CHAPTER 8

Projection of Future Climate Change on Drought Using SDSM

8.1 Overview

This study focuses on the impact of climate change on meteorological drought characteristics over 18 synoptic locations in Uttar Pradesh, India. The climate in this region is spatially heterogeneous. It ranges from humid to semi-arid, making it difficult to use the outputs of general circulation models (GCMs) directly for sustainable water management at the regional scale. To overcome this, SDSM was employed to downscale future meteorological variables, including daily precipitation, maximum temperature (Tmax), and minimum temperature (Tmin) under the climate change scenario for the future. Projected daily meteorological variables were converted into monthly data to estimate SPEI which is used to assess meteorological drought variability. Drought characteristics, such as severity, duration, and frequency, were defined based on run theory applied to SPEI time series at a selected threshold. The objectives of this article are threefold: first, to investigate the adaptability of SDSM for simultaneously downscaling Tmax, Tmin, and precipitation over 18 synoptic locations of Uttar Pradesh, India, and discuss the spatial and temporal variability; second, to provide local-scale climate change information under future emission scenarios for ongoing research on water resources assessment under future climate change. Finally, the drought characteristics under projected climate scenarios RCP 4.5 and RCP 8.5 were evaluated for the next 32 years, from 2019 to 2050. Overall, this study aims to provide important insights into the impacts of climate change on water resources and drought in Uttar Pradesh, India, which can help guide future adaptation and mitigation strategies.

8.2 Downscaling of the CanESM2 model data using the SDSM under the RCP scenarios

SDSM is a tool used to downscale the rainfall from GCMs at the regional level. It comprises of stochastic approach as well as multiple linear regression (MLR) approaches. SDSM is further divided into three sub-models, i.e., annual, seasonal, and monthly sub-models. All these models drive a regression equation. The annual sub-model derives only a single equation for a whole year, the seasonal one derives the equation separately for each season, and the monthly sub-model derives the equation for each month separately. Furthermore, the sub-models may be conditional or unconditional based on the type of parameter to be downscaled. The conditional model is considered for downscaling rainfall, and the unconditional model is ideal for downscaling temperature. Screening of predictors is the most crucial step in SDSM. Table 4.2 summarizes the twenty-six predictors used in this study for screening. In this process, the most relevant predictors are chosen with the help of the MLR model, based on P-value, histograms, scatter plots, and correlation matrix. The present study preferred a correlation matrix between predictands and CanESM2 predictors. Initially, explained variance of various predictors was estimated from NCEP/NCAR reanalysis data in order to select the most suitable predictors. The high explained variance possessing predictors was chosen for correlation analysis to analyze the relationship among predictors and predictands. The correlation coefficient (r) and degree of significance (P) were used to determine the selection of the predictor variable. The highly correlated predictor parameter has the best scatter plot, and the minimum P–

value was carefully chosen for Tmax, Tmin, and precipitation. Table 8.1 illustrates the predictors that had a high correlation value with the predictands during SDSM calibration. Selected predictor variables for the prediction of predictand (Tmax, Tmin, and precipitation) are enlisted in Table 8.1. With a few exceptions, the partial correlation (r) of observed precipitation with predictors indicate that all stations followed the nearly same correlation pattern with small variation, demonstrating that all stations can have identical predictors. For instance, the predictor set of temp, p5_z, and p500 has the most potential predictors for temperature, and prcp, p1_u, p5_u, p500, s500, shum, and p5_f are the most potential predictor variables for the prediction of precipitation in the study area. The identified predictor variables used for downscaling GCM and corresponding local climate variables demonstrated that different large-scale atmospheric variables control different local variables. The data used for calibration of precipitation, Tmax, and Tmin in this study was for 20 years (1976-1995) and the period from 1996 to 2005 is being used to validate the model. The model which was calibrated for the period from 1976-1995, is used as the base and simulates the precipitation, Tmax, and Tmin from 1996 to 2005 with the help of NCEP and CanESM2 predictors. In order to get good results, 100 ensembles were used to derive the average, which was then used for the validation from 1996-2005 with observed data. The model was developed for downscaling daily rainfall, Tmax, and Tmin using SDSM. A regression equation is applied monthly in all eighteen stations and the conditional sub-model is used. In SDSM, there are two methods to optimize the model: Ordinary Least Square (OLS) and Dual Simplex (DS). OLS is being used in this research because it performs faster than DS. The root mean square error (RMSE) and coefficients of correlation (R^2) were used to check the performance of historical and simulated data of the model during calibration as well as the validation period. The result of the statistical analysis showed that the model is much more effective at simulating Tmax and Tmin than precipitation. Precipitation is difficult to simulate due to its high dynamical properties. After a satisfactory calibration, the multiple regression model is checked against a different set of data from outside the period for which the model was calibrated. In general, the analysis of performance measures and graphical representations of observed and simulated scenarios, both for calibration and validation, demonstrated that the model is capable of accurately modeling the climate variables.

Table 8.1 The partial correlation between the selected predictors and the precipitation

Station	Predictor	Partial r	P-value	Station	Predictor	Partial r	P-value
Agra	p1_u	0.06	0.04	**Aligarh**	p1_u	0.02	0.02
	prcp	0.02	0.001		prcp	0.04	0.05
	p500	0.13	0.03		p500	0.16	0.01
	shum	0.08	0.03		shum	0.09	0.01
Allahabad (Prayagraj)	prcp	0.05	0.02	**Azamgarh**	p5_u	0.09	0.05
	p500	0.13	0.01		prcp	0.01	0.07
	shum	0.11	0.05		p500	0.17	0.04
Bareilly	p5_u	0.04	0.01	**Basti**	p1_u	0.02	0.04
	prcp	0.03	0.01		prcp	0.01	0.06
	s500	0.10	0.007		s500	0.26	0.009
Chitrakoot	p5_f	0.07	0.006	**Faizabad**	p1_u	0.02	0.3
	prcp	0.02	0.03		p5_u	0.08	0.005
	s500	0.19	0		prcp	0.04	0.003
					s500	0.18	0.001
Gonda	P8_f	0.01	0.07	**Gorakhpur**	p5_f	0.05	0.002
	prcp	0.03	0.04		prcp	0.01	0.05
	s500	0.2	0.04		s500	0.22	0.003
Jhansi	p1_u	0.02	0.02	**Kanpur**	p1_u	0.01	0.25
	prcp	0.01	0.06		p5_u	0.06	0.001
	s500	0.17	0.002		prcp	0.02	0.07
	p5_f	0.07	0.003		s500	0.15	0.04
Lucknow	p5th	0.03	0.001	**Meerut**	prcp	0.04	0.04
	prcp	0.05	0.002		s500	0.14	0.02
	s500	0.10	0.003		shum	0.07	0.06
	shum	0.10	0.004				
Mirzapur	prcp	0.06	0.002	**Moradabad**	p1_u	0.04	0.5
	s500	0.15	0.001		prcp	0.04	0.002
	shum	0.1	0.005		s500	0.2	0.003
Saharanpur	p1_u	0.01	0.05	**Varanasi**	prcp	0.05	0.001
	prcp	0.03	0.004		s500	0.15	0.002
	s500	0.2	0.003		shum	0.10	0.003

Table 8.2 The partial correlation between the selected predictors and the maximum temperature

Station	Predictor	Partial r	P-value	Station	Predictor	Partial r	P-value
Agra	*p5_z*	0.04	0.002	**Aligarh**	*p5_z*	0.025	0.01
	s850	0.1	0.003		p500	0.064	0.001
	temp	0.6	0.001		temp	0.641	0.002
Allahabad (Prayagraj)	*p5_z*	0.002	0.5	**Azamgarh**	*p5_z*	0.010	0.3
	p500	0.03	0.007		p500	0.018	0.07
	temp	0.63	0.003		temp	0.627	0.006
Bareilly	*p5_z*	0.03	0.004	**Basti**	*p5_z*	0.007	0.4
	p500	0.1	0.002		p500	0.002	0.5
	temp	0.6	0.001		temp	0.632	0.007
Chitrakoot	*p5_z*	0.002	0.5	**Faizabad (Ayodhya)**	*p5_z*	0.002	0.5
	p500	0.04	0.004		p850	0.086	0.005
	temp	0.6	0.007		temp	0.63	0.001
Gonda	*p5_z*	0.01	0.14	**Gorakhpur**	*p5_z*	0.01	0.31
	p500	0.02	0.006		p500	0.018	0.07
	temp	0.6	0.007		temp	0.627	0.01
Jhansi	*p5_z*	0.006	0.4	**Kanpur**	*p5_z*	0.015	0.14
	p500	0.02	0.007		p500	0.10	0.3
	temp	0.6	0.003		temp	0.638	0.001
Lucknow	*p5_z*	0.015	0.12	**Meerut**	*p5_z*	0.050	0.006
	p500	0.014	0.15		shum	0.167	0.026
	temp	0.639	0.002		temp	0.674	0.006
Mirzapur	*p5_z*	0.003	0.5	**Moradabad**	*p5_z*	0.004	0.004
	p500	0.019	0.003		shum	0.145	0.002
	temp	0.639	0.004		temp	0.674	0.001
Saharanpur	*p5_z*	0.05	0.003	**Varanasi**	*p5_z*	0.006	0.44
	p500	0.177	0.002		p500	0.017	0.001
	temp	0.618	0.001		temp	0.643	0.001

Table 8.3 The partial correlation between the selected predictors and the minimum temperature

