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A Biophysical Approach to Assess the Risks Associated with Climate Change for Spatial Analysis of Agricultural Drought Vulnerability

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Abstract

Global warming has led to changes in climate variability and different characteristics of extreme events. Recently, the study of compound extremes, defined as the co-occurrence of multiple events with extreme impacts, has attracted much attention because of their detrimental impacts on society and ecosystems. In countries like Iran with arid and semi-arid climate patterns, inter-annual climate variability causes severe influences on agriculture through compound dry and hot extremes. Such impacts are expected to increase due to climatic changes. Decreasing water availability as a consequence will have a direct impact on agriculture and could endanger socio-economic development and social sustainability in these regions. Assessment of the vulnerability to climate change and its resulting agricultural drought is fundamental for effective adaptation strategies in the future. This paper presents a spatial GIS-based assessment method for agricultural drought vulnerability in current and future climatic conditions in Isfahan Province, Iran, by constructing agricultural drought vulnerability maps. This assessment was conducted by evaluating changes in the severity, duration, and frequency of compound dry and hot extremes. The results expressed the spatio-temporal variability of the empirical probability of drought occurrence, and indicated the relation between the vulnerability of agricultural drought and the characteristics of drought occurrence. The results of the vulnerability assessment can be used to prioritise the counties for the implementation of long-term drought management plans and effective countermeasures, as well as to contribute to sustainable agricultural development.

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Introduction

The impacts of climate change on people, property, and nature become evident every year through more extreme weather events, including heat waves, droughts, and heavy rainfall (Clarke et al. 2022). The international disaster database, EM-DAT, has recorded 7,348 disaster events worldwide over the past twenty years, which represents a sharp increase in comparison with the previous twenty years. It records major increases in floods, storms, droughts, wildfires, and extreme temperature events (CRED & UNDRR, 2020)

Drought and hot extremes are among the most detrimental extremes, with impacts on agriculture, water availability, energy production, and human health (Mishra and Singh, 2010 ;Deryng et al., 2014 ; Zipper et al., 2016; Añel et al., 2017; Dosio et al., 2018; Hao et al., 2022).

Compound extremes may have lead to amplified impacts than individual extremes (or events) and have received increasing attention in the past decade (Hao et al., 2018).

A definition of the compound event (extreme) is given by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Extremes (SREX) in 2012 (Seneviratne et al., 2012): (1) two or more extreme events occurring simultaneously or successively, (2) combinations of extreme events with underlying conditions that amplify the impact of the events, or (3) combinations of events that are not themselves extremes but lead to an extreme event or impact when combined.

Right now, Iran is experiencing the most crucial negative impacts of climate change, due to its location at low latitude. Drought, as one of the most critical global hazards, is threatening the sustainable agriculture and food security of nations. To provide food security and to minimize the negative impacts of climate change, following adaptation strategies would be essential. The assessment of the variability of drought and hot extreme characteristics provides useful information for the mitigation of extremes under global warming, but a more prior step could be the assessment of vulnerability to agricultural drought. The results of this task would make it possible to compare regions based on their vulnerability levels and identify the most vulnerable areas. Exploring drought characteristics from the vulnerability point of view leads to consideration of underlying conditions that can exacerbate impacts, and refers to the compound event definition. Likewise, it is necessary to explore the causes of vulnerability. Measuring agricultural drought vulnerability is essential for targeting interventions to improve and sustain agricultural performance for both rainfed and irrigated cultivation.

Most of the previous efforts in drought research in Iran have explored the nature of drought in terms of its characteristics (Zamani Nouri et al., 2015), duration of wet and dry periods (Fakhri et al., 2013), and different types of drought phenomena (Rostamian et al., 2013). Nevertheless, drought vulnerability is rarely assessed in Iran. Various authors from different countries have considered vulnerability as a key issue and explored the negative consequences of drought through the perspective of communities and sectors' vulnerability (Lures et al., 2003; Wilhelmi and Wilhite, 2002; Murthy et al., 2015; Jayanthi et al., 2013; Wu et al., 2011; Zhang et al., 2015; Wang et al., 2019; Tigkas et al., 2019). However, vulnerability is a dynamic process, changing on a variety of inter-linked temporal and spatial scales.

Detecting the impacts of climate change and evaluating vulnerability have a high level of priority in a growing population to provide food security countermeasures. As a step forward in this concern, some researchers have used the vulnerability to climate change through the projection of the future to emphasise the outcome of a system facing unfavourable disturbances or disasters (Cutter et al., 2003; Thirumalaivasan et al., 2003; Metzger et al., 2005; Calvo, 2008; Ravindranath et al., 2011; Zhang et al., 2019; Fazeli Farsani et al., 2019). But a crucial issue that has received less attention is the existence of uncertainty sources, especially, the uncertainty triggered by the differences between the 4th and the 5th assessment reports of the Intergovernmental Panel on Climate Change (IPCC).

Climate change researches and Projected climatic conditions (Fakkhar and Nazari, 2014, Farzaneh et al. 2024, Farzaneh and Banimostafaarab, 2023a, Farzaneh and Banimostafaarab, 2023b, Hamzeh et al. 2023a, Hamzeh et al. 2023b, HosseinSeddighi and Jalali, 2024, Rezaeei and Roshani, 2024) will have direct impacts on the agriculture sector and could endanger socio-economic development and social sustainability in different places, such as Isfahan province in central Iran, where agriculture is the primary occupation and means of subsistence for a large part of the population. In this study, a spatial analysis of agricultural drought vulnerability analysis for current and projected future climate conditions was conducted at representative sites of Isfahan province counties to depict the circumstances of drought events for current and future time horizons. Furthermore, the differences in projected conditions arising from IPCC recommendations in the 4th and 5th assessment reports were analysed. From a theoretical point of view, the developed appropriate framework can be useful to recognise the spatial distribution of vulnerability and thus, can help in policy design, as understanding the vulnerability of a sector and its spatial distribution will orient policies towards a geographical area or population group with urgent requirements (UNDP, 2010; Ortega-Guacin et al., 2021; Ekrami et al., 2021).

