIL), the Ministry of Energy and Water (MEW), the Meteorological Department of Afghanistan (MDA), and internet data sets (GCMs) provided the observation data used in this study. General circulation models (GCMs) can significantly enhance the evaluation of possible global climate change implications (Disasa and Yan, 2022). The Daily Reanalysis Data for the baseline period was obtained from the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP/NCAR). NCEP predictors were used for screening purposes in the SDSM model, which examined the link between NCEP predictors and local predictands (precipitation) (Saddique et al., 2019; Munawar et al., 2022). The GCM (CanESM2) model provided the NCEP/NCAR data. Two well-known statistical downscaling models for downscaling GCM outputs including temperature, precipitation, and radiation are the statistical downscaling model (SDSM) and the Long Ashton research station weather generator (LARS-WG) (Saddique et al., 2021).

Hence, many recent studies have focused on the evaluation and comparison of both models in terms of their ability to simulate the mean and extreme rainfall frequencies using a parametric distribution at a local scale (Hassan et al., 2013). This study uses generated and observed climatic data under three scenarios (RCP2.6, RCP4.5, and RCP8.5) to estimate the precipitation trend. The future forecast period was 2025–2100, while the reference period was 1990–2020. For future estimates, the two models produced different findings. Hassan et al. (2013) claimed that the different results arose from the differences in their downscaling strategy and their basic concepts.

In Afghanistan, there have not been many published papers on the precipitation trend analyzed in recent years by both models. The main object of this study is the assessment of precipitation change in the reference and future periods (1990–2100). To reduce climate change, it is fundamental to assess the vulnerability of a territory and its communities, which depends not only on their exposure to climate change but also on the adaptive capacity of the different sectors and the local socioeconomic context (Gancalves et al., 2021).

MATERIALS AND METHODS

Study Area

This study was conducted in Kabul province, in the central part of Afghanistan. The geographical extent of the region exists between (34° 33' 19.258" N and 69° 12' 26.95 E), which covers a total area of about 4655.25 km2 and elevation above the mean sea level of 1805 meters. The local steppe climate influences Kabul, which receives little rainfall during the year. The average annual temperature is 11.4 °C, and the annual total precipitation is 362 mm. The driest month is June, with about 1 mm of precipitation, while March, with an average of 88 mm, is the rainiest. July, with an average temperature of 23.2 deg. C, is the warmest month of the year, Whereas January, with an average of -2.9 deg. C is the coldest month of the whole year.

Data Description

The predictands, the daily observed climatic data for precipitation, were collected from local organizations such as the Ministry of Agriculture, Irrigation, and Livestock (MAIL, 2022), the Ministry of Energy and Water (MEW, 2022), and the Meteorological Department of Afghanistan (MDA, 2022) for the baseline period. Furthermore, the outputs of GCMs based on the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) that are available in the Coupled Model Intercomparison Project Phase 5 (CMIP5) were used to provide variables for baseline and future simulation. The predictors, NCEP predictors, which provide daily reanalysis data on several variables, are applied for screening purposes for future projection and correlation with predictands (Munawar et al., 2021). The GCM data were downscaled with SDSM and LARS-WG models (large-scale data cannot be reliably applied to the small size of the area), and they were then used to project for future periods by using CanEsm2, the Canadian Center for Climate Modeling and Analysis, Canada. Three scenarios, RCPs 2.6, 4.5, and 8.5, for the period 2025–2100, according to the Intergovernmental Panel on Climate Change (IPCC, 2014), are used to estimate the patterns of rainfall. These scenarios are identified by their potential range of radiative forcing values of 2.6, 4.5, 6, and 8.5 W m-2 by 2100. Under these scenarios, a broad area of challenges including greenhouse gas emissions, air pollutants, and impacts of climate change are represented. The lowest, medium, and highest scenarios of greenhouse gases are considered for RCP2.6, RCP4.5, and RCP8.5 respectively. To avoid ambiguities, errors, and biases in the results, the bias correction method was also used. The bias correction methods are used to correct the errors and biases between predictands and predictors (the observed and GCM simulation data) for the baseline period (1990–2020) (Munawar et al., 2021).