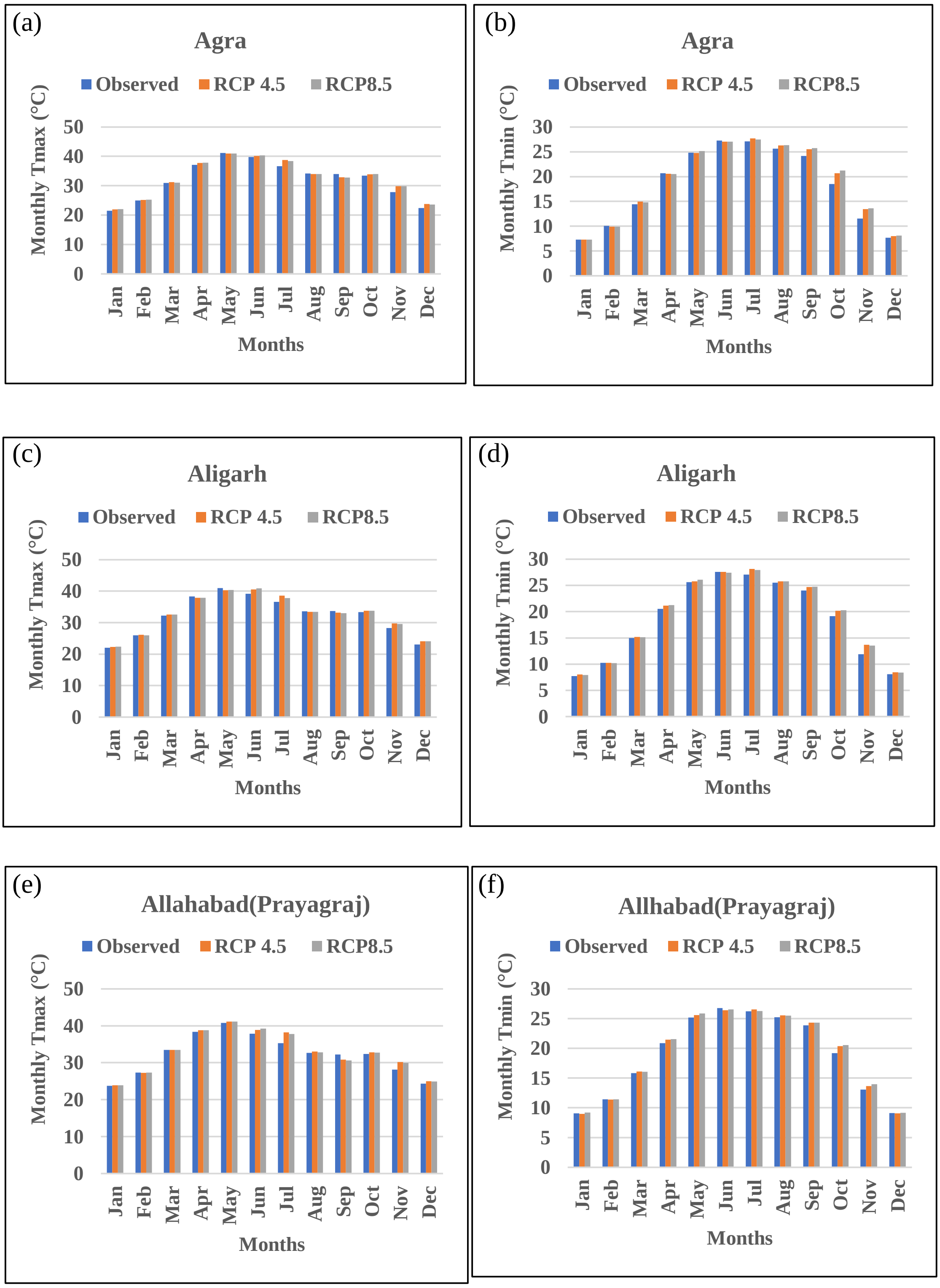
Station	Predictor	Partial r	P-value	Station	Predictor	Partial r	P-value
Agra	*p5_z*	-0.119	0.012	**Aligarh**	*p500*	-0.057	0.004
	p500	0.291	0.015		s850	0.590	0.002
	temp	0.697	0.002		temp	0.753	0.001
Allahabad (Prayagraj)	*p500*	0.091	0.5	**Azamgarh**	*p500*	0.183	0.05
	shum	0.503	0.003		shum	0.525	0.004
	temp	0.682	0.004		temp	0.629	0.003
			0.003				0.004
Bareilly	*p500*	0.145	0.002	**Basti**	*p500*	0.14	0.003
	shum	0.583	0.001		shum	0.529	0.002
	temp	0.661	0.004		temp	0.66	0.001
Chitrakoot	*p500*	0.068	0.002	**Faizabad (Ayodhya)**	*p5_z*	-0.07	0.004
	shum	0.477	0.001		*p500*	0.587	0001
	temp	0.694	0.005		temp	0.724	0002
Gonda	*p500*	0.136	0.004	**Gorakhpur**	*p5_z*	-0.10	0.31
	shum	0.549	0.007		*p500*	0.018	0.07
	temp	0.666	0.004		temp	0.627	0006
Jhansi	*p500*	0.044	0.006	**Kanpur**	*p500*	0.080	0.003
	shum	0.491	0.005		shum	0.519	0.004
	temp	0.706	0.004		temp	0.696	0.004
Lucknow	*p500*	0.121	0.003	**Meerut**	*p500*	0.1	0.001
	shum	0.526	0.004		shum	0.57	0.003
	temp	0.671	0.003		temp	0.68	0.005
Mirzapur	*p500*	0.13	0.002	**Moradabad**	*p500*	0.12	0.001
	shum	0.51	0.001		shum	0.58	0.004
	temp	0.66	0.004		temp	0.67	0.007
Saharanpur	*p500*	0.11	0.008	**Varanasi**	*p5_z*	0.15	0.002
	shum	0.5	0.006		shum	0.5	0.001
	temp	0.67	0.005		temp	0.6	0.008

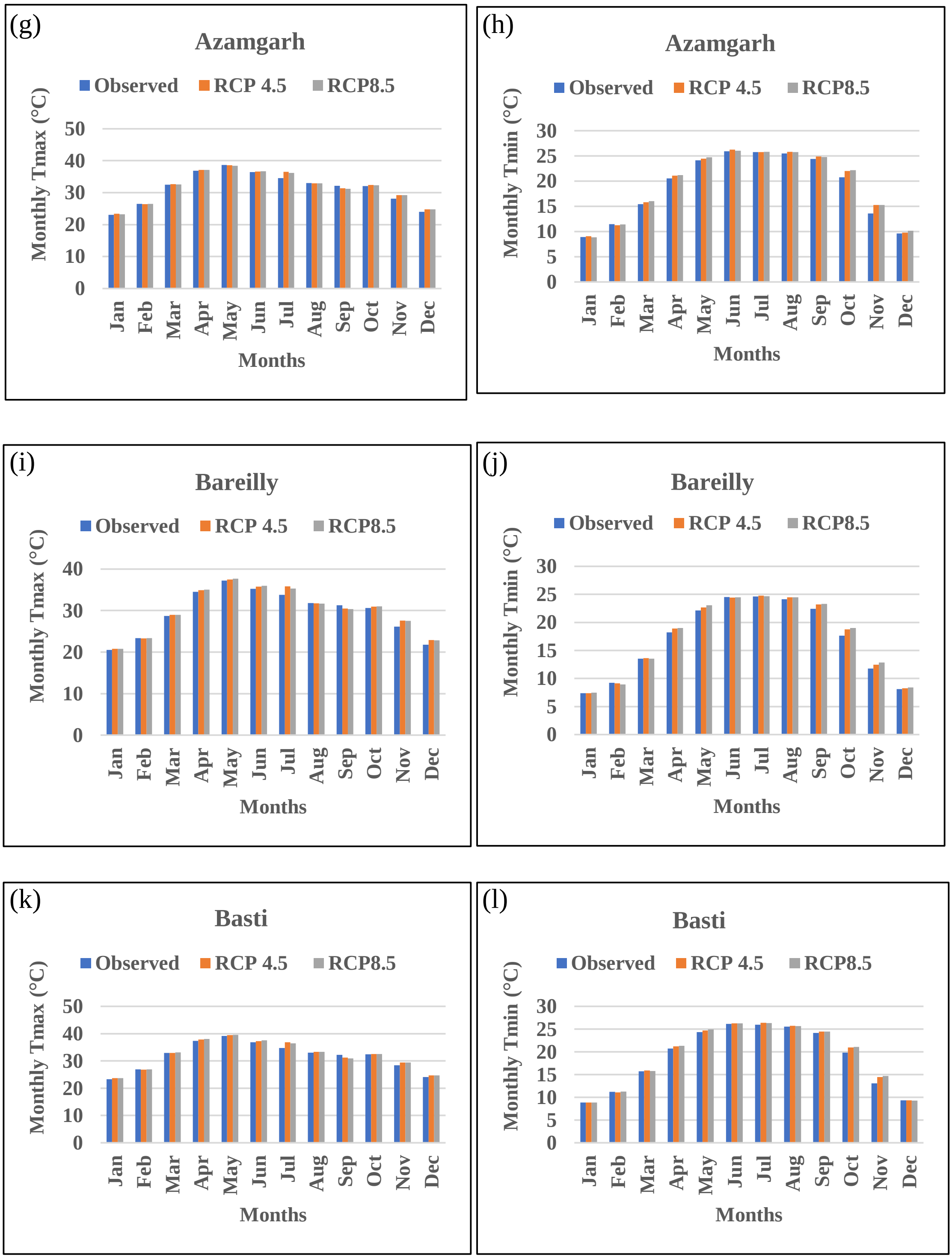
8.2.1 Changes in future monthly temperature

The local climates are projected using the selected predictors set. After the calibration and validation processes, the maximum and minimum temperatures are downscaled from the CanESM2 model under different climate change scenarios RCP 4.5 and RCP 8.5. The variation in projected changes of average monthly maximum temperature (Tmax) and minimum temperatures (Tmin) during mid-century (2050s) relative to the observed period (1971 to 2005) under the RCP 4.5 and RCP 8.5 scenarios for 18 synoptic stations of the study region is demonstrated in Figure 8.1. Figure 8.1 illustrate that the maximum temperature will rise in the future under all climate change scenarios compared to the maximum temperature recorded over the observed period. This increase in Tmax and Tmin varies spatially and temporally across the research area depending on the RCP scenario (Figure 8.1). The average monthly maximum and minimum temperature increase will be increased between 0.3°C to 0.7°C in the near future for RCP 4.5 and RCP 8.5. The projected change in maximum temperature and minimum temperature is greater during the months of the post-monsoon season. It will vary from 0.6°C to 1.5 °C and 0.6°C to 2.1°C, respectively RCP 4.5 and RCP 8.5 scenarios. Significant increases in Tmax and Tmin are projected during the monsoon season ranging from 0.3 °C to 0.8 °C. In the near future, the post-monsoon season minimum temperature is anticipated to increase by 0.1°C to 0.6°C relative to the maximum temperature. And, the least rise in Tmax and Tmin is projected from December to March. The increase in the average monthly maximum and minimum temperature projected under RCP 4.5 is higher compared to RCP 8.5.

The result of simulated temperature from CanESM2 demonstrated by the middle of the century the maximum, and minimum temperatures was projected to increase more significantly for two seasons post-monsoon followed by the monsoon season. Another inference made from the foregoing discussion is that minimum temperatures are rising more rapidly than maximum temperatures. A continuous warming trend can be noted in all the seasons from the modeled data of Tmax and Tmin. Warming is more pronounced in the post-monsoon season, followed by the monsoon season under both scenarios. In other words, based on the results of the simulation of all scenarios generated from the model, during the middle century (2006 to 2050), the maximum and minimum temperature of Uttar Pradesh, India will be increased between 0.3°C and 2.1°C as compared to the observed period (1971–2005). Again, the spatial patterns of Tmax and Tmin under RCP 4.5 and RCP 8.5 are much more similar, with substantial differences in the magnitude of temperature change. In the near future, RCP 4.5 is expected to be more intensive than RCP 8.5.

