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A drought study in the basin of Lake Urmia under climate change scenarios with higher spatial resolution to understand the resilience of the basin

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ABSTRACT

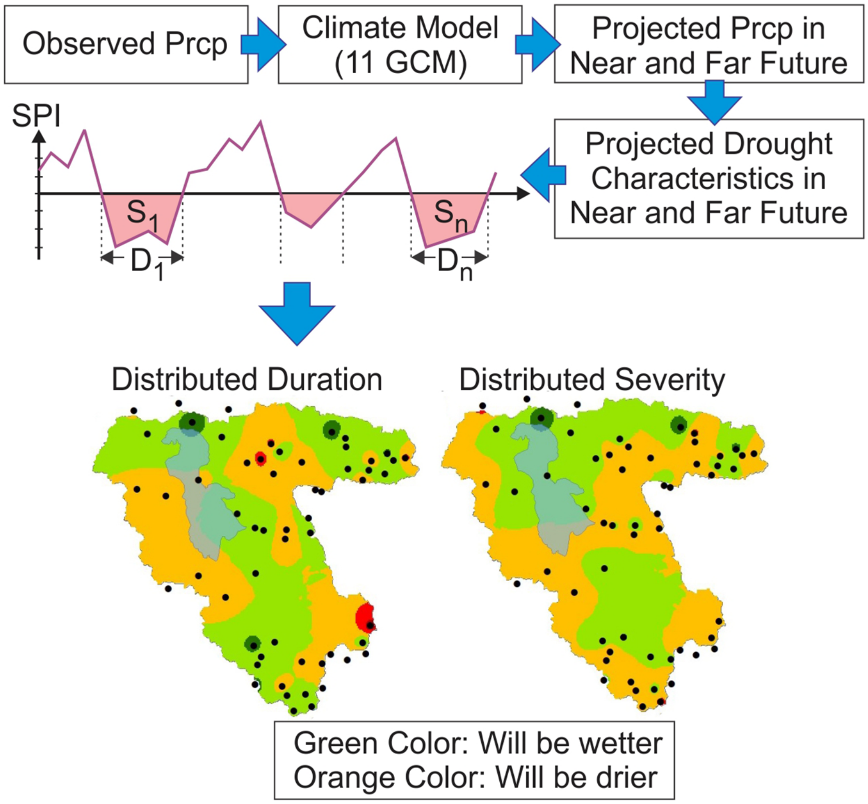
The exposure of the basin of Lake Urmia to meteorological droughts under climate change scenarios is investigated in this study. Should the catastrophic disappearance of the lake be explained by climate change, the basin would not be resilient to droughts in the future. This is examined by a climate change modelling involving *downscaling*: use 11 general circulation models to provide climate variables downscaled to a high spatial resolution of 57 stations deriving a correlation between observed time series at the base period and climatic variables; *projection*: derive precipitation at near/far future using the equations; and *drought studies*: derive 1-month standard precipitation index at the base and near/far future periods. The results identify the following: (i) in the base period, the lowest and highest biases are −2.5 and 3.7 mm, respectively; (ii) in the near/far future periods, the zones are less prone to meteorological droughts in the south, where water is plentiful, but prone in its north, where water is relatively scarce; (iii) the areas are likely to get drier or wetter but their ratios are unlikely to change. This resilience underpins the urge to appropriate policymaking, decision-making, and planning systems to ensure that the basin is made incrementally more resilient.

Key words: downscaling/projection, Lake Urmia, mismanagement, planning/policymaking, resilience/vulnerability

HIGHLIGHTS

- Spatial drought characteristics of the Standardised Precipitation Index were projected in the basin of Lake Urmia (LU).
- Drought duration and severity were estimated by considering the uncertainty of general circulation models.
- The results do not identify any drastic drought characteristic in future, and hence the basin is resilient.
- The modelling results are strong enough to discern anthropogenic impacts from natural forcing.
- The results serve as evidence to underpin the problems of LU to arise from mismanagement.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Topical research works on Lake Urmia have hardly investigated the hydrological resilience of the catchment in the sense of recovering from the ongoing catastrophic changes, but this study takes a preliminary step towards that. Owing to the construction of some 44 dams in three decades, the basin ought to be regarded as a socio-ecological system, but the capacity of the basin towards adverse effects is unknown. A critical view can be obtained from precipitation patterns, annual average precipitation over the basin, or the study of drought patterns. This study aims to study the evidence for the natural capacity of the basin to cope with droughts, which require precipitation values. If the basin is resilient to droughts, the restoration of Lake Urmia can gain impetus. Equally, attention needs to be given to the discernment between natural causes and policymaking, decision-making, and management identifying the role of encroachments onto water resources. This study investigates meteorological droughts in its socioeconomic, policymaking, decision-making, and management context.

The desiccation of Lake Urmia reached its final stage in 2023. Arguably, common sense is enough to attribute it to the construction of some 44 dams, which are operational and none with any known environmental impact assessment. Surprisingly, there have been very few critical reviews regarding the cutting off of the environmental flow to the lake necessary for maintaining its level. Any overlooking or assumptions not examined critically are bound to give rise to conflicting results, and there are plenty of such conflicts in the body of research on the catastrophe of Lake Urmia making knowledge integration quite impossible. To this end, the feasibility of the revival through the basin-wide precipitation capacity was studied, and this led to the Integrated Management Plan, issued and adopted in 2010, see IMP (2010). The plan was developed by the United Nations Development Program (UNDP), the Global Environment Facility (GEF), the Iranian Department of Energy (DOE), and provincial working groups. The plan put in place an action program to restore it by 2023 but due to non-action in the intervening years, Lake Urmia desiccated. This is despite the availability of the budget for the revival of the lake that might have been taken for granted owing to an international propensity and willingness to revive Lake Urmia. This reinforces the widely held perception that the problem is due to mismanagement. Thus, the drivers towards its restoration remain stronger owing to this investigation but seeking a more scientific basis to explain some of the drivers.

This study is a link in the authors' program of research activities to explain the catastrophe of Lake Urmia, some already presented (see Sadeghfam *et al.* 2022) and others are under active research (see the Discussion section). The authors' review of the literature on Lake Urmia, yet to be finalised, reveals that, on the one hand, the basin of Lake Urmia remains a topical multifaceted research field and, on the other hand, research conclusions suffer from multifaceted conflicts. This is unhelpful for the review of the past published works. Consider research activities addressing the impacts of climate change on the catastrophe of Lake Urmia. Some studies throw doubt into the role of climate change in the catastrophe, and these include Sadeghfam *et al.* (2022), Jani *et al.* (2023). Some published works put climate change or natural factors at the centre of the catastrophe and these include Radmanesh *et al.* (2022) and Delju *et al.* (2013). As research findings are conflicting, the detection of the real cause of the decline of the lake needs care and inclusivity, as in this research. A critical view of the above conflicting outcomes is discussed after presenting the result, but for now, the key is that they have different impacts on policymaking.

Kelman *et al.* (2016) argued that 'development decisions creating and perpetuating vulnerability are the root causes of disasters, not environmental phenomena which sometimes become hazardous'. They report on the literature that environmental disasters are not 'natural', neither in the sense of being from nature nor of being acceptable. The focus is on human actions, behaviour, decisions, attitudes, and values leading to vulnerabilities causing disasters. They cite numerous authors who hold disasters not to stem from 'natural' causes but in the disaster-related development literature they are held to be embedded in modern developments, and this sense is also accepted by development policymakers and practitioners. The authors also use this sense of definition as a bedrock assumption in the study.

Kelman *et al.* (2016) also give attention to the societal dimension of environmental risks in considering vulnerabilities and resilience. Vulnerability refers to the propensity to be harmed by a hazard without being able to deal with that harm stemming from the social processes. It encompasses human decisions, values, governance, attitudes, and behaviour forming situations in which hazards could potentially cause harm, e.g. casualties, social and business interruption, or property damage. Resilience refers to the capacity of a social–ecological system to cope with a hazardous event; maintain its essential function, identity, and structure; and maintain the capacity for adaptation, learning, and transformation. This study formulates a modelling strategy to project historical precipitation in the basin of Lake Urmia into the future and use the results to gain insight into droughts in future. The gained insight is fed into considering qualitatively the vulnerability and resilience of the system.

Drought is an inevitable climatic event, and unlike crisp, fuzzy, or random variables, droughts are sometimes referred to as an anomaly. The occurrence of droughts and their impacts are topical research. Meteorological droughts arise from below-normal precipitation and hence understanding the diversity in drought characteristics is necessary to develop mitigation measures (Jehanzaib *et al.* 2020; Shiru *et al.* 2020). This study is concerned with meteorological droughts, which are complex spatiotemporal characteristics such as onset, termination, duration, severity, and spatial extent. The Standardised Precipitation Index (SPI) and Standardised Precipitation and Evapotranspiration Index (SPEI) are among the most widely used meteorological drought indices (Laimighofer & Laaha 2022). SPI is widely defined as the number of standard deviations (often ± 1 standard deviation) from the long-term mean by which the observed anomaly (i.e. droughts) deviates from the long-term mean (see, e.g. https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi). SPI studies are characterised by severity and duration, calculated from the SPI time series, in which the area under the curve for negative SPI values indicates the severity and the corresponding time period represents the duration of the drought. SPEI accounts for both precipitation and temperature and thereby aridity.

Both SPI and SPEI are similar and their comparative studies are outlined as follows. Danandeh Mehr *et al.* (2019) report that SPI and SPEI indices are highly correlated; and Li *et al.* (2020) deemed both indices to be suitable for monitoring major drought events. Conversely, based on an anecdotal case, Yang *et al.* (2017) report that SPI tends to produce wetter results in arid and semi-arid regions but drier results in humid regions; Lotfirad *et al.* (2022) use 59-year monthly precipitation and temperature data and conclude that in temperate climates SPI and SPEI are strongly correlated at various time scales, but this is weak for the data from arid and hot climates. The study uses SPI for the following reasons: (i) even though it does not reflect droughts caused by changes in different climate variables, the World Meteorological Organisation recommends it (Hayes *et al.* 2011); (ii) the study area is in arid and semi-arid climate zones and therefore not much correlation is expected with SPEI and thereby with temperatures; and (iii) many studies also report that it provides reliable results in terms of drought duration and severity and the return period of extreme events (Li *et al.* 2021).