Model Performance

The performances of the models were estimated by comparing the observed and generated data using statistical indicators. The parameters such as the correlation coefficient, the determination coefficient (R2), mean absolute error (MAE), root mean square error (RMSE), and normalized root mean square error (NRMSE) are used to verify the results of the models during the calibration and validation process, as equation 2 – 6, respectively.

$$R = \frac{\sum(X-\bar{x})(y-\overline{y})}{\sqrt{(x-\overline{x})^2 - \sum(y-\overline{y})^2}} \qquad (1)$$

$$R^2 = Var\text{-}Exp\ by\ mod/\ Total\ variance \qquad (2)$$

$$MAE = \frac{\sum_{i=1}^{n}[x_i - y_i]}{n} \qquad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}((Xi-Yi)2}{n}} \qquad (4)$$

$$NRMSE = RMSE/\ Xi \qquad (5)$$

$$P_{de-biased} = P_{sim\ (2025-2100)}\ \text{x}\ (P_{obs}\ (1990\text{-}2020)/P_{sim\ (1990\ -2020)}) \qquad (6)$$

Here, R is the correlation coefficient; R2 is the determination coefficient; MAE is the mean absolute error; RMSE is the root mean square error; NRMSR is the normalized root mean square error; X and Y are the values of variables, and $\bar{y}$ are the means of variables. Xi is the observed value of variables; Yi is the simulated value by the models; and n is the measured number (Ababaei et al., 2010; Delavar et al., 2016; Munawar et al., 2022).

Trend Analysis

Climate trends were analyzed using the Mann-Kendall test method. The MK test has been widely used to analyze climatic trends for a long period in the environmental time series (Haldar et al. 2023; Sudarsan and Lasitha, 2023). The MK test determines whether a time series has a monotonic upward or downward trend in a time series. The test doesn't require data that is randomly distributed and has a low sensitivity to abrupt breaks because of inhomogeneous data (George and Athira 2020; Bayu et al. 2024). The MK test examines how observation and simulation data change over an extended period (Donald et al. 2011; Monforte and Ragusa, 2022). Each later-measured value is compared to all values that are measured earlier, and it assumes that a value can be computed as 1 (positive difference), 0 (no difference), and -1 (negative difference) than to another value (Donald et al. 2011). This method was used to check the null and alternative hypothesis validation for a given time series. The null hypothesis assumes that there is no trend in the observed series, while the alternative hypothesis indicates the existence of a monotonous trend, increasing or decreasing, in the examination data (George and Athira 2020). The MK test statistic (S) was computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n-1} sgn\ (xj - xi), \qquad (1)$$

Where xi and xj are the orderly data recorded in the i and j years; n is the span of the time series data (Munwar et al. 2021).

Where sgn *(xj – xi)*, $= \begin{pmatrix} +1, & (xj - xi) & > 0 \\ 0, & (xj - xi) & = 0 \\ -1, & (xj - xi) & < 0 \end{pmatrix}$ (2)

When S is a positive number (S>0), later-measured values tend to be larger than earlier values and it indicates an increasing trend in a climatic variable (x). If S is equal to zero (S =0), it shows neither a decrease nor increase in a climatic variable (x), and if S <0, it presents a decreasing trend in the climatic variable (x) for long climatic time series data (Donald et al. 2011; Bayu et al. 2024). The variance of S is given by equation 3:

$$Var(s) = \frac{1}{18}[\, n(n-1)(2n+5) \sum_{p=1}^{q} tp\,(tp\,(tp-1)(2tp+5)] \qquad (3)$$

Where q is the number of tied groups, tp is the number of observations in the group (Munaware et al. 2021; Bayu et al. 2024).