Temperature Maximum **Temperature Minimum**

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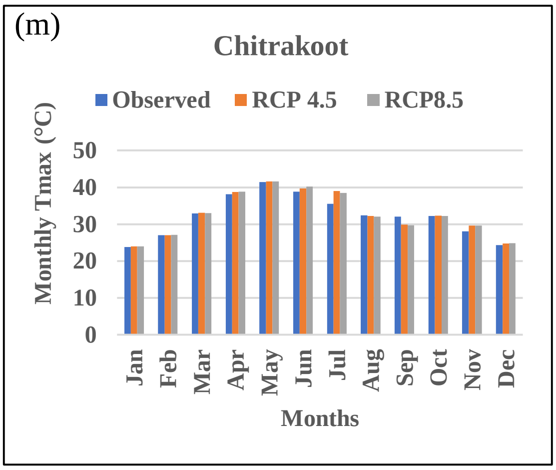
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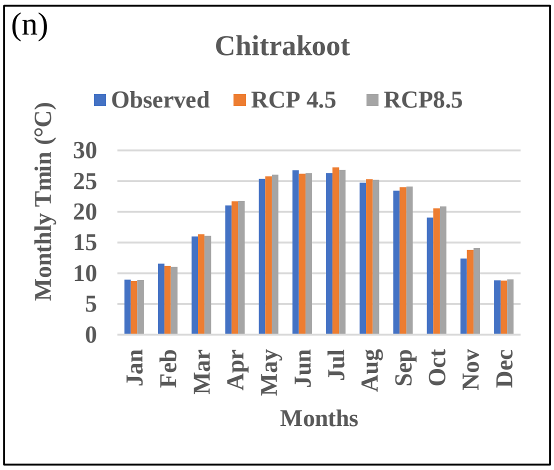
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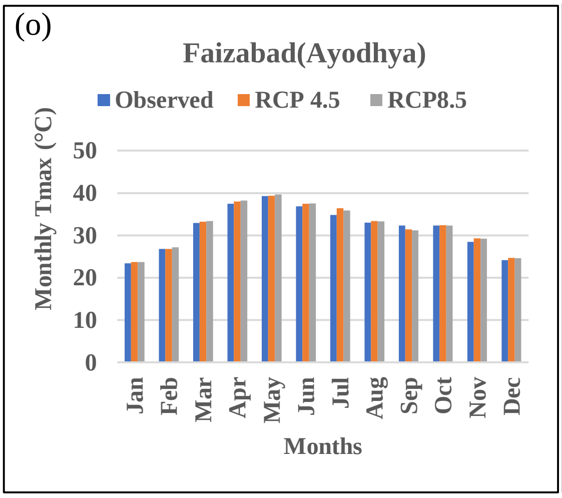
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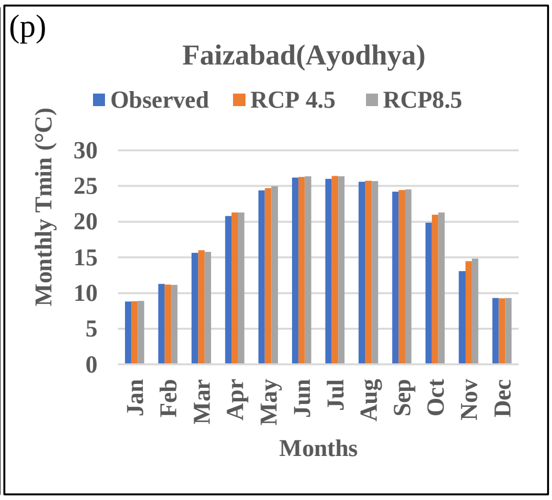
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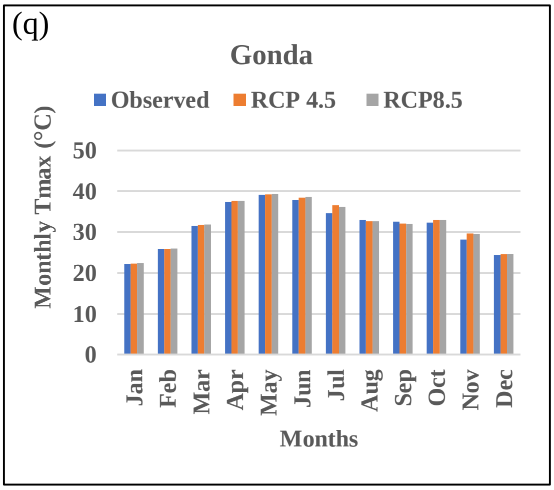
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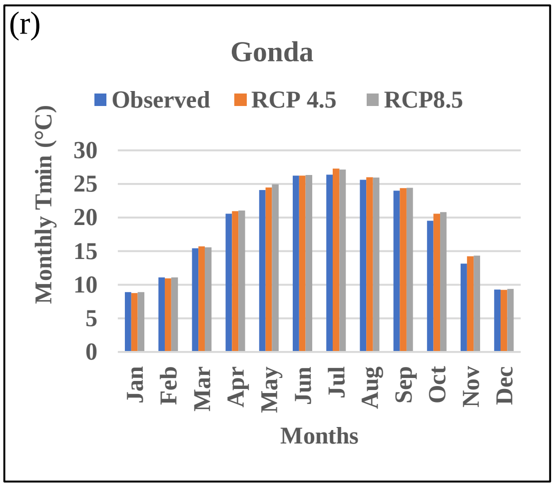
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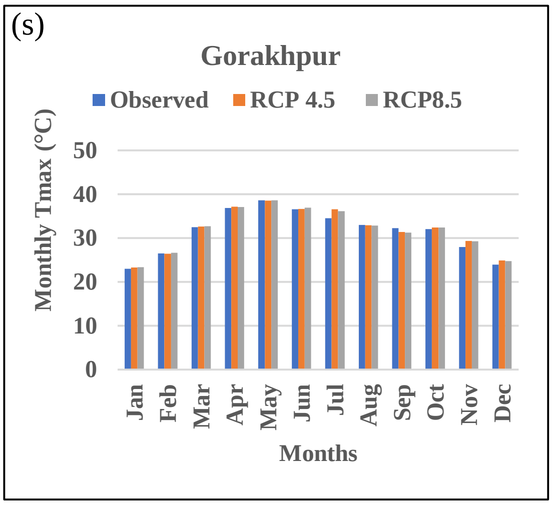