The tools for projecting historical records into the future are based on using general circulation models (GCMs), which describe atmospheric processes with mathematical equations. Environmental forcing on various carbon emissions and their probable future scenarios have been fed to these models to project (predict) scenarios of future precipitation patterns. However, these models have coarse resolutions and need to be downscaled at local scales, for which various techniques are available to take on board downscaling (DS). Statistical and dynamic DS techniques are available in the literature, where statistical techniques can be easily applicable and interpretable. The dynamic DS techniques are data-intensive and require high expertise to interpret, making these techniques less accessible (Zhou *et al.* 2018). Despite the simplicity, statistical techniques render more accessible temporal and spatial resolution for precipitation (Akhter *et al.* 2019; Alam *et al.* 2020).

DS models transfer uncertainties to the local scale (Akhter *et al.* 2019), and no individual models can describe the overall process of climate systems due to inherent uncertainties within future climate projections (Yao *et al.* 2020). To manage uncertainties inherent within GCM results and emission scenarios, it is recommended to use multiple GCMs (Sha *et al.* 2019; Duan *et al.* 2021; Khazaei 2021). The literature review also highlights that uncertainty within the scenarios is tolerable compared with uncertainty within GCMs (Song *et al.* 2020). The main advantage of the studies dealing with uncertainty is estimating an uncertain range for precipitation and temperature in future periods (Karandish *et al.* 2017). This study uses Long Ashton Research Station Weather Generator (LARS-WG), among the available statistical techniques, to predict the trend of meteorological variables (Vallam & Qin 2018) for projecting precipitation into the future and thereby studying droughts in the historical period and the future.

The novelty of this study stems from creating new knowledge by extending climate change scenarios to drought studies of the basin of Lake Urmia. In spite of the plethora of research on the basin, the clear-cut evidence for mismanagement of the basin is often overshadowed by attributing its catastrophic disappearance to climate change and sometimes to such red herring as the construction of a causeway through the lake to connect Tabriz and Urmia, the capital cities of East and West Azerbaijan. Decision-makers may be influenced by such non-scientific anomalies to justify their non-action. So, a contribution towards a better understanding of the root causes is the primary aim and novelty of this study. Thus, this study produces modelling results to detect the resilience of the basin towards droughts until 2080. The results will be the basis for drawing conclusions on the resilience of the basin, the manner of management, and the need for a planning system to stop any arbitrary encroachments onto water usage at the basin.

2. AREA

The Lake Urmia basin, with an area of about 51,800 km^2, is located northwest of Iran (see Figure 1(a)). The basin has a unique socio-ecological area, and the lake plays a pivotal role in the local microclimate. The catastrophic decline in the water level of Lake Urmia in the living memory of just two recent decades has triggered severe environmental problems. The rapid disappearance of Lake Urmia is increasingly attributed to some 44 dams constructed across any significant watercourse since 1990 in the basin, but there are a host of other factors to be outlined in the Discussion section. There is no natural or rational reason for the loss of the lake as it can be revived within the next two decades or so to save the basin from an impending disaster. For more details on some of the critical aspects of the basin of Lake Urmia, see the studies by Sadeghfam *et al.* (2022), Jani *et al.* (2023), and Khatibi *et al.* (2020).

The study incorporates the daily precipitation data in 57 stations within the basin during the statistical base period of 2000–2020 (see Figure 1(b)). The base period was used for calibrating and validating the DS stage. If the base period length was considered longer, the data at many of the stations had to be rejected, but such a choice would be at the expense of the accuracy of the spatial model. However, the base length of 20 years is acceptable according to Semenov & Barrow (2002), who recommended at least 20–30 years of data. This condition is in compliance with the data available in this study. Figure 1 shows the spatial distribution for annual precipitation during the base period.

The annual average precipitation and temperature within the basin are 363 mm and 13.7 °C, respectively. Precipitation is normally higher at altitudes above the average values, where the Sehend mountains have 17 peaks above 3,700 mAMSL and Mount Savalan is as high as 4,811 mAMSL; also, it is lower at altitudes in the plains with altitudes below average with its lowest level at 1,200 mAMSL. The seasonality signals in the data signify that minimum precipitation and temperature are observed in April and July, respectively. Based on Emberger (1930) and using the average precipitation and temperature, the climate of the basin is cold and semi-arid. Other statistical features of data are given in Table 1.

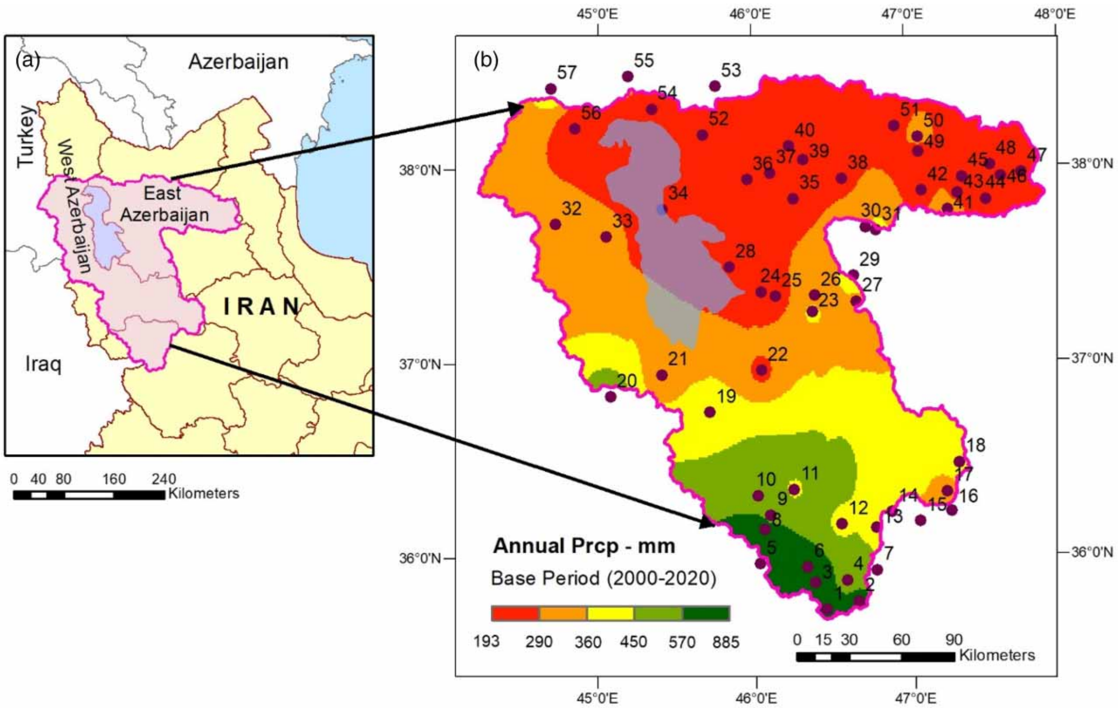


Figure 1 | Study area: (a) location map and (b) annual precipitation with spatial distribution and spatial locations of incorporated stations and station numbers with black circles.

3. METHODOLOGY

This section presents the details of the modelling strategy outlined above together with an overview of data availability and performance metrics.

3.1. The modelling strategy and its components

3.1.1. The strategy

The basis for the modelling strategy in this study is depicted in Figure 2 as a flowchart in five steps: (i) assemble the dataset for the study from raw data by conducting an outlier test and gap-data analysis; (ii) project precipitation onto the near and far future using modelling results from 11 GCMs using the LARS-WG software application; (iii) calculate SPI and drought characteristics (duration and severity) in the base period and the near/far future; (iv) calculate the maximum and average drought characteristics; (v) interpolate drought characteristics in the base period, and percentage change of near/far future to base period; (vi) quantify the uncertainty within GCM results in terms of coefficient of variation (CV). These steps are described in this section.

3.1.2. DS and projection models

There are large-scale climate data obtained by the atmospheric GCMs, which can be mapped onto a number of observation stations with historical precipitation data representing the base period. The modelling strategy uses the atmospheric GCMs of the IPCC's Fifth Assessment Report (AR5), and there are software applications, such as LARS-WG, which are capable of projecting future precipitation. This is a stochastic weather generator that can simulate climate data at a station under current and future climate conditions (Racsko *et al.* 1991; Semenov *et al.* 1998). It uses the output of GCMs to generate precipitation, solar radiation, and maximum/minimum temperature data on a daily time scale.

This study uses LARS-WG, which is a software tool capable of generating local-scale climate scenarios using global climate models. As described by Racsko *et al.* (1991) and Semenov & Barrow (1997), it is mainly a tool for climate research and modelling to generate climate and weather variations in different geographical locations. LARS-WG considers multiple climate variables such as temperature, precipitation, wind speed, and solar radiation to produce weather data for future climate