Results and Discussion

Evaluation Criteria

The results of the statistical measures proved both models efficient for the validation period for the variable. Table 1 illustrates the measured indices of the statistical downscaling models. The models (SDSM and LARS-WG) were performed (validated) by using statistical measures: R, R2, MAE, RMSE, and NRMSE(%) between observation and projection data. The results of statistical measurements proved that both models are efficient for the estimation of rainfall, as shown in Table 1.

Table 1. Performance indicators

	R	*R^2*	*MAE*	*RMSE*	*NRMSE(%)*
LARS-WG	0.98154	0.96	1.81	4.30	8
SDSM	0.93	0.86	8.39	12	19

Precipitation Trend Analysis for the Reference Period

In this period, the precipitation is calculated monthly and presented in Figure 1. The maximum precipitation is observed for the months of February (52.22 mm), March (57.67 mm), and April (46.60 mm), whereas June, July, and September are the driest months with less than 3.93mm for this period. August and October were considered the driest months, with less than 10 mm of precipitation as well. There is only December greater than 15 mm (Figure 1).

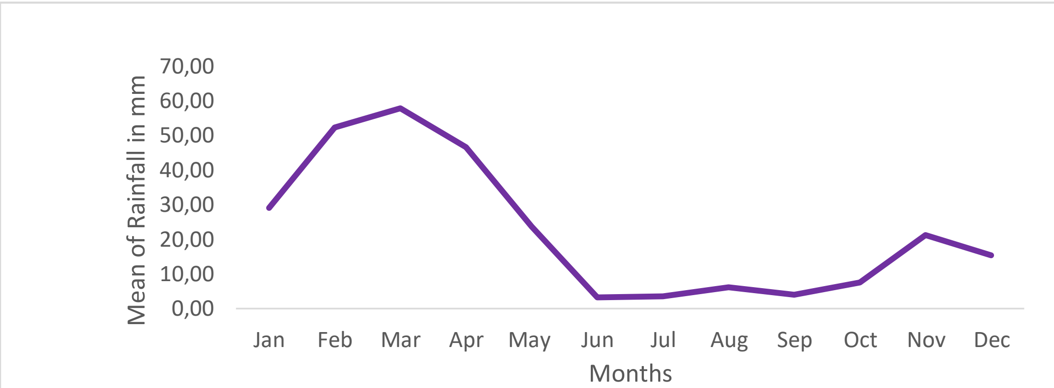

Figure 1. Average monthly precipitation for the predictand data in the study area.

In this study, heavy rainfall, very heavy rainfall, and consecutive wet days (CWD) are also indicated in the reference period. Heavy rainfall (R10 mm) indicates the number of days that have rainfall greater than 10mm in a year, and very heavy rainfall (R20 mm) indicates the number of days that have rainfall greater than 20 mm in a year. Furthermore, CWD is the maximum number of consecutive wet days in a year. The trends of R10 and R20 are decreasing, while the trend of CWD is increasing for the baseline period (Figure 2).