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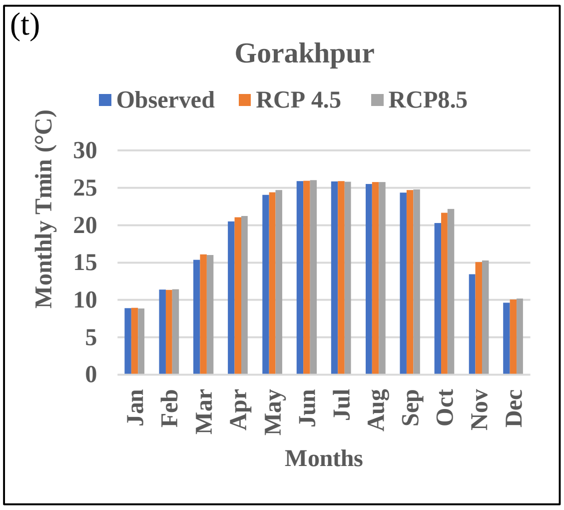
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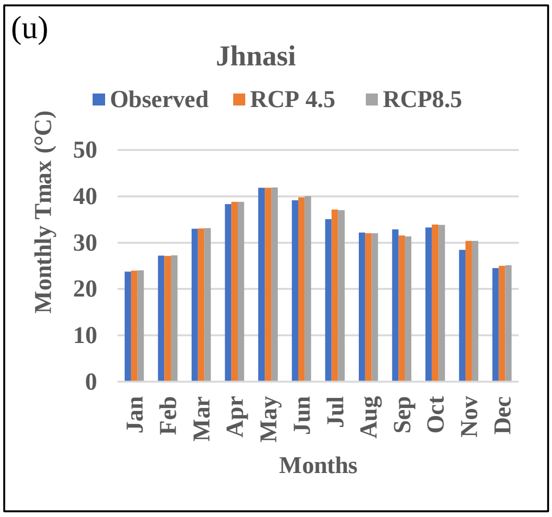
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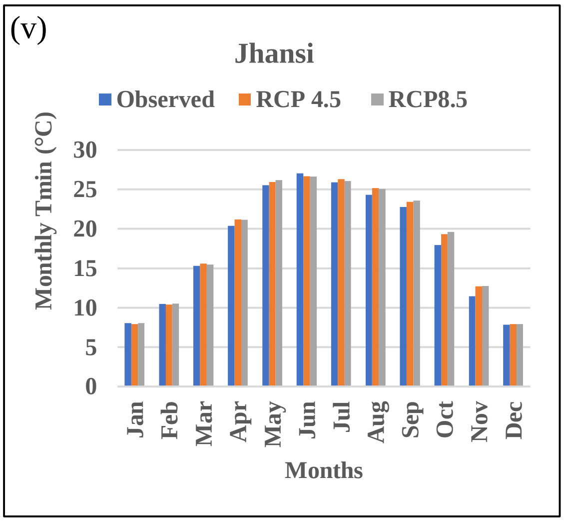
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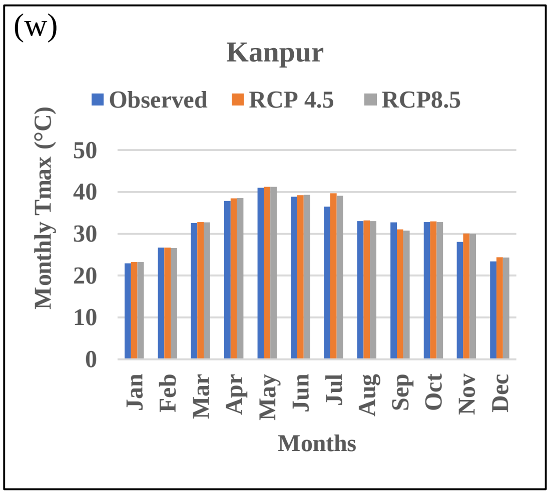
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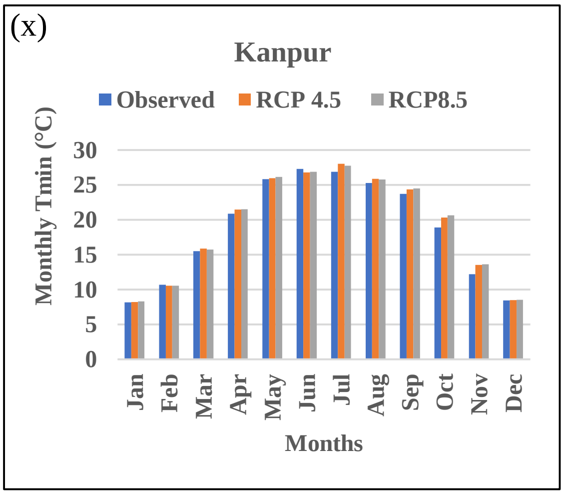
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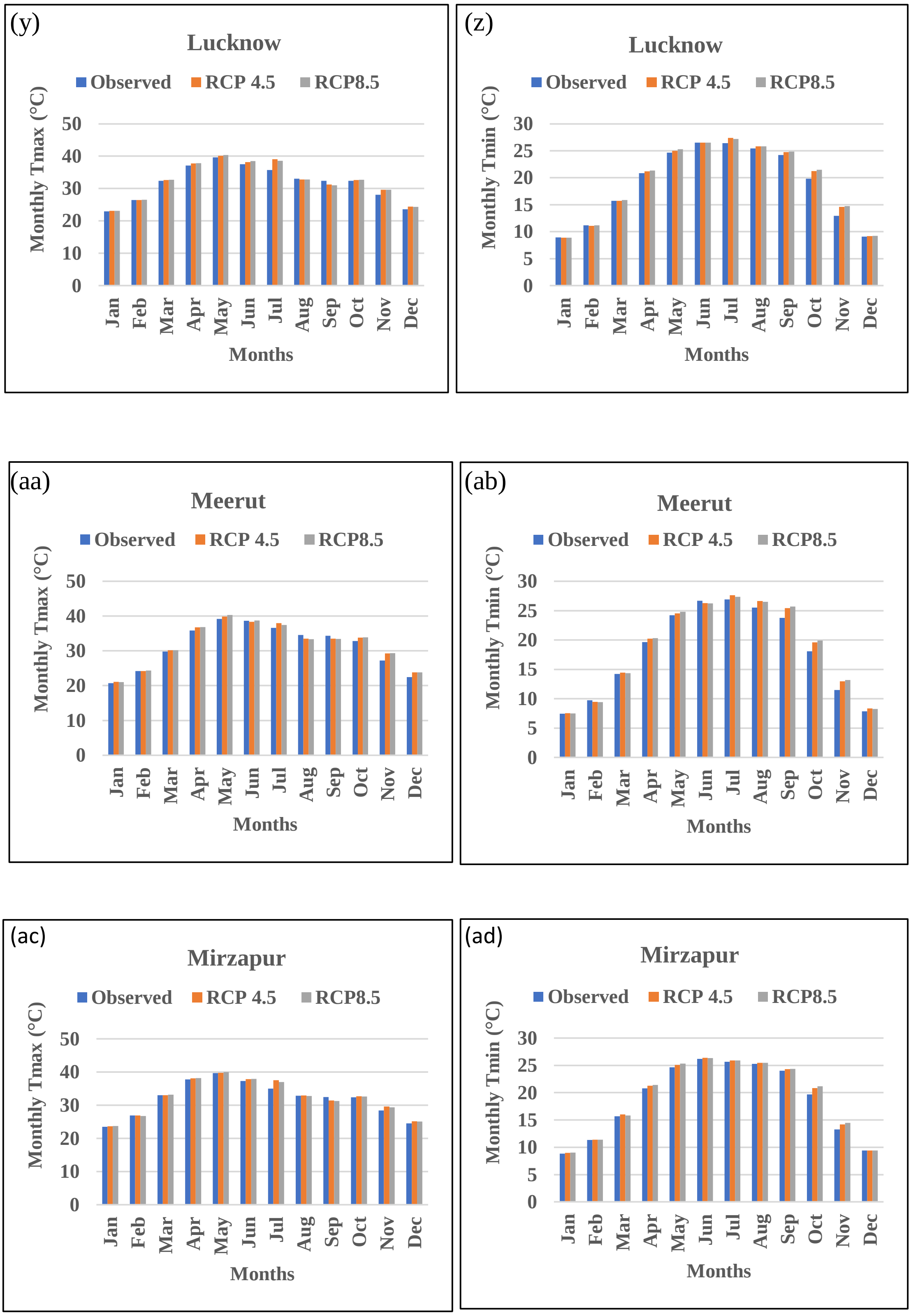
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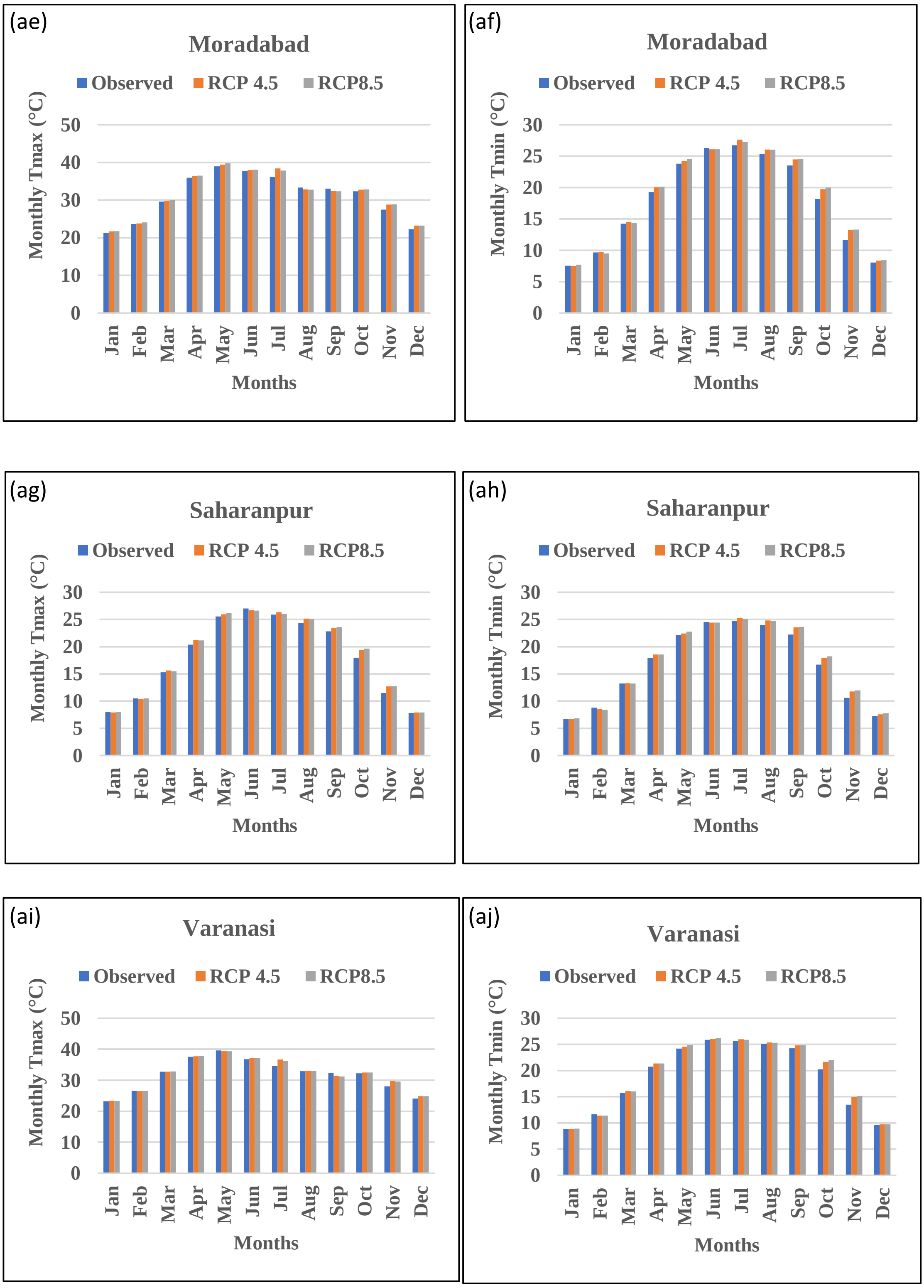
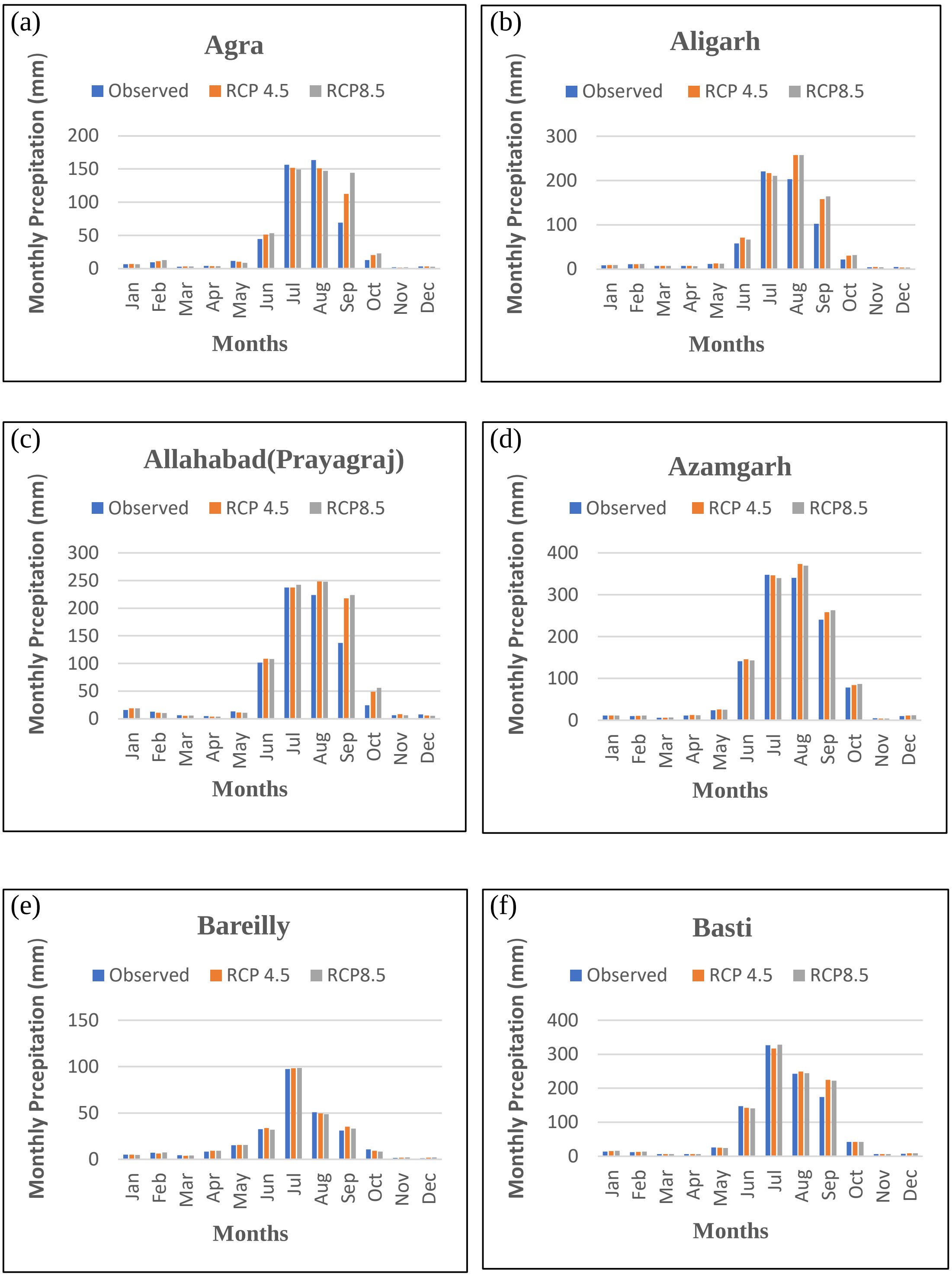