Table 1 | Statistical features of data in the period of 2000–2022

Station	Average annual precipitation (mm)	Standard deviation (mm)	Max daily precipitation (mm)	Max monthly precipitation (mm)	Missing data (%)	Station	Average annual precipitation (mm)	Standard deviation (mm)	Max daily precipitation (mm)	Max monthly precipitation (mm)	Missing data (%)
1	787.8	6.30	77	406	0.4	**30**	325.4	3.40	57	141	6.9
2	637.4	5.99	87	386	2.4	**31**	400.4	3.68	59	162	5.6
3	665.5	5.85	79	295	0.3	**32**	309.7	4.02	70	350	6.9
4	500.0	4.00	49	194	0.3	**33**	303.0	3.33	55	148	0.0
5	963.6	10.12	140	461	0.0	**34**	228.5	2.94	56	131	6.4
6	622.8	5.73	75	275	0.4	**35**	278.8	2.99	60	115	8.0
7	430.6	3.94	59	176	0.3	**36**	230.5	2.64	50	110	5.7
8	661.3	5.59	73	265	0.0	**37**	236.9	2.62	54	114	6.4
9	520.3	4.75	66	223	0.0	**38**	275.7	2.70	38	116	8.5
10	512.3	4.90	63	207	0.3	**39**	192.7	2.24	64	119	0.0
11	431.9	4.15	80	223	0.3	**40**	259.1	2.58	58	115	0.0
12	411.3	4.21	69	196	0.3	**41**	382.4	3.80	46	252	9.2
13	408.2	3.64	50	201	0.3	**42**	245.7	2.79	60	107	7.4
14	396.9	3.66	48	158	0.4	**43**	256.4	2.57	42	133	7.4
15	289.6	2.73	43	112	0.3	**44**	230.0	2.42	55	96	7.4
16	355.2	3.59	57	223	7.5	**45**	280.5	2.63	37	113	7.2
17	302.3	3.64	64	226	9.8	**46**	251.6	2.61	32	103	7.3
18	447.5	3.58	54	164	0.0	**47**	244.4	2.62	31	142	10.0
19	372.2	3.77	68	134	0.0	**48**	232.9	2.39	29	104	7.2
20	522.8	4.85	64	194	0.0	**49**	251.8	2.71	50	142	6.8
21	314.8	3.45	65	169	0.5	**50**	324.3	3.54	75	119	13.3
22	272.7	2.97	49	133	0.5	**51**	266.5	3.31	70	118	13.6
23	380.2	3.89	85	193	6.6	**52**	225.0	2.39	44	94	1.0
24	262.9	2.87	50	123	0.8	**53**	244.3	2.76	33	89	13.2
25	255.9	2.72	42	115	0.0	**54**	245.1	2.92	50	139	9.7
26	314.6	3.29	62	128	6.6	**55**	312.3	3.38	47	129	11.4
27	355.5	3.91	92	182	8.4	**56**	234.9	2.38	41	104	0.0
28	235.0	2.67	43	112	0.0	**57**	409.7	3.87	65	192	4.1
29	412.1	4.00	69	179	6.2						

Note: For the year 2012, there were 23 out of 57 stations with missing data.

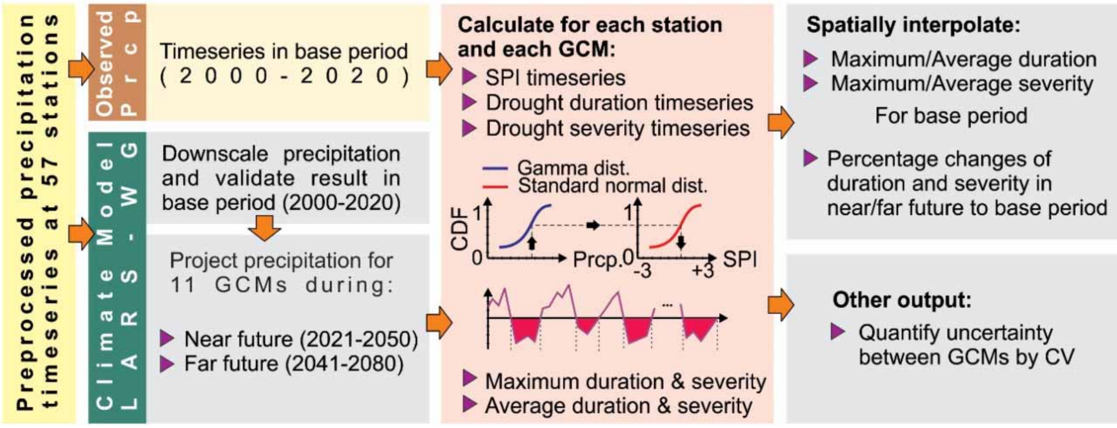


Figure 2 | Methodological flowchart.

projections. Modelling with LARS-WG comprises three steps: calibration, validation, and generating future weather variables. Model calibration is tested by the Kolmogorov–Smirnov (K–S) test to compare probability distributions, the *t*-test to compare the mean, and the *F*-test to compare the standard deviations of generated and observed data (Rotich & Mulungu 2017). The *p*-values from these tests present the similarity between the observed and simulated climate. *p*-value of 0.05 is used as the minimum acceptable significance limit of results. The validation of the simulated and observed precipitation in the DS stage is carried out using the coefficient of determination (R^2) and the root mean square error (RMSE). After ensuring the validity of LARS-WG models, data generation for the future (2021–2080) is carried out by using a pseudo-random number generator. This generator identifies dry and wet days by considering precipitation values and generates precipitation data using semi-empirical probability distributions for each month for the lengths of a series of wet and dry days and for the amount of precipitation on a wet day (Khajeh *et al.* 2017).

The study of historical and projected precipitation values are divided into the near future (2021–2050) and the far future (2041–2080) under the scenarios of the Coupled Model Intercomparison Project (CMIP5), RCP4.5 and RCP8.5, which are taken to be mutually exclusive. The periods are selected for capturing patterns in spatiotemporal variations. Notably, CMIP6 GCMs were not available when the study was initiated but discussed in due course. Also, 11 GCMs, specified in Table 2, are incorporated in each station, which are taken to be mutually inclusive, and therefore their means increase the reliability at the projection stage and enable the investigation of their inherent uncertainty (see Table 2).

3.2. Drought characteristics

This study uses the SPI on the 1-monthly time scale (denoted as SPI-1) to study drought occurrence and characteristics in terms of duration and severity, which is one of the most widely used indices. Developed by Mckee *et al.* (1993), it describes meteorological drought for various time scales and is now recommended by the World Meteorological Organisation, see Hayes *et al.* (2011). SPI-1 to SPI-3 are referred to as shorter accumulation periods and are suitable to investigate shorter impacts of drought, but higher accumulation periods are also topical research. SPI is based on two assumptions: (i) precipitation variability is greater than temperature and atmospheric evaporation demand and (ii) the rest of the variables remain insensitive to changes over time (Gaitán *et al.* 2020).

SPI quantifies observed precipitation in terms of the standard deviation of a selected probability distribution function that models the raw precipitation data by often fitting a gamma distribution or a Pearson type III distribution to the data and then transforming it into a normal distribution. SPI values can be interpreted as the number of standard deviations (often ± 1 standard deviation) from the long-term mean by which the observed anomaly (i.e. droughts) deviates from the long-term mean (Aryal *et al.* 2022). As mentioned in the Introduction section, the severity and duration, as two essential characteristics of drought, are calculated by the SPI time series so that the area under the curve for negative SPI values indicates the severity and the time period represents the duration of the drought when the SPI value is negative. For more details, see Mckee *et al.* (1993).

Table 2 | The characteristics of incorporated GCMs

ID	Incorporated GCMs	Modelling centre	Resolution (latitude × longitude)	References
1	CanESM2	National Centre for Atmospheric Research, Canada	2.7906° × 2.8125°	https://www.canada.ca
2	CMCC-CM	Euro-Mediterranean Centre on Climate Change, Italy	3.7111° × 3.75°	https://www.cmcc.it/
3	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	2° × 2.5°	https://www.gfdl.noaa.gov/
4	GISS-E2-R-CC	NASA Goddard Institute for Space Studies, USA	2° × 2.5°	https://www.giss.nasa.gov/
5	HadGEM2-ES	Met Office Hadley Centre, UK	2° × 2.5°	https://www.metoffice.gov.uk
6	INMCM4	Institute for Numerical Mathematics, Russia	1.5° × 2°	https://www.inm.ras.ru
7	IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France	1.2676° × 2°	https://www.ipsl.fr
8	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	1.4008° × 1.40625°	https://www.aori.u-tokyo.ac.jp
9	MPI-ESM-MR	Max-Planck Institute for Meteorology (MPI-M), Germany	1,8° × 1,8°	https://mpimet.mpg.de
10	MRI-CGCM3	Meteorological Research Institute (MRI), Japan	1,2° × 1,2°	https://www.mri-jma.go.jp
11	NorESM1-M	Norwegian Climate Centre, Norway	1.8947° × 2.5°	Bentsen *et al.* (2013)

3.3. Uncertainty quantification

In the study, the CV quantifies the uncertainty in the results of different GCMs as the ratio of the standard deviation of GCM results to the mean. The values range from 0 to a high positive value. The closer the value to '0', the lower the variations between GCM results and subsequently the lower the uncertainty. In contrast, higher CV values render higher uncertainty. Previous studies also use it as a measure of uncertainty in climate studies (see Sharafati *et al.* 2020; Lee *et al.* 2021). This study uses it as a measure of uncertainty in a loose sense and acknowledges that the classic term of uncertainty has different connotations and formulations.

3.4. Performance metrics

The inbuilt performance metrics in LARS-WG were outlined above for the stages of calibration, validation, and generating future weather variables using the K–S test to compare probability distributions, the *t*-test to compare the mean, and the *F*-test to compare standard deviations of the generated and observed data and using the *p*-values from these tests to present the similarity between observed and simulated climate.

This study uses the following performance metrics: R^2, RMSE, bias values, and homogeneity tests. Their calculations are necessary to validate LARS-WG modelling results by using the simulated and observed precipitation in all stations. Bias values are calculated as the difference between predicted and measured precipitation.

This study also uses the homogeneity test to investigate any significant trace of break (jump) signals in the base period using the SNHT (Standard Normal Homogeneity Test, see Alexandersson 1986; Alexandersson & Moberg 1997) and Buishand's test (Buishand 1982). The null hypothesis in these tests is based on the absence of any break in the data, and if it is not rejected, precipitation data from a population are homogenous and do not have detectable break signals in the recorded data. Notably, when *p*-values are close to zero, the null hypothesis is rejected.

3.5. Pre-processing of data

In the pre-processing step, the data quality was checked in terms of outliers and gaps. There were no outliers based on using the interquartile range (Salgado *et al.* 2016) since all the data were pre-processed by the Iran Meteorological Organisation. Any missing data for less than 3 years were estimated by fitting regression equations using other stations with correlation coefficients higher than 0.8. Table 1 presents the percentage of missing data for each station. Most of the synoptic stations used in the study are new, but there is no information on the data quality of the older stations.

4. RESULTS

4.1. Calibration of LARS-WG

Table 3 presents the performance metrics of R^2, RMSE for the 57 stations, in which R^2 varies between 0.89 and 0.99, and the RMSE values between 1.2 and 8.7 mm. Hence, the LARS-WG results are considered to be fit-for-purpose, and as such, they justify the ability of LARS-WG to project and generate data for the future.