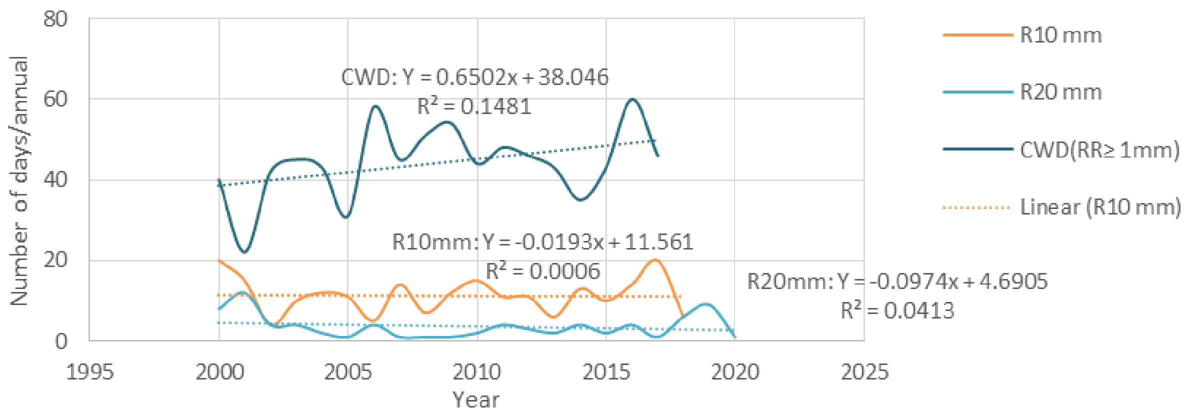

Figure 2. The number of R10 mm, R20 mm, and CWD for the observed period

MK-Trend Analysis

To analyze the presence of trends in precipitation during the reference period, the Mann-Kendall trend model was applied to the available time series, with a significance level of 95%. The positive of Kendall's tau shows an increasing precipitation trend, while the negative values indicate a decreasing trend. Moreover, the p-value < 0.5 presents a significant trend whereas p-value is > = 0.5 indicating there is no trend in the time series of data (Munaware et al., 2022). In this study, the negative value of Kendall's tau showed a decreasing precipitation trend in the reference period (Table 2). Moreover, the p-value of 0.599 is greater than the alpha value of 0.05, indicating statistical significance.

Table 2. Results of the Mann-Kendall test for precipitation data in the reference period

Variable	Minimum	Maximum	Mean	K-tau	S	P-value	Std. deviation
Ref.	140.500	385.600	297.093	-0.14	-14.00	0.599	65.316

Annual precipitation was examined by the MK test in the baseline period as Figure 3 illustrates.

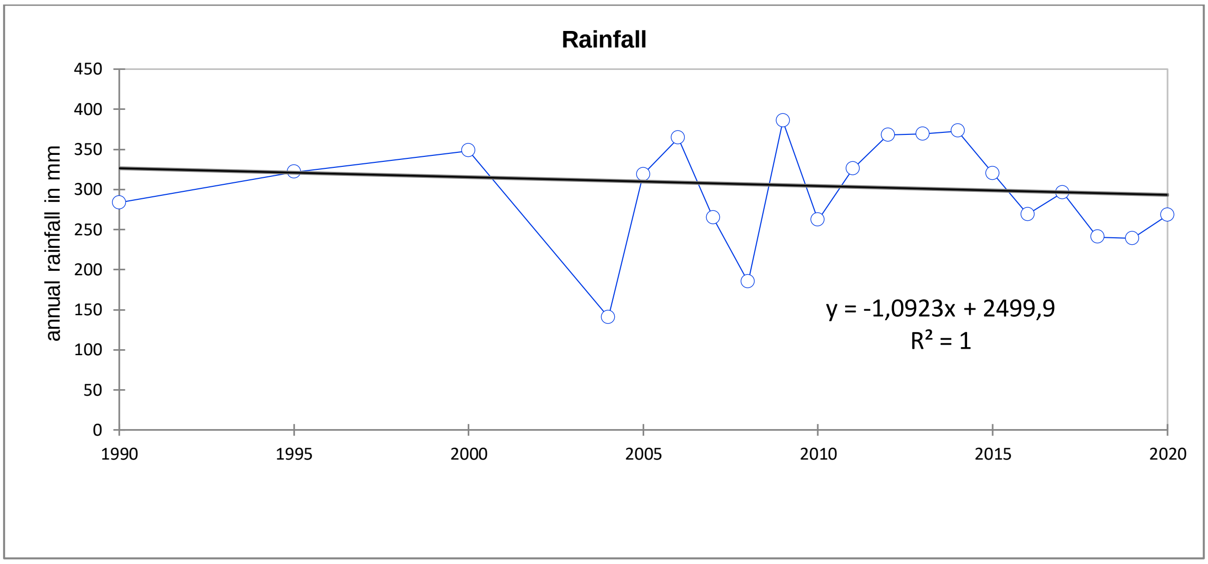

Figure 3. Trend of yearly precipitation in the reference period (1990 – 2020).