Figure 8.1 Projected change in the maximum temperature (Tmax) and minimum temperature (Tmin) under RCP 4.5 and RCP 8.5 for the future period (2019 to 2050) compared to the observed period

8.2.2 Changes in future monthly precipitation

Following the calibration and validation processes, the precipitation is downscaled from the CanESM2 model under different climate change scenarios RCP 4.5 and RCP 8.5. The variation in projected monthly changes during the mid-century (2050s) relative to the observed period (1971–2005) for 18 synoptic stations in the study region shown in Figure 8.2. The percent change in the monthly precipitation has been calculated for different RCP scenarios to investigate the changes in precipitation in the future climate compared to the observed period. It is worth noting that the obtained results based on each model scenario represent an increase in monthly precipitation at all study stations except at Bareilly, Gonda, and Mirzapur and during the future decades. However, this change in precipitation is different at each station and for future period (2006 to 2050) (Figure 8.2). Under both climate change scenarios, RCP 4.5 and RCP 8.5, it is anticipated that Agra, Jhansi, Kanpur, Lucknow, Basti, Gonda, Gorakhpur, and Saharanpur will experience a slight increase (less than 10% relative to the observed period) in annual precipitation change in near future. The precipitation projection showed a rise for both scenarios but a slight decrease for RCP 8.5 compared to RCP 4.5. The Precipitation will increase from -0.18 to 24% at an annual scale across the study area. Figure 8.2 depicts that the maximum increase in precipitation is projected to occur during the monsoon season, followed by the post-monsoon season, whereas peak precipitation will occur during July, August, and September. A slight decrease in precipitation was observed during the pre-monsoon season in the near future under both scenarios. A mixed pattern of precipitation change has been projected in the near future, including a slight increase and decrease across the region during the winter and the months before and after the monsoon season. The significant spatial variability in change in precipitation was observed over the study region where stations Varanasi, Allahabad (Prayagraj), Lucknow, and Aligarh will have a higher increase in precipitation in the mid-century compared to other stations. The pre-monsoon season will be characterized by the least or no precipitation increase in the near future. Projected precipitation during the winter season demonstrates significant variation over the study area. Another result of the precipitation downscaling is that precipitation will gradually increase in the near future, with significant variations: 66% of the locations will see an increase in precipitation of less than 10% over the study area. Again, the spatial patterns of precipitation change under RCP 4.5 and RCP 8.5 are much more similar, with a significant difference in magnitude. The study area susceptible to climate extremes in the near future is caused by a region with a slow rise in precipitation combined with the increase in temperature.


(a)
Agra
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
200
150
100
50
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months
(b)
Aligarh
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
300
200
100
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months
(c)
Allahabad(Prayagraj)
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
300
250
200
150
100
50
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months
(d)
Azamgarh
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
400
300
200
100
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months
(e)
Bareilly
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
150
100
50
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months
(f)
Basti
Observed RCP 4.5 RCP8.5
Monthly Prcepitation (mm)
400
300
200
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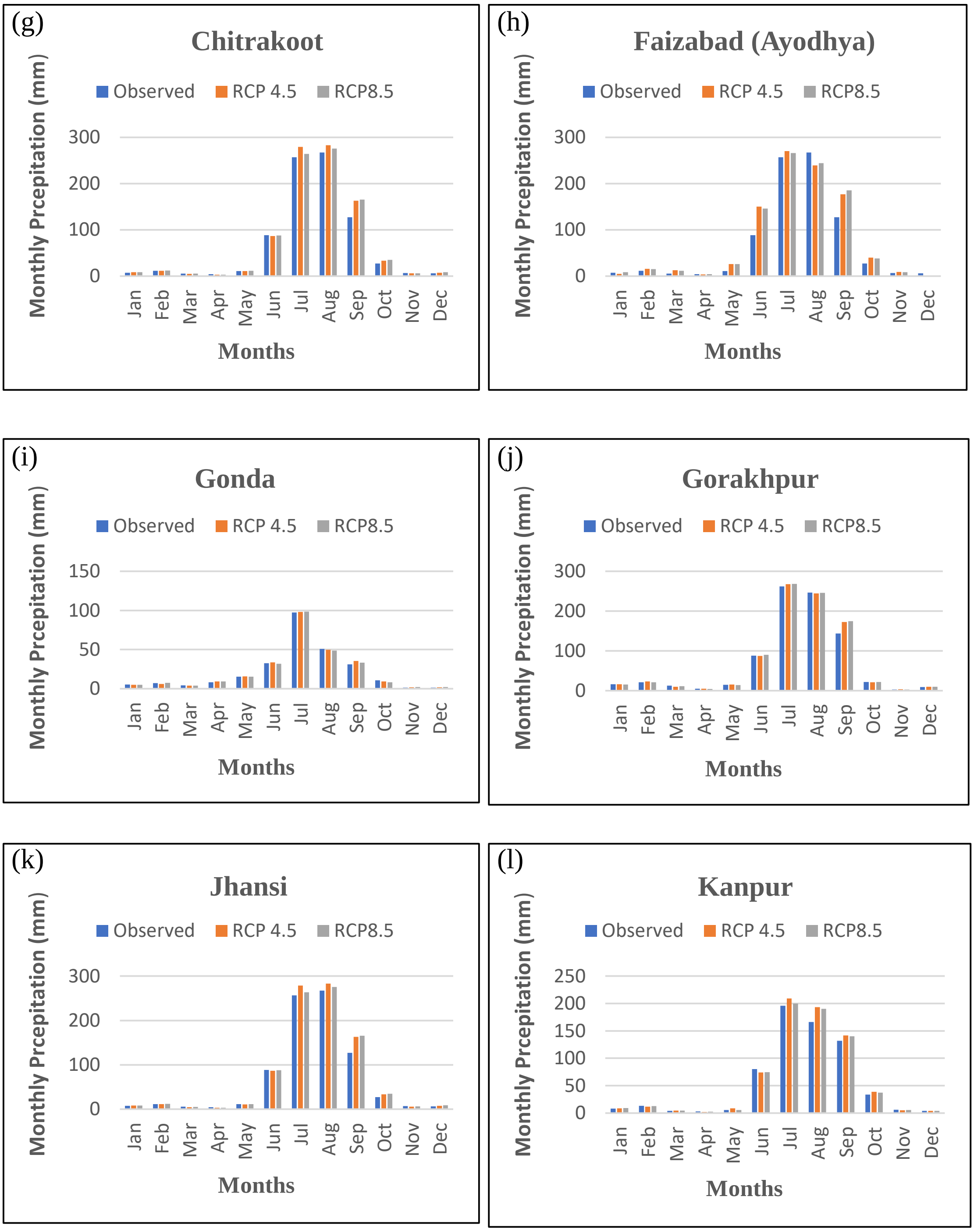
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months


(g)
Chitrakoot
(h)
Faizabad (Ayodhya)
(i)
Gonda
(j)
Gorakhpur
(k)
Jhansi
(l)
Kanpur
Observed
RCP 4.5
RCP8.5
Monthly Prcepitation (mm)
Months
Jan
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Mar
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May
Jun
Jul
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Nov
Dec

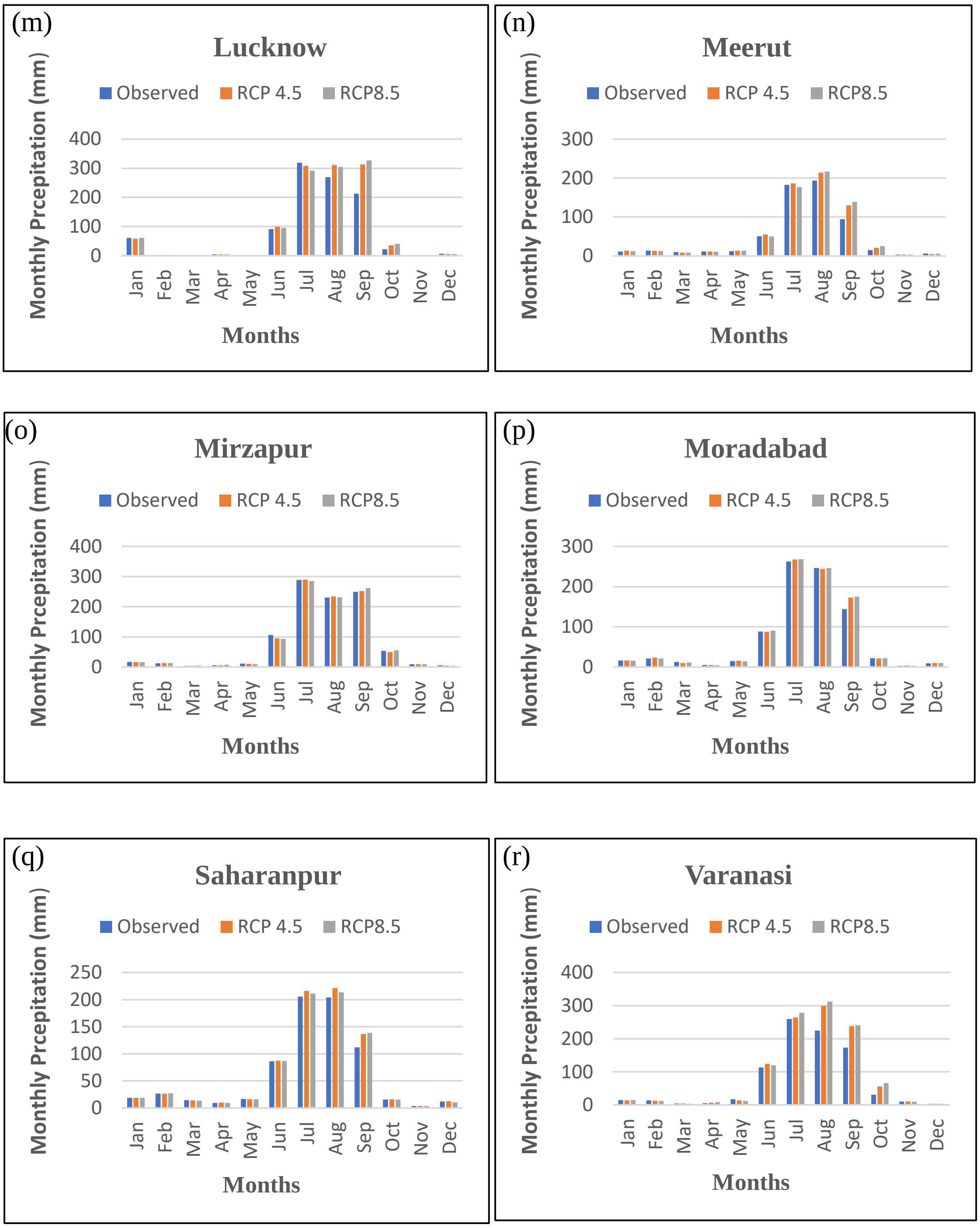

Figure 8.2 Projected change in the monthly precipitation under RCP 4.5 and RCP 8.5 for the future period (2019 to 2050) compared to observed period