4.2. Climate change

The bias values for the 57 stations are also presented in Table 3, and they vary from −2.5 to 3.7 mm, which divides the stations into overestimating and underestimating groups. In this way, there are 15 stations with underestimation and 42 stations with overestimation. These provide strong evidence that the modelling results for the base period are good. Further information on monthly or seasonal variations will be reflected in a separate paper. The null hypothesis, see Section 3.4, was rejected for only 4 from 57 stations as per Buishand's test (highlighted in red in Table 3), in which *p*-values are close to zero. Therefore, the results are not indicative of any significant breaks in the base period as per two homogeneity tests. As such the data are homogeneous and few inhomogeneous ones were ignored, as they only appeared in one test.

4.3. Drought characteristics in the base period

Figure 3 shows the spatial distribution of maximum and average drought characteristics for the base period (2000–2020) within the basin. The selected time scale is 1-month, and severity is dimensionless, both varying in the range of 0–9 intervals. The key findings for the maximum drought duration from Figure 3(a) are (i) it shows insignificant variations between 6 and 7 months; (ii) in the northern margins of the basin and the north of the lake, it is higher than in other areas and varies in the range of 7–8 months; (iii) for the northeast region it is 5–6 months, which extends to limited parts of northwestern areas. Figure 3(b) shows the maximum drought severity (dimensionless), which indicates (i) it is of a lower magnitude in the southern regions of the basin; (ii) it is of higher magnitude (varies between 6 and 7 months) in the northern margins; and (iii) it is of a lower magnitude (range: 4–5 months) at the south/southeast/southwest margins and some areas in the northwest and northeast.

Figure 3(c) depicts the average drought duration and shows two distinguishable southern and northern parts in the study area: (i) in the southern part, the average duration varies between 3 and 4 months; and (ii) in the northern part, it is 2–3 months. In general, the average duration does not change significantly within the basin, as shown in Figure 3(d), which replicates the behaviour for average durations but with an even lower magnitude of the variability range between 2 and 3 months. The northern and a limited segment of the southeastern parts have lower average severity variations (range: 1–2 months).

An intercomparison of the above results provides an insight into the drought behaviour within the basin at the base period: (i) operational drought (onset, intensity, and end) is critical in the southern portion of the basin in terms of average duration and severity where precipitation is plenty (southeastern parts of the basin); and (ii) meteorological drought becomes critical in terms of average duration and severity where precipitation is not plentiful (northern/northwestern parts of the basin).

4.4. Maximum drought characteristics in future

Although the projection results are produced for the two RCP4.5 and RCP8.5 scenarios, the detailed results are presented for RCP8.5 alone as the pessimistic outcome. The decision was made by preliminary investigations, which showed that the spatial distribution of drought characteristics derived from these scenarios are similar but slight intensification is observed from RCP4.5 to RCP 8.5.

4.4.1. An insight into future maximum drought characteristics

Figure 4 shows the spatial distribution for percentage changes of the maximum duration and severity in the near future (2021–2050) and the far future (2041–2080), both compared with the base period. Positive values in these comparisons indicate

Table 3 | Performance metric for calibrated LARS-WG model

						p-value ($\alpha = 0.05$)								p-value ($\alpha = 0.05$)	
Stations	**Lat**	**Lon**	**R^2**	**RMSE (mm)**	**Bias (mm)**	**SNHT test**	**Buishand's test**	**Stations**	**Lat**	**Lon**	**R^2**	**RMSE (mm)**	**Bias (mm)**	**SNHT test**	**Buishand's test**
1	35.73	46.45	0.99	6.34	1.010	0.067	0.001	**30**	37.70	46.73	0.94	3.88	0.840	0.487	0.123
2	35.77	46.65	0.98	5.82	1.830	0.000	< 0.0001	**31**	37.68	46.80	0.97	3.87	0.540	0.123	0.003
3	35.87	46.38	0.99	5.33	1.650	0.208	0.003	**32**	37.72	44.73	0.95	4.64	− 1.610	0.033	< 0.0001
4	35.88	46.58	0.99	3.92	2.530	0.033	0.037	**33**	37.66	45.06	0.98	2.46	0.330	0.189	0.134
5	35.97	46.03	0.98	8.75	2.300	0.334	0.015	**34**	37.80	45.42	0.97	2.98	0.570	0.522	0.620
6	35.95	46.33	0.99	4.49	1.080	0.274	0.133	**35**	37.85	46.27	0.98	2.68	1.160	0.865	0.514
7	35.93	46.77	0.98	3.55	− 0.940	0.074	0.263	**36**	37.95	45.97	0.95	3.51	− 0.170	0.119	0.117
8	36.15	46.06	0.98	5.83	− 0.170	0.079	0.020	**37**	37.98	46.12	0.93	3.39	− 0.370	0.264	0.039
9	36.22	46.10	0.99	3.36	− 0.500	0.086	0.334	**38**	37.95	46.58	0.98	1.91	0.460	0.356	0.161
10	36.32	46.02	0.99	3.41	1.170	0.219	0.030	**39**	38.05	46.33	0.99	1.24	0.470	0.024	< 0.0001
11	36.35	46.25	0.97	4.08	− 0.040	0.306	0.497	**40**	38.12	46.24	0.97	2.43	0.590	0.250	0.037
12	36.17	46.55	0.99	3.01	1.400	0.141	0.089	**41**	37.78	47.27	0.97	4.18	2.290	0.001	< 0.0001
13	36.15	46.77	0.97	4.56	1.960	0.025	0.005	**42**	37.88	47.10	0.89	3.97	0.110	0.456	0.098
14	36.23	46.87	0.98	3.30	1.390	0.121	0.004	**43**	37.87	47.33	0.98	2.16	1.170	0.419	0.134
15	36.18	47.05	0.98	2.37	− 0.770	0.065	0.015	**44**	37.83	47.52	0.95	3.07	− 1.330	0.261	0.320
16	36.23	47.25	0.97	3.83	0.210	0.165	0.005	**45**	37.95	47.37	0.96	2.82	1.350	0.182	0.059
17	36.33	47.22	0.96	4.01	1.580	0.279	0.025	**46**	37.95	47.62	0.98	2.35	0.950	0.299	0.338
18	36.48	47.31	0.98	4.96	3.670	0.083	0.054	**47**	37.97	47.75	0.99	2.87	2.140	0.436	0.218
19	36.75	45.72	0.98	4.06	1.710	0.229	0.023	**48**	38.01	47.55	0.99	1.74	0.580	0.196	0.243
20	36.83	45.08	0.98	4.72	− 2.450	0.059	0.013	**49**	38.08	47.08	0.98	2.49	1.260	0.163	0.006
21	36.95	45.41	0.97	3.93	2.090	0.429	0.299	**50**	38.16	47.08	0.96	3.69	0.930	0.514	0.263
22	36.97	46.05	0.97	2.83	0.430	0.351	0.235	**51**	38.22	46.93	0.96	2.63	0.250	0.220	0.016
23	37.27	46.38	0.97	4.02	− 0.330	0.187	0.265	**52**	38.18	45.68	0.97	1.87	− 0.550	0.104	0.115
24	37.37	46.05	0.96	3.02	− 0.340	0.272	0.393	**53**	38.43	45.77	0.98	2.22	0.850	0.223	0.562
25	37.35	46.15	0.98	2.35	0.710	0.417	0.279	**54**	38.32	45.35	0.98	2.27	0.250	0.151	0.096
26	37.35	46.40	0.94	4.46	− 0.200	0.101	0.028	**55**	38.49	45.20	0.96	3.93	2.540	0.539	0.582
27	37.32	46.67	0.96	5.03	2.410	0.377	0.076	**56**	38.22	44.85	0.98	2.00	0.660	0.120	0.045
28	37.50	45.85	0.96	2.77	− 0.260	0.455	0.367	**57**	38.42	44.69	0.99	4.05	3.170	0.169	0.075
29	37.45	46.65	0.98	3.87	1.010	0.183	0.309								