Futur Precipitation Projection

The annual and seasonal changes in precipitation under three RCPs for the mid-and end-century (2025-2100) were projected. Table 3 shows a summary of RCPs for future periods by two statistical downscaling models, SDSM and LARS-WG. According to projections with the SDSM model, the precipitation has a decreasing trend under RCP2.6 and RCP8.5 and an increasing trend under RCP4.5. Furthermore, the rainfall trend is decreasing under RCP4.5 and increasing under RCP2.6 and RCP8.5 with the projection of LARS-WG (Figure 4). A decreasing trend in precipitation has been reported by UNDP (2017).

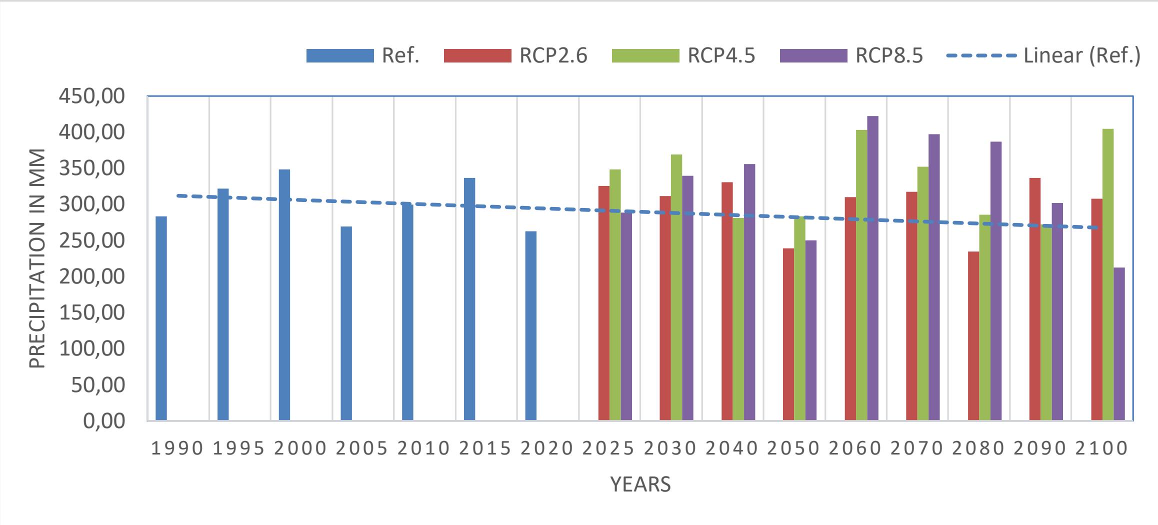

Figure 4. Precipitation is projected from 2022 to 2100.
Annual changes in precipitation were inserted in Table 3.

Table 3. Shows the change in trend in the precipitation (%).

	SDSM			LARS-WG		
	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5
2025	-0.99	1.06	-0.88	1.75	-0.9	0.83
2030	-0.95	0.82	-1.03	1.37	-1.13	1.15
2035	-1.13	0.81	-0.76	1.62	-1.79	1.72
2040	-1.01	0.79	-1.08	0.84	-2.03	1.95
2045	-1.44	1.03	-1	1.18	-0.98	1.06
2050	-0.73	0.86	-0.76	1.06	-1.03	0.99
2055	-0.92	0.69	-0.81	2.08	-1.75	1.93
2060	-0.94	1.22	-1.28	2.1	-1.95	1.91
2065	-1.03	0.73	-0.73	1.03	-0.77	1.21
2070	-0.97	1.07	-1.21	1.05	-0.92	0.96
2075	-0.62	1.32	-0.85	1.78	-1.44	1.23
2080	-0.71	0.87	-1.17	1.94	-1.63	1.95
2085	-1	0.97	-0.73	1.07	-0.77	1.4
2090	-1.24	0.83	-0.92	1.02	-0.95	1.17
2095	-1.03	1.15	-1.12	2.07	-1.45	1.28
2100	-0.93	1.23	-0.65	1.86	-1.59	1.32
Ave.	-0.98	0.96	-0.94	1.49	-1.32	1.38