8.3 Drought Characterization under Observed and Future Period.

SPEI time series estimated for the future period (2019 to 2050), respectively, using CanESM2 data downscaled using SDSM across 18 synoptic locations of Uttar Pradesh under RCP 4.5 and RCP 8.5. All of the study locations will experience an increase in temperature which varies spatially. This will eventually lead to an increase in PET across the entire study area. Another result drawn from precipitation downscaling is that precipitation will gradually increase in the near future, with significant variations: 66% of the locations will see an increase in precipitation of less than 10% over the study area. The study region will be vulnerable to the concurrent occurrence of dry and wet events in the near future as a slow increase in precipitation combines with a significant rise in temperatures. This present study assessed drought characteristics by employing run theory at SPEI <-1 threshold based on the severity, duration, and frequency. Based on the conclusion drawn from the previous chapters 6 and 7, the research area's southwestern, Bundelkhand, and Vindhyan regions are more severely hit by severe drought conditions. Due to the local geology, drought conditions in the Bundelkhand and Vindhyan regions are getting worse. Bundelkhand and Vindhyan regions are largely covered with hills and plains, and they are characterized by severe temperatures and a lack of rainfall. These regions of the study area are characterized by a semiarid climate and a meteorological drought with a 3-year return time. As a result, meteorological drought has a major impact on this region in particular. Therefore, in this section, Agra, Jhansi, and Mirzapur locations were chosen to depict the change in drought characteristics across the observed and projected periods.

Table 8.4 to 8.6 depicts the pattern of severity, duration, and frequency of drought occurrence for the synoptic locations of Agra, Jhansi, and Mirzapur under observed and projected climate scenario RCP 4.5, and RCP 8.5. SPEI output with a shorter timescale, SPEI-3, and SPEI-6, which occur frequently and for shorter periods, represent short-term seasonal fluctuations, whereas drought indices with longer timescales, such as SPEI-9 and SPEI-12, occur less frequently but for a more extended duration, and so represents the medium or annual water balance status. SPEI time series are sensitive to the timescale where drought characteristics have changed with the timescale of SPEI. Similarly, drought events of maximum severity with extended duration are associated with SPEI-9 and SPEI-12. The results summarized in Table 8.4 to 8.6 depict significant variation in the drought characteristics estimated under RCP 4.5 and RCP 8.5 compared to the observed period. Drought frequency has risen significantly for both Jhansi and Mirzapur under RCP 4.5 and RCP 8.5. Under both climate change scenarios, the average drought severity and duration varied significantly over the future period compared to the observed period.

The statistical analysis of drought characteristics over these three synoptic locations demonstrates an increase in the frequency of drought events in near future (2019 to 2050). Whereas the average drought severity and duration varied spatially over the future period compared to the observed period. As depicted in previous section 8.2, during the period of the next 32 years, there will be an increase in the temperature and a slow rise in precipitation over the study that significantly varies spatially, so that can be seen in the drought characteristics. As we have demonstrated, there will be more frequent drought over the Mirzapur and Jhansi in the future period compared to the Agra. So, there will be significant variation in the pattern of drought characteristics in the future over Uttar Pradesh. According to the previous section 8.2, during the next 32 years, there will be an increase in temperature and a substantial change in monthly precipitation estimated, which significantly varies in magnitude over the study area. As a result, drought characteristics will likewise vary spatially. Thus, future drought patterns in Uttar Pradesh will exhibit substantial spatial heterogeneity. The following section will evaluate the spatial distribution of drought characteristics of all synoptic stations under RCP 4.5 and RCP 8.5 for future periods (2019 to 2050).

Table 8.4 Observed and future drought characteristics based on the standardized evapotranspiration precipitation index (SPEI) for location Agra

Scenario	SPEI Timescale	Frequency	Severity			Duration (Months)		
Observed			Max	Mean	Median	Max	Mean	Median
	SPEI-3	29.86	17.23	3.5	2.3	11	2.5	2
	SPEI-6	10.76	18.42	4.9	2.4	12	3.45	2
	SPEI-9	5.76	18.8	2.82	5.72	2	12	4
	SPEI-12	1.9	37.94	12	12.49	23	8.63	10
			Max	Mean	Median	Max	Mean	Median
RCP 4.5	SPEI-3	30.2	16.6	2.9	1.4	10	2.09	1
	SPEI-6	8.33	22.87	3.37	2..32	11	2.3	2
	SPEI-9	4.86	28.7	3.55	2.2	13	2.4	2
	SPEI-12	7.98	29.49	5.9	3.5	13	3.9	3
			Max	Mean	Median	Max	Mean	Median
RCP 8.5	SPEI-3	30.20	12.77	3.05	2.3	7	2.1	2
	SPEI-6	9.37	17.45	4.6	2.7	9	3.1	2
	SPEI-9	5.55	22.7	5.44	2.59	12	3.7	2
	SPEI-12	1.5	37.14	15.88	14.18	23	11	10

Table 8.5 Observed and future drought characteristics based on the standardized evapotranspiration precipitation index (SPEI) for location Jhansi

Scenario	SPEI Timescale	Frequency	Severity			Duration (Months)		
Observed			Max	Mean	Median	Max	Mean	Median
	SPEI-3	29.86	15.3	3.33	2.33	10	2.51	2
	SPEI-6	12.5	36	3.74	2.44	18.58	2.03	1
	SPEI-9	6.48	28	4.94	3.64	32	2.06	2
	SPEI-12	1.73	37.6	10.6	7.77	26	6.40	6
			Max	Mean	Median	Max	Mean	Median
RCP 4.5	SPEI-3	34.41	5.96	1.9	2.9	9	4.37	2
	SPEI-6	12.5	13.05	3.12	2.3	10	5	2
	SPEI-9	6.94	15.57	3.55	6.10	12	8.11	2
	SPEI-12	3.125	20.37	2.67	1.75	5	5.6	5
			Max	Mean	Median	Max	Mean	Median
RCP 8.5	SPEI-3	34.4	7.89	2.65	1.75	5	1.8	1
	SPEI-6	12.5	13.5	3.47	1.45	8	2.29	1
	SPEI-9	6.59	18.3	4.75	2.5	10	3.6	2
	SPEI-12	4.166	23.65	5.53	1.87	15	3.8	1.5

Table 8.6 Observed and future drought characteristics based on the standardized evapotranspiration precipitation index (SPEI) for the location Mirzapur

Scenario	SPEI Timescale	Frequency	Severity			Duration (Months)		
Observed			Max	Mean	Median	Max	Mean	Median
	SPEI-3	29.16	14	3.50	2.72	7	2.40	2
	SPEI-6	10.41	17.48	5	3.4	13	3.5	2.5
	SPEI-9	5.32	22.47	6.39	3.22	13	4.45	3
	SPEI-12	3.4	23.98	7.34	4.17	13	5.25	3
RCP 4.5			Max	Mean	Median	Max	Mean	Median
	SPEI-3	35.41	8.56	2.94	2.55	6	2.11	2
	SPEI-6	13.54	10.39	3.59	2.26	7	2.88	2
	SPEI-9	6.9	18.88	5.197	2.19	12	3.9	1.5
	SPEI-12	3.6	25.32	7.2	6.51	15	5.28	5
RCP 8.5			Max	Mean	Median	Max	Mean	Median
	SPEI-3	29.1	7.83	3.33	2.86	7.83	2.32	2
	SPEI-6	10.41	13.48	4.33	2	7	2.25	2.8
	SPEI-9	4.51	22.57	6.5	3.5	12	4.38	3
	SPEI-12	2.86	22.74	7.75	3.08	13	5.09	3

8.3.1 Projected change in the drought frequency

To assess the effects of global warming and climate change on drought characteristics for the upcoming 32 years between 2019 and 2050, SPEI time series calculated using precipitation and temperature have been estimated using CanSEM2 data that has been downscaled using SDSM. Drought frequency based on SPEI based on run theory estimated at SPEI <-1 threshold according to different scenarios RCP 4.5 and RCP 8.5, respectively. Figure 8.3 depicts the spatial variability of drought frequency estimated at different timescales for the 18 synoptic locations of Uttar Pradesh from 2019 to 2050 under RCP 4.5 and RCP 8.5. There is a change in the spatial pattern and magnitude of frequency occurrence recognized at different scales of SPEI. SPEI time series projected under RCP 4.5 and RCP 8.5 scenarios demonstrate that drought occurrences occur with higher frequency at shorter timescales (SPEI-3 and SPEI-6), whereas at a longer timescale show a significant drop in the frequency of drought events with SPEI-9 and SPEI-12. All 18 locations will experience an amplification of drying event in the future and varies significantly spatially under RCP 4.5 and RCP 8.5 scenarios. Under RCP 4.5 scenarios, the drought frequency is higher over 77% of synoptic locations compare to RCP 8.5 scenarios. The magnitude and spatial extension of drought event decrease with increasing SPEI timescale. The spatial distribution map of drought frequency demonstrates that the study region will likely experience more frequent drought occurrences from 2019 to 2050 under the RCP 4.5 scenario than RCP 8.5. Drought frequency at shorter timescales (SPEI-3 and SPEI-6) under RCP 4.5 and RCP 8.5 scenarios show that the frequency of occurrence varies spatially (Figure 8.3 a & b). Compared to other areas of the study area, the eastern plain stretching along the Vindhyan region and the Bundelkhand region of Uttar Pradesh is likely to experience more frequent drought occurrences under RCP 4.5. However, under RCP 8.5, these regions will likely see more frequent episodes of droughts with smaller magnitudes than under RCP 4.5. Drought frequency under RCP 4.5 and RCP 8.5 scenarios for longer timescales (SPEI-9 and SPEI-12) portrayed in Figure 8.4 c and d, exhibiting the different regional patterns of drought frequency. Under RCP 4.5 scenarios, the frequency of drought events for SPEI-9 and SPEI-12 decreases significantly to 2.4 and 1.5, respectively. For SPEI-9 timescale, compared to the other synoptic stations, Varanasi, Meerut, Mirzapur, Jhansi, Lucknow, Azamgarh, and Bareilly have a higher incidence of drought events. As the spatial map depicts, drought frequency is expected to increase over the synoptic location Agra, Varanasi, Azamgarh, Bareilly, and Kanpur for the SPEI-12 timescale. Under the RCP 8.5 scenario, for SPEI-9 timescale, compared to the rest of the synoptic stations, is greater at Varanasi, Azamgarh, Meerut, Saharanpur, Agra, Jhansi, and Mirzapur. For the SPEI-12 timescale, drought frequency increases over Varanasi, Saharanpur, Azamgarh, and

Jhansi. The red color on the spatial map region represents the region with higher frequency. The spatial map of SPEI-12 shown in Figure 8.3 (d) demonstrates that the region with greater frequency is not likely to affect a large portion of the study region. Long-term drought will be less prevalent in the research area in upcoming future. The spatial map demonstrates that most of the study region will become less likely to experience drought events of longer timescale, specifically at the SPEI-12 timescale. The study region is majorly impacted by the frequent occurrence of drought at short-term timescale in the near future. The frequency of drought events in the study area increases under RCP 4.5 scenarios compared to RCP 8.5 at nearly all timescales.