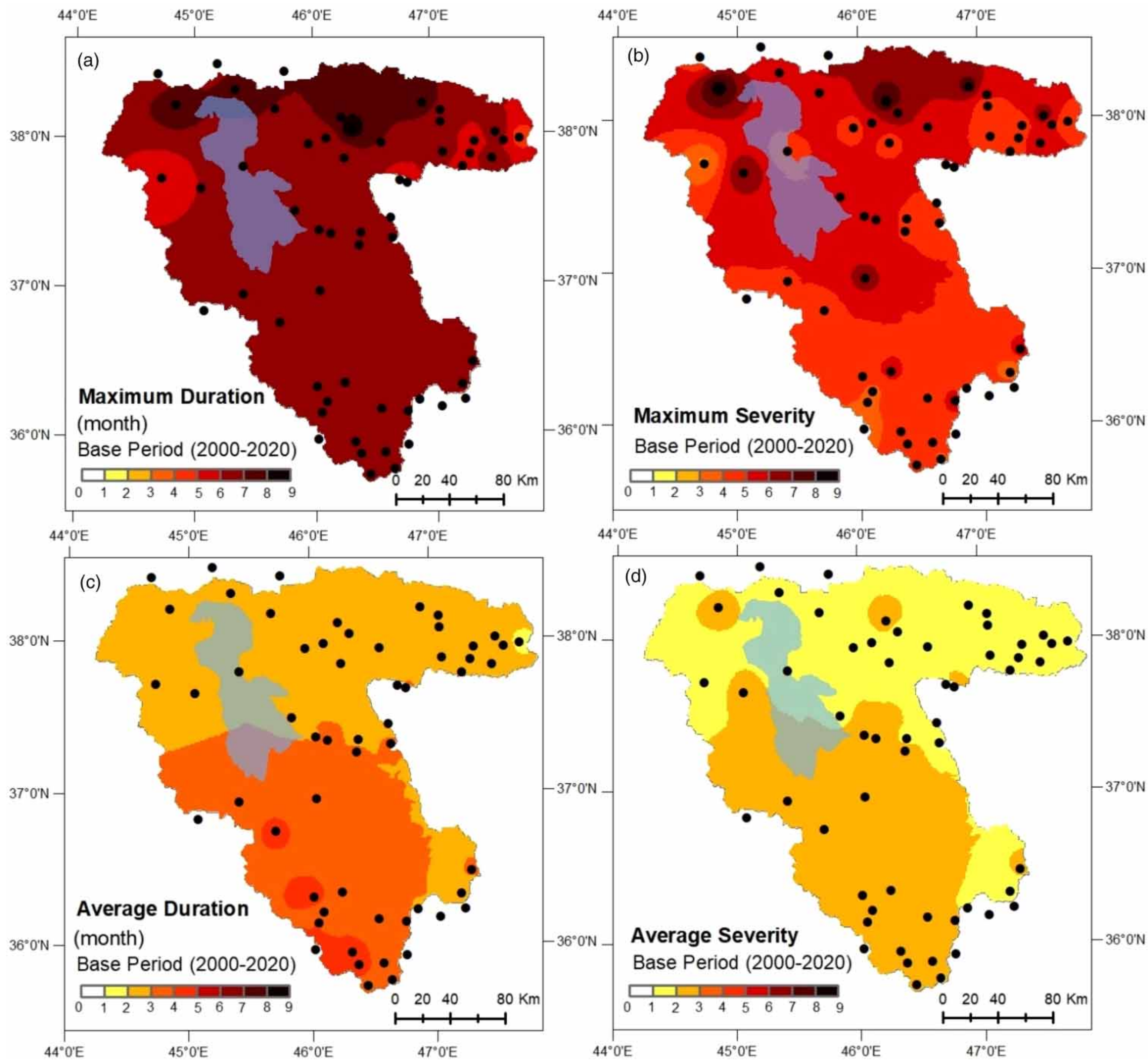


Figure 3 | Spatial distribution of drought characteristics in the base period (2000–2020): (a) maximum duration, (b) maximum severity, (c) average duration, and (d) average severity.

'drying' areas compared with the base period, where drought characteristics are likely to increase in future, whereas in contrast, negative values indicate 'wetting' areas, where drought characteristics are likely to decrease in future. Comparisons of the results in Figure 4(a) (maximum duration of near future) with Figure 4(c) (maximum duration of far future) and Figure 4(b) (maximum severity of near future) with Figure 4(d) (maximum severity of far future) show that the patterns of change from the near future to the far future can strikingly be similar and, therefore, the analysis invokes a remarkable consistency.

The information contained within the peak drought characteristics is extracted by simple arithmetic for the base period, as in future, changes in drought characteristics in terms of their absolute values are likely to vary in the range of $\pm 20\%$. These results for the near and far future periods compared with the base periods indicate that (i) approximately half of the basin will be wetter and the other half drier for both duration and severity, both in the near and far future; (ii) there will be some tendency to get drier towards the far future and sensitivity to drier outcomes for severity. Likewise, the information content within the mean SPI values is extracted similarly, which indicates that in the near and far future periods, some 90% of the

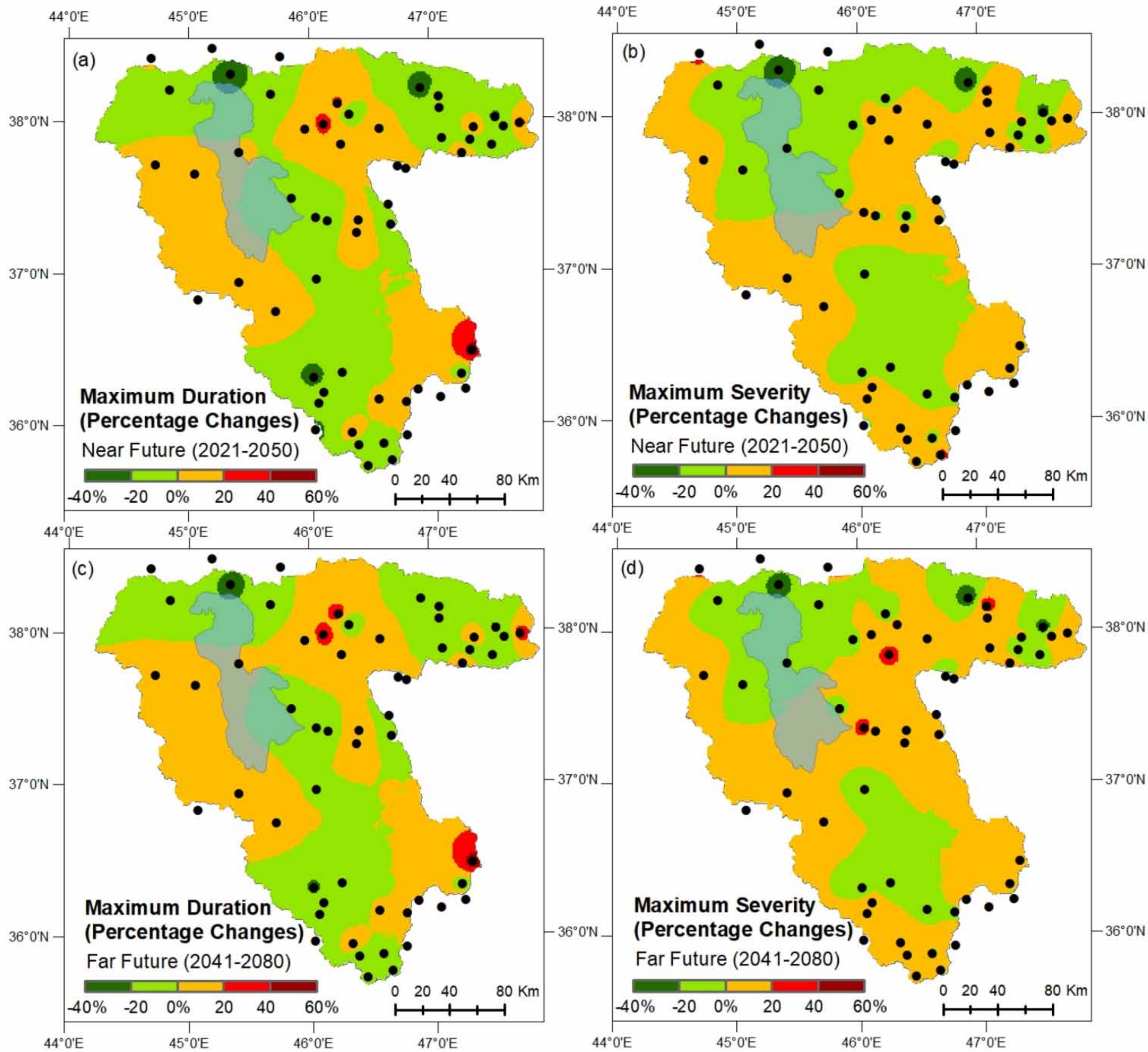


Figure 4 | Percentage changes of maximum drought characteristics: (a) max duration in the near future, (b) max severity in the near future, (c) max duration in the far future, and (d) max severity in the far future.

area of the basin is likely to become wetter but only 10% become drier considering the duration. Nonetheless, some 70% of the area of the basin is likely to become wetter and 30% drier considering the severity. Conversely, some of these wetter areas are likely to turn drier ever from the near future onwards, and the sensitivity of severity for duration is likely to be amplified in the far future. The overall conclusion is that climate change is likely to alter future drought patterns, and if proper management practices are established, adaptation is likely to be feasible.

4.4.2. Uncertainty in results of future drought characteristics

CV is used here as a measure of the inherent uncertainty associated with the results of different GCMs and thereby of drought characteristics presented above. The CV values for the maximum duration in the near future (2021–2050) are given in Figure 5(a), which shows that a few stations located in the northern segment of the basin have CV values between 0.07 and 0.18, but the remaining stations have CV values lower than 0.07. So, their information content invokes greater confidence in the results. The CV of max severity for the near future (2021–2050) is depicted in Figure 5(b).