Table 3 shows annual changes in precipitation (%) under three scenarios for future periods as predicted by the models. The average annual precipitation falls by 0.98% and 0.94% under RCP2.6 and RCP8.5, respectively, and rises by 0.96% under RCP4.5 by SDSM projection. Moreover, the average annual precipitation decreases under RCP4.5 by 1.32%, whereas it increases under RCP2.6 and RCP8.5 by 1.49% and 1.38%, respectively (Table 4).

Table 4. Monthly changes in precipitation (%)

Months	RCP2.6	RCP4.5	RCP8.5
Jan	1.0	1.2	1.7
Feb	0.4	0.6	0.5
Mar	0.4	0.4	0.4
Apr	2.5	2.7	2.8
May	1.5	1.3	1.3
Jun	0.6	0.8	0.7
Jul	1.1	1.1	1.1
Aug	2.7	2.4	2.2
Sep	2.0	2.2	2.1
Oct	1.3	1.3	1.4
Nov	1.1	0.9	1.1
Dec	0.3	0.8	0.9

Monthly precipitation changes ranged from 0.3 to 2.7 under RCP2.6 in December and August, from 0.4 to 2.7% under RCP4.5 in March and April, and from 0.4 to 2.8% under RCP8.5 in March and April, respectively. The predicted precipitation for the months of February, March, and December is decreasing, whereas it is increasing for the months of January, April, July, September, October, and November. There is no definite change in precipitation for June and August.

Table 5. Seasonal changes of Precipitation (%)

Season	RCP2.6	RCP4.5	RCP8.5
spring	4.87	4.59	4.89
summer	0	0	0.01
autumn	2.43	1.47	1.76
winter	4.35	4.8	4.63

Table 5 shows the projected changes in seasonal precipitation. The mean seasonal precipitation changes for the three RCPs ranged from 4.87 to 4.89% in spring, 0.01% in summer, 2.43 to 1.76% in autumn, and 4.35 to 4.63% in winter.

The analysis reveals that the trend in rainfall is decreasing in February, March, and April and increasing in September, October, December, and January. There is no significant change in May, July, August, and November compared with the observation period (Figure 5). The decrease in precipitation in February–June, the growing months, has a great effect on plant production due to the plant's requirement for water.