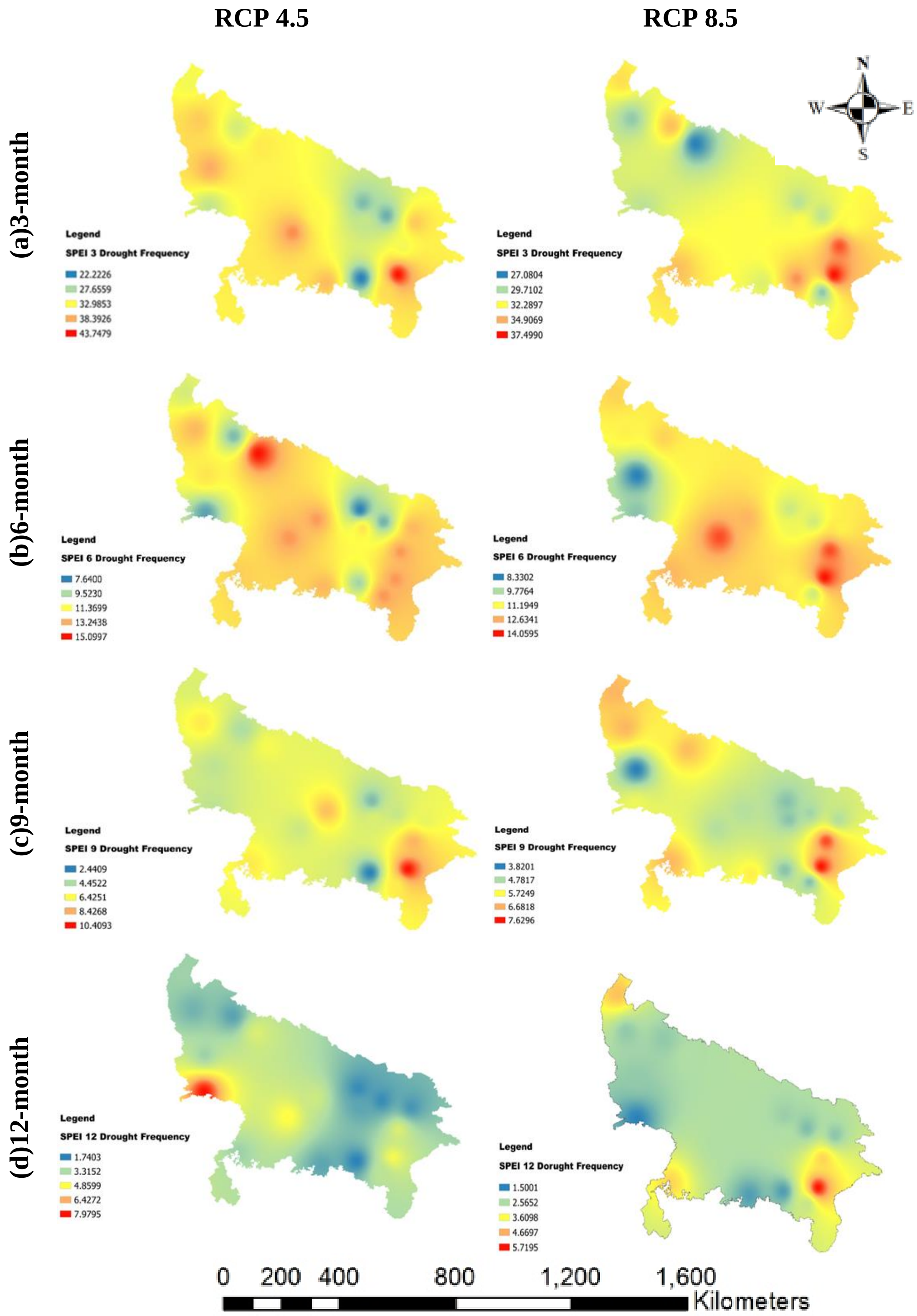

Figure 8.3 Spatial distribution of the drought frequency over the study area at different timescale of SPEI timeseries (a) 3-month, (b) 6-month, (c) 9-month, and (d) 12-month under RCP 4.5 and RCP 8.5 for the future period (2019 to 2050)

8.3.2 Projected change in the drought severity

To assess the impact of climate change and warming on drought severity under different climate projections RCP 4.5 and RCP 8.5 for 2019 to 2050. Figure 8.4 illustrates the spatial distribution of the average severity of each synoptic region under climatic scenarios RCP 4.5 and RCP 8.5. Changes in the spatial distribution and magnitude of drought severity observed at the different timescale of SPEI as well as different climatic scenarios (RCP 4.5 and RCP 8.5). The magnitude of drought severity increases with the SPEI timescale where the most severe drought event occurs with the SPEI12. The study region is expected to experience the most severe drought over a shorter timescale SPEI-3 and SPEI-6 under the RCP 4.5 scenario, while the most severe drought event is likely to occur over longer timescale SPEI-9 and SPEI-12 under the RCP 8.5 scenario. According to RCP 4.5 scenarios for SPEI-3 timescale, synoptic locations across the eastern plain are likely to face more severe drought events (Figure 8.4 a) and the most severe drought event in the near future projected to occur over the synoptic location Jhansi. The research area is more likely to have the same severity of drought event with minimal difference in magnitude as demonstrated in the spatial distribution map of drought severity of SPEI-3 under RCP 4.5 and RCP 8.5 (Figure 8.4 a). There is a significant increase in the magnitude of drought severity estimated over the study region at SPEI-9 and SPEI-12, where the most severe drought event will likely occur under RCP 8.5 (Figure 8.4 c & d). The significant difference in the spatial pattern of drought is depicted in Figure 8.4 (c and d.) The spatial distribution map of SPEI-9 time series (Figure 8.4 c) illustrates that the most severe drought event is expected to occur at the synoptic location over the eastern plain and the central western plain under the RCP 4.5 and synoptic location over the eastern plain and the western plain under the RCP 8.5 climate scenario. The spatial distribution map of SPEI-12 (Figure 8.4 d), the most severe drought is predicted to occur over the synoptic location of the eastern plain under RCP 4.5, whereas the synoptic location over the western plain and eastern plain along the Vindhyan region is projected to face more severe drought under RCP 8.5. Under RCP 4.5 scenario, drought event with average severity is projected to increase in Allahabad (Prayagraj), Gorakhpur, and Meerut, among all 18 locations, compared to the observed period. The research area will experience more severe drought events in the near future, over 61.6% of the synoptic location under climate change scenarios RCP 4.5 compared to RCP 8.5. SPEI-12 time series exhibit a considerable increase in drought severity relative to the observed period at synoptic sites Agra, Aligarh, Allahabad (Prayagraj), Chitrakoot, Gorakhpur, Meerut, and Moradabad. Compared to the observed period, average drought severity will decrease in the near future for synoptic locations Jhansi, Kanpur, Lucknow, and Saharanpur.

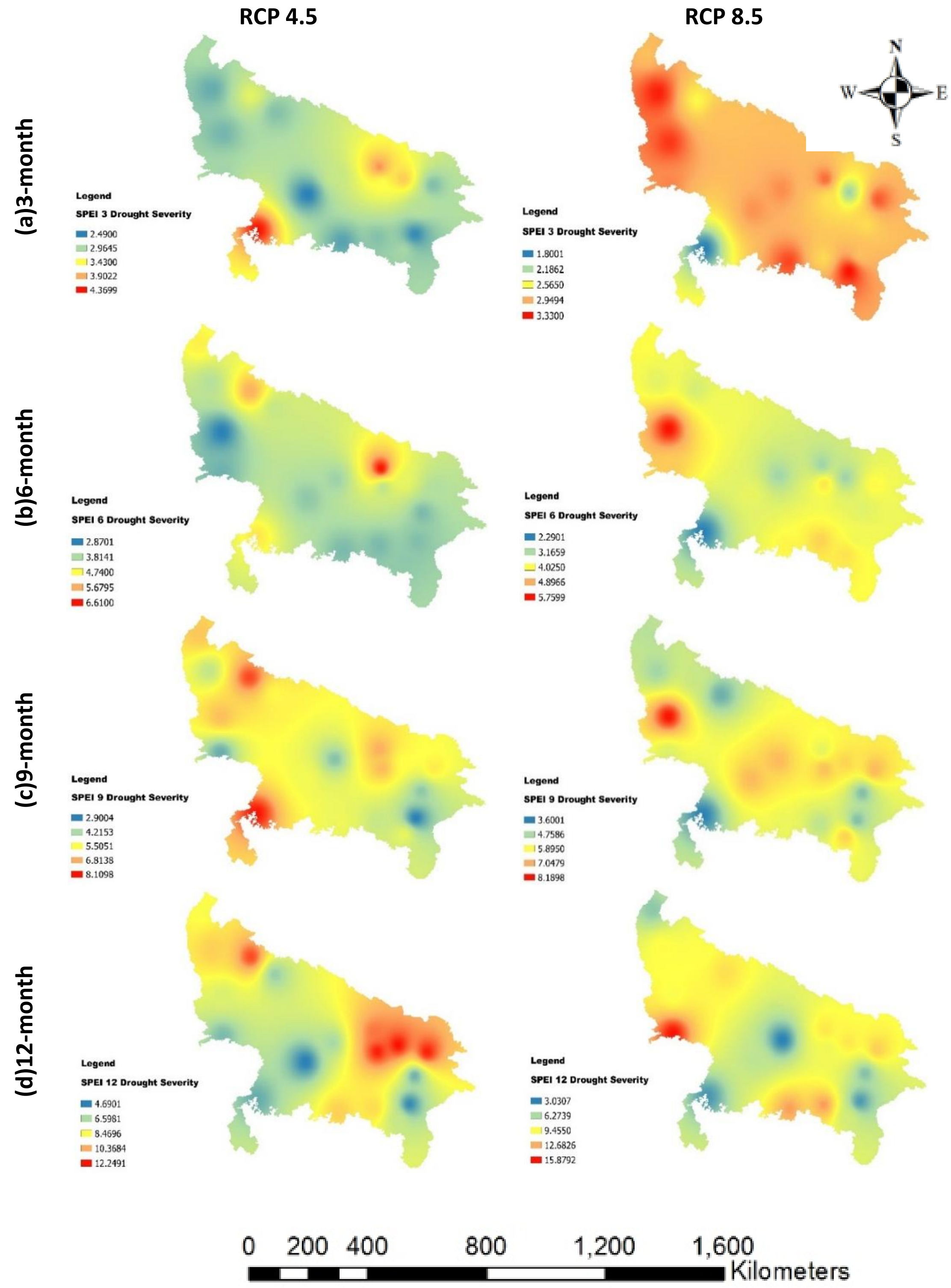

Figure 8.4 Spatial distribution of the drought severity over the study area at different timescale of SPEI timeseries (a) 3-month, (b) 6-month, (c) 9-month, and (d) 12-month under RCP 4.5 and RCP 8.5 for the future period (2019 to 2050)