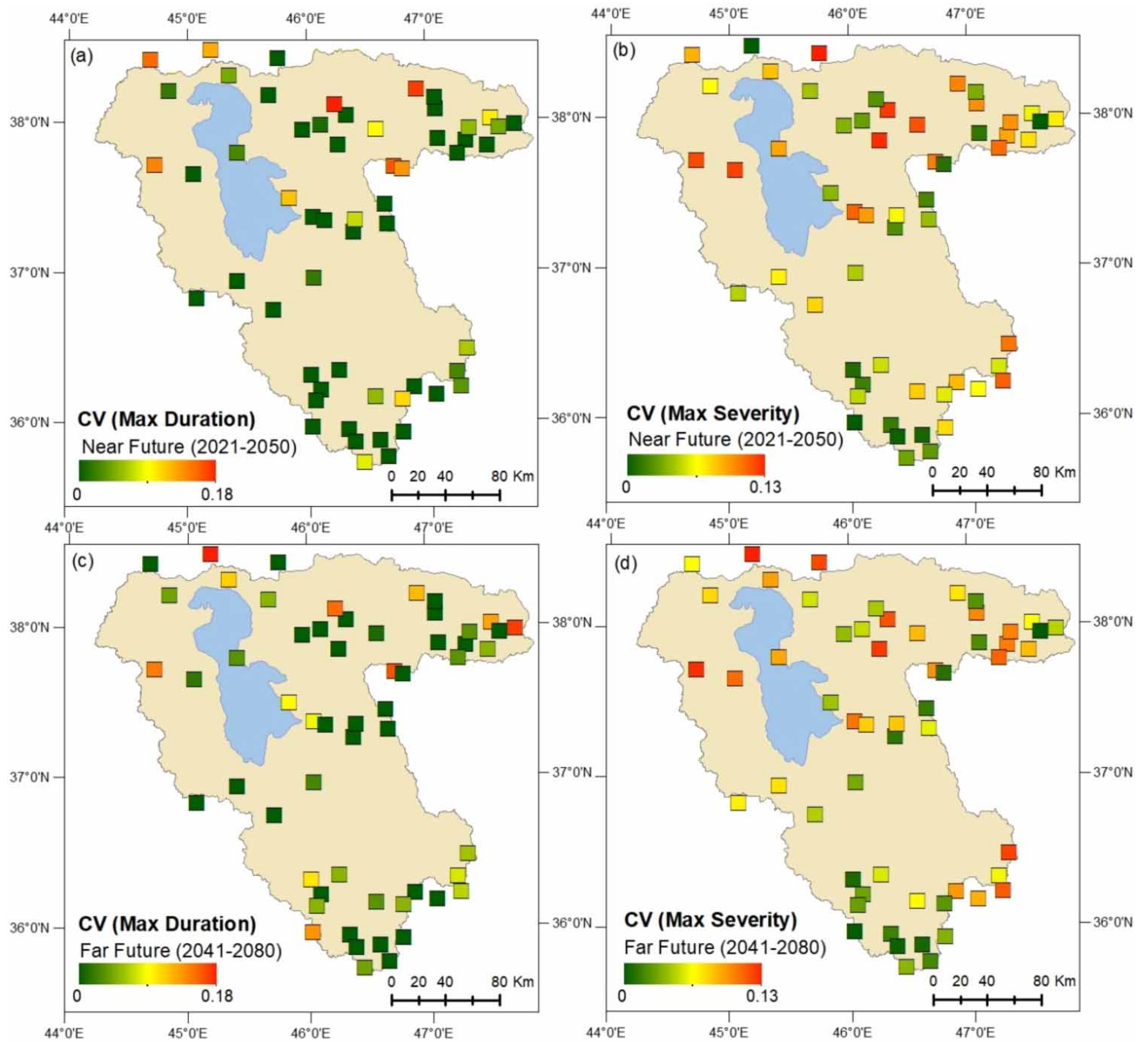


Figure 5 | Uncertainty between GCM results in terms of the CV for (a) maximum duration in the near future, (b) maximum severity in the near future, (c) maximum duration in the far future, and (d) maximum severity in the far future.

Likewise, a few stations have CV values between 0.015 and 0.1, but the values are mostly lower than 0.015 for the remaining stations, by which their information content invokes a greater confidence in the results. The corresponding results for the far future period show somewhat deterioration in uncertainty as a few more stations have their CV values in the range of 0.07–0.18 (see Figure 5(c) and 5(d)). However, the range of uncertainty underpins the reliability of the evidence for a large proportion of the stations.

4.5. Average drought characteristics in future

4.5.1. An insight into future average drought characteristics

Figure 6 presents the spatial distributions for percentage changes of the average duration and severity in the near future (2021–2050) and the far future (2041–2080) compared with the base period. They indicate that (i) most parts of the basin

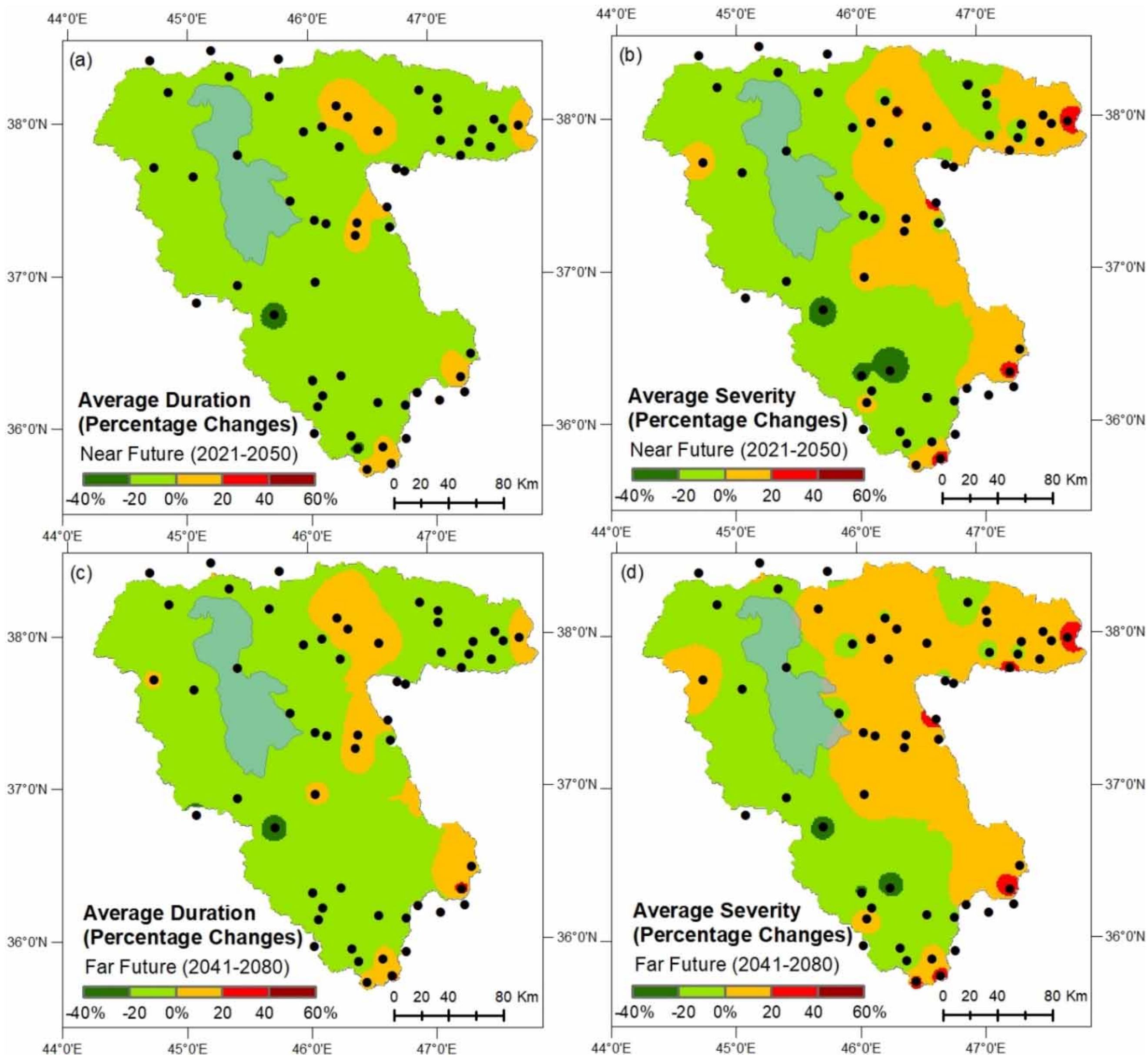


Figure 6 | Percentage changes of average drought characteristics: (a) average duration (near future), (b) average severity (near future), (c) average duration (far future), and (d) average severity (far future).

are likely to get wetter in terms of average duration but some local patches get drier; (ii) dry areas in severity are likely to be of a greater spatial extent compared with the duration (see Figure 6(a) and 6(b)), i.e. eastern parts can get drier but wetter in western parts; (iii) the areas to get drier are likely to increase in the far future compared with the near future; and (iv) changes in drought characteristics in future are unlikely to destabilise the basin hydrological cycle, although this needs to be investigated further using longer accumulation periods.

4.5.2. Uncertainty in results of future drought characteristics

Figure 7 shows the CV for the average duration and severity in the near future (2021–2050) and the far future (2041–2080), which indicates the following: (i) Figure 7(a) indicates that $0.033 < \mathrm{CV} < 0.12$, $\mathrm{CV} < 0.033$ for approximately half of the stations, and CV is between 0.033 and 0.12 for the remaining ones; (ii) Figure 7(b) shows that $0.033 < \mathrm{CV} < 0.13$, $\mathrm{CV} < 0.033$ for approximately half of the stations, and CV is between -0.033 and 0.13 for the remaining ones; (iii) these ranges

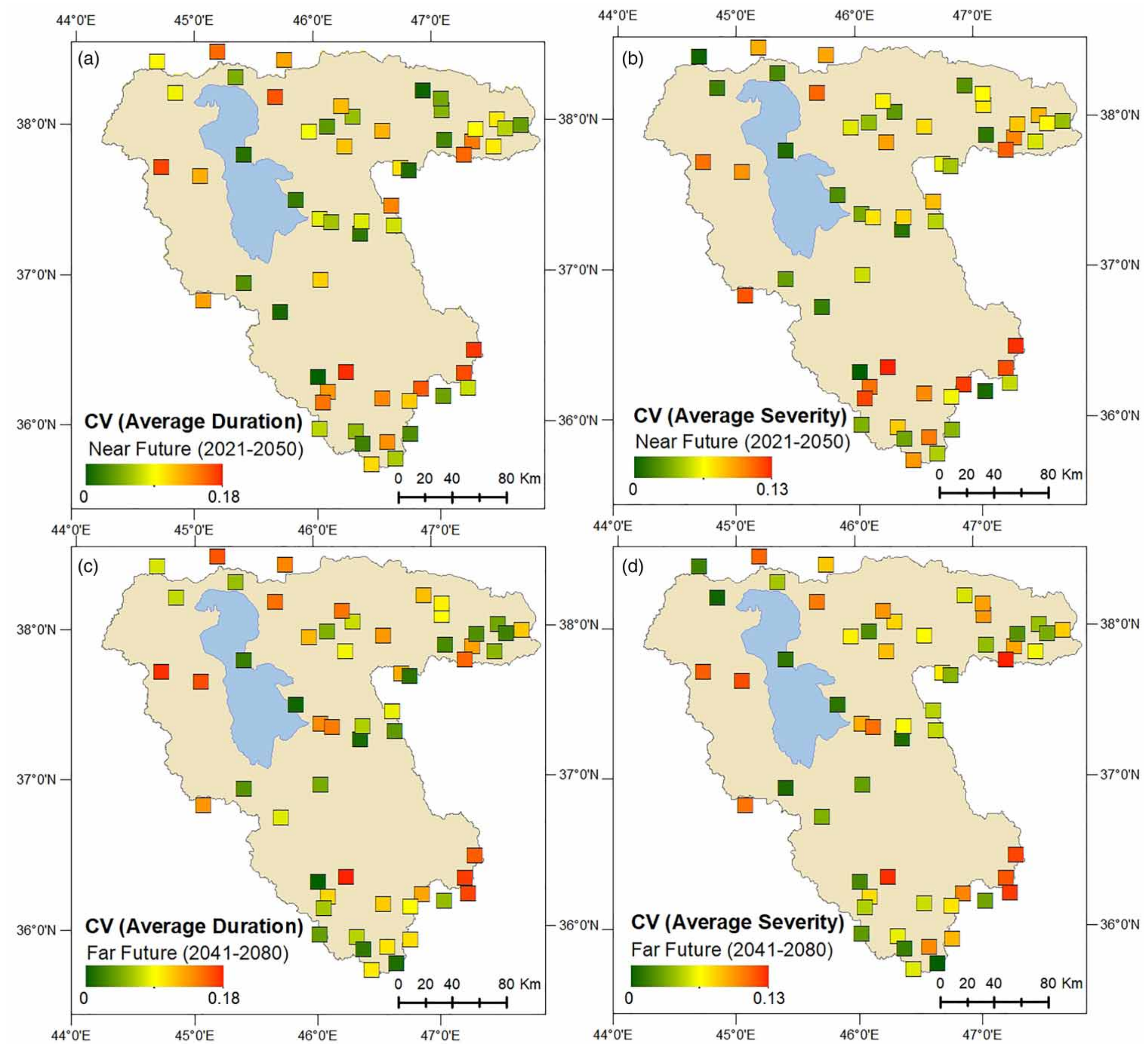


Figure 7 | Uncertainty between GCM results in terms of the CV: (a) average duration in the near future, (b) average severity in the near future, (c) average duration in the far future, and (d) average severity in the far future.

in uncertainties and the maximum CV value of 0.18 underpin less variability in the results and thereby more reliability, although CV for the far future shows a somewhat slight increase from the near future to the far future (see Figure 7(c) and 7(d)).