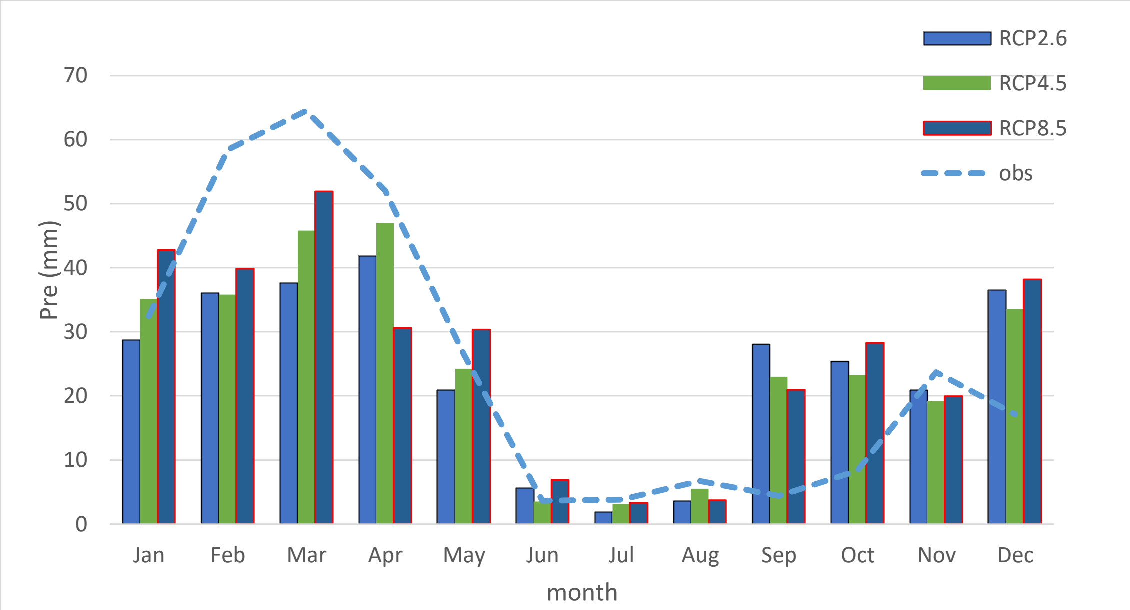

Figure 5. Average of monthly Rainfall Projections under RCPs for future periods (2025-2100).

According to the MK trend test, the negative value of K-tau, the precipitation has a decreasing trend in the period of baseline (Figure 3 and Table 2). UNDP (2017) reported a decreasing trend in the rainfall from 2004 to 2016 (UNDP, 2017). The trends of R10 and R20 are decreasing, while the trend of CWD is increasing for the baseline period (Fig. 4). This result is recommended by the UNDP report (2017). UNDP (2017) reported an increase in the CWD for the observed period of 2004–2016 for the central agricultural zone of Afghanistan. Annual average precipitation would change by -0.98%, 0.96%, and -0.94% with SDSM model and 1.49%, -1.32%, and 1.38% with LARS-WG under RCP2.6, RCP4.5 and RCP8.5, respectively by 2100. However, there were no higher changes in the amount of annual precipitation, but the shift of precipitation during the year months (Figure 5) are most vulnerable to crop production. During the baseline period, the maximum precipitation was observed in the spring months (February, March, April, and May), and in the projection period, this precipitation would shift from the growing months to autumn (September, October, and December). This variation would impact on crop production and increase drought duration, crop water requirements, and crop irrigation requirements due to an increase in evapotranspiration. NEPA (2018) reported that the mean precipitation in March-May decreased by 5–10% in the central region of Afghanistan, whereas it increased in October–December from 2006 to 2050. Future projections showed that rainfall would change during 2021-2050 in a range of -1.6 –3.8 % (Sarwary et al., 2023). The direct impact of rainfall on crop yield was reported in many studies: Khan and Khan (1988) found that an increase in rainfall by 1 mm led to an increase in crop yields of about 0.29% (Shafiq et al., 2021).

CONCLUSION

The average monthly precipitation for the period of reference shows that February, March, and April have maximum precipitation and June, July, and September have minimum precipitation. The performances of SDSM and LARS-WG were evaluated to downscale precipitation for three RCPs. According to the statistical performance, the best method for data simulation in precipitation is LARS-WG, but the two models slightly overestimated the precipitation with different magnitudes. However, the simulated results for both models were close to observations in February, April, June, July, and August, but both models overestimated in January, whereas the predicted change in rainfall with LARs-WG was overestimated in September, October, November, and December.

The annual mean precipitation under RCP2.6, RCP4.5, and RCP8.5 would decrease by about 2.1%, 2.5%, and 3.9%, respectively, with the SDSM method, whereas it would decrease under RCP4.5 and RCP8.5 except for RCP2.6 with the

LARS-Wg method. A decreasing precipitation trend was also reported by UNDP in 2017. The predicted total precipitation increased in January, April, and May when compared with the observed variables, whereas it decreased in February, March, August, and December. The trend of precipitation analysis shows that precipitation has decreased in the study area. Based on the results, the precipitation trend has decreased during spring (March-May), increased during autumn and winter, and remained stable during summer. A decrease in precipitation has a great effect on plant growth and production. Reductions in rainfall increase the water requirements of plants. If the water cannot be available to plants, they will suffer significant damage. It is recommended to study the approaches to reducing climatic challenges of crop production and livelihoods for the coming years.

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