8.3.3 Projected change in the drought duration

To assess the impact of climate change and warming on drought characteristics under different climate projections, RCP 4.5 and RCP 8.5, SPEI time series was estimated using predicted monthly precipitation and temperature calculated using CanSEM2 data that was downscaled using SDSM for the next 32 years between 2019 and 2050. Drought duration estimated based on SPEI time series based on run theory at SPEI <-1 threshold according to different scenarios RCP 4.5, and RCP 8.5, respectively. Figure 8.5 spatial distribution map portrays the projected change in drought duration for SPEI-3, SPEI-6, SPEI-9, and SPEI-12 under RCP 4.5 and RCP 8.5 in the near future (2019 to 2015). Under the RCP 4.5 scenario, the spatial distribution map of SPEI-3 depicts that most of the study region is at high risk of experiencing a drought episode of relatively short duration (Figure 8.5 a). This analysis concludes that the study region will likely experience drought events with short duration ranges of 1.80 to 2.42 months under RCP 4.5 at the SPEI-3 timescale. According to the spatial map for the RCP 8.5 scenario, the study region is projected to undergo drought events of short durations, most of which will last for about two months. The study area is anticipated to undergo a comparatively short drought event under both climate scenarios RCP 4.5 and RCP 8.5. Under the RCP 4.5 scenario for SPEI-6, Gonda, Jhansi, Moradabad, and Saharanpur will have more extended drought events over the study area (Figure 8.5 b). The spatial map depicts that most of the region will experience drought events of an average duration of 2.50 months. Across the study area, drought conditions are marginally worse and will experience a longer duration of drying event at each location under the RCP 8.5 scenario. The spatial distribution map of SPEI-9 (Figure 8.5 c) demonstrates that half of the study region under RCP 4.5 scenarios is projected to have a drought lasting more than four months, while the other half is projected to undergo a drying event of a shorter duration. Whereas, under RCP 8.5 scenarios, each area will likely experience a prolonged drought in the near future. Drought events lasting longer than 5 and 7.30 months were recorded in Allahabad (Prayagraj) and Aligarh. The spatial distribution map of SPEI-12 (Figure 8.5 d) depicts that the study area is characterized by significantly longer duration at each station, with drought events expected to last more than seven months in Agra, Allahabad (Prayagraj), Kanpur, Lucknow, and Jhansi under RCP 8.5. The spatial distribution and magnitude of drought duration changes were observed at the different timescale of SPEI under the RCP 4.5 and RCP 8.5 scenarios. The duration of a drought event varies with the SPEI timescale, with more extended drought events occurring with the SPEI12 time series. Under the RCP 8.5 scenario, the research area is expected to experience longer-duration meteorological drought events in the near future.

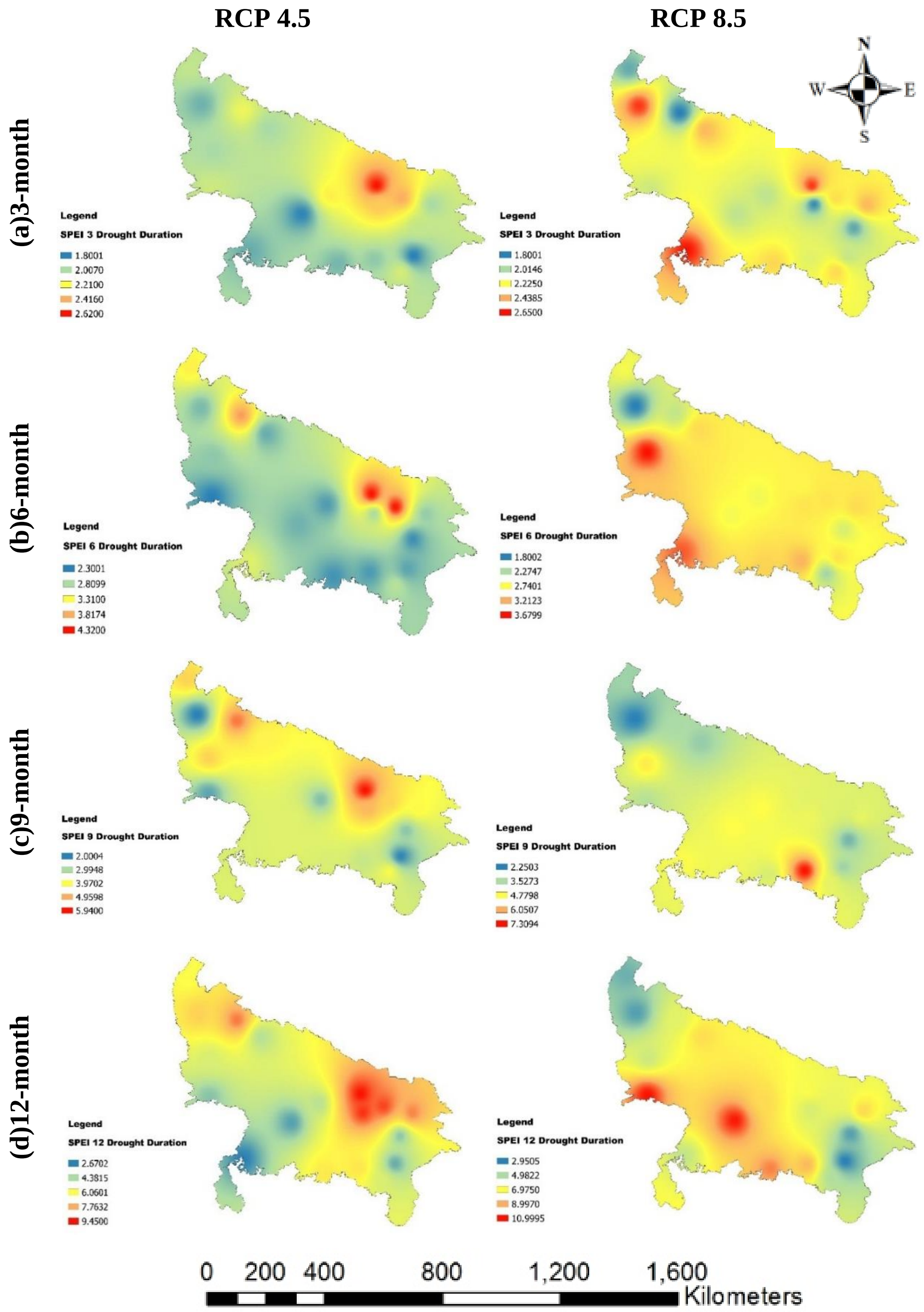

Figure 8.5 Spatial distribution the drought duration over the study area at different timescale of SPEI timeseries (a) 3-month, (b) 6-month, (c) 9-month, and (d) 12-month under RCP 4.5 and RCP 8.5 for the future period (2019 to 2050)

8.4 Summary

This chapter evaluated the drought characteristics in Uttar Pradesh under the climate change scenarios RCP 4.5 and RCP 8.5. Researchers used the CanESM2 of the CMIP5 model under two different climate change scenarios, RCP 4.5 and RCP 8.5 to investigate the future droughts characteristics. For a study of the effects of climate change on a particular sector to be successful, a comprehensive and appropriate historical and future climate dataset is required. As a result, the primary goal of this study was to use the SDSM tool to construct daily rainfall, maximum and minimum temperatures for the upcoming periods over the 18 synoptic locations of Uttar Pradesh, India. The projected change in the climatic variable shows that temperature will rise in all of the study locations with spatial variation in magnitude. The precipitation projection depicts that precipitation will gradually increase in the near future, with significant variations in the magnitude of precipitation change, where 66% of the synoptic locations will experience an increase in precipitation of less than 10% over the study area. As temperatures increase and precipitation gradually increases, the study region will be vulnerable to dry and wet events in the near future. In the RCP 4.5 emission scenario, the increase in temperature and precipitation is more intense than in the RCP 8.5 scenario. The globally employed drought index SPEI estimated drought characteristics at the timescale of 3, 6, 9 and 12-month under-projected climate scenarios in near future from 2019 to 2050. SPEI combines the sensitivity of evapotranspiration demand due to the rise in temperature on the drought characteristics. Its multiscalar capability enables this index to detect and monitor droughts of different categories and update the understanding of drought jeopardy over the State. For the future time period, the corresponding changes in climatological SPEI under RCP 4.5

and RCP 8.5 show a different spatial pattern, indicating a significant impact of emissions scenarios on the projected change in drought. The result reflects that study regions experience an increase in the frequency of drought occurrence with a short duration of a drought event at every location in near future under RCP 4.5 scenarios.

A drought event with maximum severity and prolonged duration of drought events is associated with RCP 8.5. However, the drying tendency is more pronounced and has a wider spread region under the RCP 4.5 scenario than under the RCP 8.5 scenario. Drought severity shows a mixed pattern in both scenarios, with some areas experiencing more severe drought compared to others. There was a significant variation in drought severity spatially and along the SPEI timescale. The spatial distribution and magnitude of average duration changes were observed at various SPEI scales under the RCP 4.5 and RCP 8.5 scenarios. The duration of a drought event varies with the SPEI timescale, with more extended drought events occurring with the SPEI-12 time series. Under the RCP 8.5 scenario, the research area is expected to experience longer-duration meteorological drought events in the near future. The findings of this study can serve as a starting point for improving risk management strategies, farming methods, and water use in this sector. SDSM downscaling techniques can provide more accurate and localized information on drought risk and vulnerability in Uttar Pradesh, improving our understanding of future climate change impacts and supporting better decision-making related to drought management in the region. Additionally, this study can contribute towards methodological advancements in statistical downscaling techniques, improving the accuracy of the statistical relationships between large-scale climate variables and local climate variables. Ultimately, the findings of this study can inform the development of appropriate adaptation strategies to reduce the impacts of drought on socio-economic and environmental systems in Uttar Pradesh, India.