4.6. Projected changes in drought patterns

Detailed patterns of droughts in the base, near, and far future presented above show patterns of changes in both duration and severity, but these are complex to reflect an overview of the salient features. The overview is captured in Figure 8 by aggregating the differences between the duration and severity at the near future and base periods, as well as between those at the far future and base periods. The calculations are carried out using the RCP8.5 scenario. The figure displays the aggregated wetter areas and the aggregated drier areas. Evidence is clear that under the research parameters (the shorter accumulation period of 1 month), sensitivity to future conditions is not that significant.

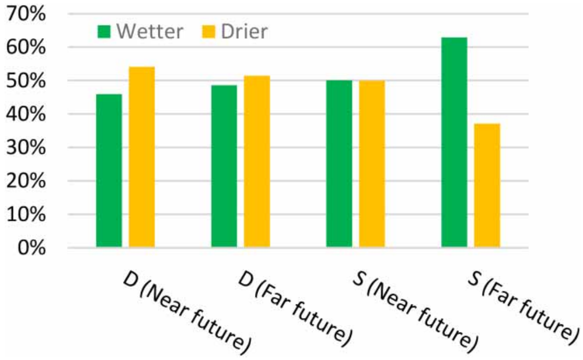


Figure 8 | Salient features of impacts of climate change on drought in the basin of Lake Urmia in terms of areas becoming wetter or drier.

5. DISCUSSION

In processing the data and results, the following principles are observed: (i) the results of using different GCMs are mutually inclusive and can therefore be subjected to further processing such as taking their means; (ii) the results of different climate change scenarios are mutually exclusive and they are not operated collectively by any mathematical processes.

The results presented in the paper provide some foresight to the possible drought patterns at the basin of Lake Urmia projected until 2080. They certainly do not predict future conditions but help understand the risks and identify a possible incremental approach to risk management. The integrity of the models, the results, and the conclusions are discussed next.

5.1. Integrity of conclusions for modelling assumptions

Various approaches are used to demonstrate that the conclusions are robust, defensible; and they are drawn from a modelling study, in which the quality of the results does not depend on the particular assumptions of the modelling strategy. It is noted that there are 57 stations in three periods (base period, near, and far future) using two emission scenarios, and this study uses outputs from 11 GCMs. Therefore, the analysis requires $57 \times 3 \times 2 \times 11 = 3{,}762$ drought characteristics, which is a considerable constraint, and therefore the various sensitivity tests are subject to this constraint. Thus, computational costs were a significant driver in the following decisions. (i) This study selected the CV to study the uncertainty within the results, even though further insight could have been gained by other techniques, e.g. uncertainty quantification by using statistical analysis such as Bayesian model averaging (see Wasserman 2000; Moazamnia *et al.* 2019) or inclusive multiple modelling, see Khatibi *et al.* (2020), Sadeghfam *et al.* (2021a). (ii) This study sufficed to use shorter durations of SPI alone without testing the performance of longer accumulation periods and without testing SPEI. (iii) Two CMIP5 scenarios (RCP4.5 and RCP8.5) were deemed sufficient, but the paper presented detailed results for RCP8.5, as the most pessimistic scenario. Nonetheless, preliminary evaluations showed that RCP8.5 would produce similar but more severe results. (iv) GCMs based on CMIP6 have some advantages comprising finer spatial resolution, enhanced parameters of the cloud microphysical process, and biogeochemical cycles and ice sheets. These were not available when the study was initiated and, therefore, this study presents the best available data at the time of the research work. Notably, some of these limitations have been investigated by the authors and are discussed further later in this section.

5.2. Connecting with similar research on the basin

The projected precipitation results are outside the scope of the paper, and the review presented in Table 3 pools together the basic parameters underlying research findings on droughts investigated over the basin of Lake Urmia in the base and future periods. These parameters are spatial resolution, temporal resolution, time scales, GCM outputs, DS algorithms, scenarios (Scen.) employed, periods employed, and indices investigated. The salient points suggested by the table are as follows: (i) the scale of variations in the reported research works are wide; (ii) due to the variability of the research parameters, knowledge integration becomes a serious issue and this is concerning. There are always variations among modelling results produced by different software houses for specific problems and this is accepted, some aspects of which are discussed by Khatibi (2004). Some choices have positive contributions but some others may be concerning. For instance, the spatial resolution used in this study is the highest among the similar studies, and this is bound to contribute to the reliability of the results. Conversely, the choice of one accumulation period requires some justification, else is a cause for concern, but as discussed above, this has been addressed, indicating no cause for concern.

Discrepancies as large as conflicting results cannot be explained by simple attributions to research parameters. Under such circumstances, the following strategy is often a norm in professional organisations. (i) A defensible approach is to benchmark the relevant software capabilities in the first place to ensure that the candidate model applications can solve the same specified problems and data and comply with prescribed performance metrics. Such benchmarked platforms are not available for research works on climate change, and research environments do not normally standardise their practices to such a level. (ii) To ensure that results are reproducible, further specifications need to be applied under best practice modelling procedures, which specify the assumptions, record a whole range of decisions, and systematise checking the data quality. (iii) If conflicts or major discrepancies persist, the modelling tasks need to be quality-assured to rule out the role of different arrays of possibilities.

The primary conflicting result concerning the drought studies of the basin of Lake Urmia is that some papers report the droughts under the spell of climate change in base periods (e.g. Delju *et al.* 2013; Radmanesh *et al.* 2022) but some do not detect any predominant signal yet (e.g. Sadeghfam *et al.* 2022; Jani *et al.* 2023). The present article does not identify any strong signals explaining the precipitation record in the basin of Lake Urmia. Its research parameters are specified in Table 4 and it stands out for its high spatial resolution owing to using 57 synoptic stations. Furthermore, model performances are good in terms of the bias metric, according to which underestimations and overestimations are in the range from −2.5 to 3.7 mm. Nonetheless, the temporal resolution of the recorded precipitation is 21 years of data, dictated by the sparsity of the data. Nonethless, the homogeneity test was carried out for 18 other stations in the basin of Lake Urmia with 34 years of data. Without presenting the results, it may be confirmed that their precipitation data were found to pass the SNHT homogeneity test at 16 stations, giving an added assurance on the results. Also, the accumulation period is 1 month, dictated by computational burden but the authors addressed this limitation in a later study yet to be published. It may be confirmed without presenting the result that the 3-month accumulation period is likely to produce the worst condition, although the conclusions reported here remains unchanged.

5.3. Possible mitigations

Droughts are managed in modern times by an organisational arrangement and appropriate policies and planning strategies. In Iran, the National Drought Warning and Monitoring Centre (NDWMC) was established to cater for drought, which is attached to the Ministry of Agricultural Jihad (MoJA). Other stakeholders include the Iranian Space Agency (ISA) under the Ministry of Communication and Information Technology (MOCIT), the Ministry of Energy (MOE), and the Department of Environment (DOE). However, in practice, there seems to be no law to initiate policies, and this is reflected in reactive responses to drought situations in Iran, although these institutions have initiated some infrastructure provisions with subsequent controversies, e.g. the numerous dams in the basin of Lake Urmia. It is often commonplace that during operational droughts, water supplies to even households are rationed. Conversely, developed countries have drought plans, which specify appropriate actions (before, during, and after the drought) to maintain a secure supply of water, assess the environmental effects of the actions, and provide measures to mitigate the impacts of the actions or the droughts.

The Sustainable Development Goals (SDGs), often viewed as a global action plan, aim to alleviate the problems at the social dimension, protect the planet, and ensure the vibrancy of economic activities for all people to enjoy peace and prosperity. They consist of 17 goals, 4 of which directly address environmental issues and the remaining 13 have some indirect roles. Notably, Goal 13 formulates urgent actions to combat climate change and its impacts. Although the catastrophe of Lake Urmia is ostensibly attributed to climate change, Sadeghfam *et al.* (2022) and Jani *et al.* (2023) do not confirm such findings but show that climate change is yet to kick in any significant way, in the near future. So, the fundamental question is that even after the catastrophic drying up of Lake Urmia, does the basin have a sufficient hydrological capacity to maintain its sustainability and possibly restore the lake in the future? The answer is related to the vulnerability and resilience of the study area as discussed below.

Based on the review by Kelman *et al.* (2016), the central theme in the SDG discourse is that in disaster management it is neither natural nor acceptable to regard disasters as natural but the focus of policymakers and practitioners is on human actions, behaviour, decisions, attitudes, and values leading to vulnerabilities that cause disasters. The vulnerability in the study area stems from the propensity to be harmed by hazards, the ineffectiveness of the planning system to deal with the

Table 4 | Studies on the basin of Lake Urmia related to climate change

Reference	Spatial Res (stations)	Temporal Res. (years)	Time scale (months)	Data and model	Notes on findings
Studies with stations inside the basin of Lake Urmia					
Current paper: **Drought study:** *Studying meteorological drought using SPI with enhanced spatial resolution*	57 stations	21	1	• **DS**: LARS-WG • **GCM**: 11 CMIP5 outputs • **Scen.**: RCP4.5 and RCP8.5 • **Periods**: Base, near, and far future • **Index**: SPI	• Homogeneity: SNHT and Buishand's tests • Bias: – 2.45 to 3.67 • Detected no significant climate change signal
Jani *et al.* (2023) **Projecting climate zones to future** A study of climate change at the basin of Lake Urmia and its vicinity	7 stations within the basin and its adjacent	40	1	• **DS**: LARS-WG • **GCM**: CMIP3 • **Scen**: A1B, A2, and B1 • **Period**s: Base, near, middle, and far future • **Index**: **DMI** (to characterise the climate of each station)	• Climate zoning did not identify any significant impacts of climate change • Some zones are likely to receive more precipitation, some less
Sadeghfam *et al.* (2022) **Drought study:** *Meteorological and GW drought study by Copula*	48 synoptic stations +158 GW stations	21	1	• **DS**: Just base period with no project • **GCM**: none • **Period**: historical period • **Index**: SPI and SGI	• Droughts at the basin are explained by anthropogenic activities in the first place with little impact of climate change
Radmanesh *et al.* (2022) **Drought study:** *Studied impacts of climate change on lake levels and its shrinkage, and the correlation of SPI and SPEI with the lake level*	1 station in the basin	55	3, 6, 12, 24, and 48	• **DS**: LARS-WG • **GCM**: 10 CMIP5 GCMs • **Scen.**: RCP4.5 and RCP8.5 • **Periods**: Base and future • **Index**: SPI and SPEI	• Report seasonal decreases/ increases in precipitation • Correlation of SPI and SPEI with lake level increases with the time scale • For arid zones, SPI and SPEI correlated poorly
Davarpanah *et al.* (2021)	7 stations	20	3, 6, 9, 12, and 24	• **DS**: SDSM • **GCM**: 1 CMIP5 GCM • **Scen**: RCP2.6, RCP4.5, and RCP8.5 • **Period**: Base, near, and far future • **Index**: SPI	• Increased droughts • Future increases in drought probability • Increases in drought persistence, intensity • Drought and wet spells decreased but their persistence increases
Mirgol *et al.* (2021) Investigated the spatial and temporal drought conditions	7 stations	30	1, 3, and 12	• **DS**: LARS-WG • **GCM**: 5 CMIP5 GCMs • **Scen**: RCP 2.6, RCP 4.5, and RCP 8.5 • **Period**: Base, near, and future • **Worked out** joint variability of precipitation and temperature by the Mann–Kendall test • **Index**: SPI and SPEI	• Slightly positive trends of SPI in three stations during 2051–2080 under RCP 8.5 • SPEI predicts more drought events than the SPI • The future periods would encounter fewer droughts conditions than the present • 3 stations (Urmia, Tabriz, and Maragheh) would have more frequent quarterly droughts in future • Serious actions need to be taken
Delju *et al.* (2013) **Drought and climate study:** *Assessing impacts of climate*	1 station	42	1	• **Statistical time series analysis**. Use	• Analysed time series and concluded the onset of

(*Continued.*)

Table 4 | Continued

Reference	Spatial Res (stations)	Temporal Res. (years)	Time scale (months)	Data and model	Notes on findings
change on drought over the Lake Urmia basin				o Dry bulb temperature o Max and min temperature and precipitation o Number of rainy/snowy days • **Periods**: Base and future • **Index**: PDSI for drought	climate change at the base period • Correlated lake levels with precipitation and temperature
Ahmadebrahimpour *et al.* (2019) *Assessing impacts of climate change on drought in the basin*	59 stations	30	1, 3, 6, 9, 12, and 24	• **SD**: NCEP software • **GCM**: 1 CMIP5 GCM • **Scen.**: RCP2.6 and RCP8.5 • **Periods**: Base, near, middle, and far future • **Index**: SPI and SPEI	• SPEI preferred to SPI • Increased droughts with RCP8.5
Abbasian *et al.* (2021) *Monitoring and predicting drought in the Urmia synoptic station were investigated using the SPEI and AI*	9 stations	21	1, 3, 6, 12, 24, and 48	• **SD**: GHLM software • **GCM**: 9 CMIP5 GCMs • **Scen.**: RCP4.5 and RCP8.5 • **Periods**: Base, near, and far future • **Index**: PTDI	• Increased frequency of dry/hot months by 4.7–24.0% in 2060–2080

DS: Downscaling; GCM: Global Circulation Model; Scen: Scenario, also: PTDI: XXX; PDSI: XXXX; SDSM: XXXX; SGI: XXX and DMI: XXX.

harms, and the absence of decision-making by participation; these principles are prerequisites of SDGs. It follows from the results that the meteorological–ecological systems in the study area have the resilience for restoration but there is a lack of management or institutional capacity to cope with maintaining their essential function, adaptation, learning, and transformation.

Khatibi (2022) discusses the need for a possible framework to integrate research activities and practices in three dimensions: (i) governance to account for policymaking and planning; (ii) goal-oriented learning organisations to ensure sustainability; and (iii) decision-making to implement reliable projects and manage risks. However, the procedure and best practices recommended by the United Nations on any of these three dimensions are not normal with the changes created in the basin of Lake Urmia. The disaster in the basin of Lake Urmia is multifaceted, and since its emergence in 1990, the drying of Lake Urmia has come about by (i) cutting compensation flows (see Khatibi *et al.* 2020) to meet its ecological demands, (ii) the ongoing depletion on the aquifers of the basin (see Sadeghfam *et al.* 2022), (iii) subsequently induced subsidence in many of the plains of the basin (see Gharekhani *et al.* 2021; Nadiri *et al.* 2021), and (iv) widespread contamination on surface and underground (Sadeghfam *et al.* 2021b).

To the best of the authors' knowledge, vast changes inflicted since 1990 are without any environmental impact assessment or strategic environmental assessment, and therefore severe encroachments onto the natural regime of the basin are not surprising. Risk realisations are multifaceted, and the most explicit is manifested as the shrinkage of Lake Urmia in the living memory during 2008–2015. To date, there were no re-examinations of the past decisions, but implementing past ambitious plans still has not been carried out.

The results provide evidence that using climate change to justify the unfolding catastrophe at the basin of Lake Urmia is not justifiable. To this end, climate change may be regarded as a risk of lower order. The absence or ineffectiveness of the past planning and policymaking practices in Iran has given rise to catastrophic failures, which are not attributable to climate change in any significant way. To this end, anthropogenic impacts are regarded as risks of higher order. Thus, climate change has not impacted the catastrophe of Lake Urmia, and if it has any impact, it should be of a lower order. The higher-order risks from anthropogenic impacts on the shrinkage of Lake Urmia have reached catastrophic proportions, but this is likely to get worse, as some climate change impacts are likely to prevail in the near and far future. However, with a good planning system, policymaking, and management, the impacts on the basin in the near future are a matter of urgency. An incremental policy is needed to reduce the inherent vulnerabilities and strengthen its resilience. Best practice procedures recommended by the United Nations are the starting point and should be embedded in appropriate policies in the medium term, but in the short-run, a great deal of quick-win action plans are needed to halt the ingress of the catastrophe and a good example of this was the integrated management plan as discussed above, see IMP (2010) but it was not implemented.

5.4. Future investigations

Further investigations are planned by using the CMIP6 scenario, owing to its main advantages over CMPI5 GCMs, for using socioeconomic pathways with CMIP5 scenarios. Consequently, CMIP6 provides more realistic future scenarios (O'Neill *et al.* 2014; Song *et al.* 2021). Performances of CMIP6 compared to CMIP5 depend on the geographical location of a study area, and various studies show different improvements (Gusain *et al.* 2020; Kamruzzaman *et al.* 2021). Therefore, there is room for future research studies by updating results using CMIP6 GCMs in the basin of Lake Urmia. The authors conducted a post-sensitivity analysis of results using CMIP5 and CMIP6 for more than 10 sample stations and several GCMs. The results indicate that projected precipitations by CMIP6 are somewhat higher compared to CMIP5 almost in all months. However, this result depends on the characteristics of the study area and may contradict some previous studies. Thus, the results offered by the paper may be considered conservative towards any future conditions of the basin of Lake Urmia. The studies planned for the coming years include using CMIP6, using SPEI and SPI, testing the performance of different time scales (1, 2, 3, 6, 12, 24, 36, and 48 months), and updating the station data.

6. CONCLUSION

Lake Urmia, a vibrant self-sustaining lake under its pristine conditions and focal point in the international literature, reached its last moments in 2023, a process that started circa 1995. Under climate change conditions, the basin under its pristine conditions would likely witness altering future drought patterns and is unlikely to reach a breaking point. The encroached basin can still be revitalised to its past vibrancy if proper management practices are established. This study underpins the disaster reduction literature that environmental disasters are all manmade and provides evidence that Lake Urmia is no exception.

The results are used to delineate zones where droughts are matters of operational management at the present times, as well as zones where droughts can stem from meteorological forcing, i.e. the zone with sparse water availability. Existing patterns of droughts in the basin are unlikely to change drastically, and best practice drought management is required to maintain social, ecological, environmental, and economic vibrancy in the basin.

The study employed a modelling strategy to project recorded precipitation into the future by the statistical DS techniques and investigated the subsequent drought characteristics based on 11 CMIP5 GCMs. The study of the homogeneity of recorded precipitation time series at 54 out of 57 stations in the basin did not identify any trace of climate at a 1-monthly time scale. The drought characteristics along with uncertainties in GCMs were spatially distributed in the base, near, and far future periods. The results provide evidence that drought intensity or period in the near and far future is unlikely to exceed $\pm 20\%$ compared with the base period. Therefore, the disruption in the resiliency of Lake Urmia should not be attributed to climate change, and appropriate planning and policymaking systems are necessary to manage water resources in the basin, cope with operational hydrological droughts, and even restore the lake.

DATA AVAILABILITY STATEMENT

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

CONFLICT OF INTEREST

The authors declare there is no conflict.

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