Material and Methods

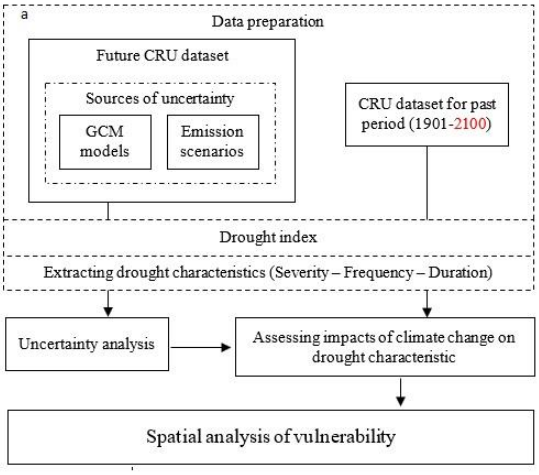
1. Study Area

This study is conducted in Isfahan province, located in central Iran, which covers a total area of 107045 km^2. The climatic pattern of the study area is arid and semi-arid. While the eastern part of the province is on the western margin of the arid and semi-arid zones of Iran, its western areas lie on the eastern hillslopes of the Zagros mountains. The mean annual temperature is 13.6 ˚C, and its annual amount of precipitation is about 160 mm. The amount of annual rainfall varies from 800 mm in the western region to 75 mm in the eastern part. The impact of drought in lower regions of the study area, where the amount of annual rainfall shows significant variability, can be widespread and affect various sectors like agriculture.

In this study, the precipitation records from 30 years (1975-2005) were selected to calculate the SPI index for the study area. The methodology of the study is based on extracted data and the investigation of characteristics considering uncertainty analysis, as illustrated in Fig 1.

2. Understanding the vulnerability concept

Vulnerability links with some ideas such as resilience, marginality, susceptibility, adaptability, fragility, and risk. Currently,



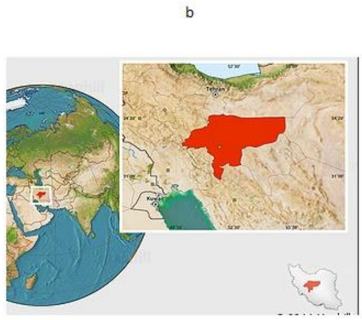


Fig 1. The methodology(a) and study area(b)

vulnerability is used in climate change research to emphasise the result of a system facing unfavourable disturbances or disasters . The literature on vulnerability has two major perspectives: the biophysical perspective and the social one. In the biophysical approach, the focus is predominantly on the event itself, in terms of magnitude, frequency, rapidity of onset, and spatial distribution. In contrast, the social perspective focuses primarily on the human determinants or drivers of vulnerability, namely, the social, political, and economic conditions that make exposure unsafe or challenging.

3. Quantifying vulnerability

In this research, the vulnerability of the agricultural system in Isfahan province is explored from a biophysical perspective. The conceptual model for the vulnerability of the community to climate change is outlined here as follows:

$$\text{Agricultural drought vulnerability} = \frac{\text{Drought characteristic} \times \text{Agricultural area of each county}}{\text{The total area of each county}} \quad (1)$$

4. Preparing data

In this study, the downscaled CRU dataset at a 0.5° grid resolution was used. Rainfall data of the past 100 years and the data of the future period were extracted from CRU under uncertainties induced from HadCM3, PCM, ECHAM, CGCM, and CCSIRO general circulation models (GCMs) as well as A1, A2, B1, and B2 emission scenarios.

5. Calibration and validation

As it can be seen in Fig. 2, drought characteristics in Isfahan station were extracted primarily based on observed rainfall data and then based on CRU rainfall data for both calibration and validation. The results were evaluated using the Nash-Sutcliffe efficiency index.

$$E = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (2)$$

where P_i is the amount of rainfall calculated by GCMs; O_i is the observed rainfall value; Ö is the number of samples; and is the average of observed values.

The Nash-Sutcliffe efficiency index varies in the range of (-∞,1) and the models with values higher than 0.5 are acceptable.

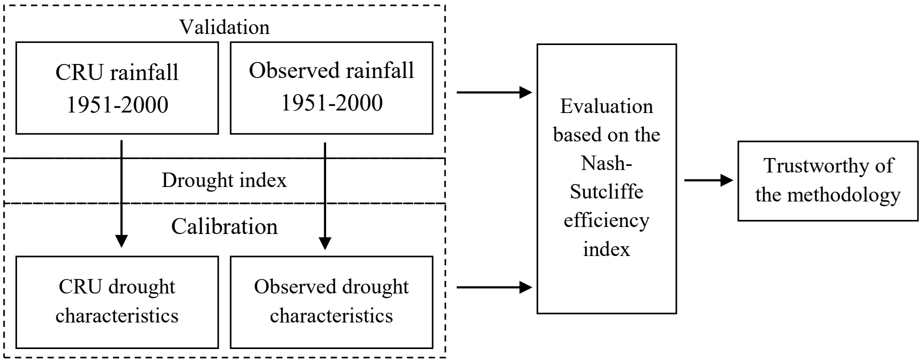


Fig 2. Procedural framework for calibration and validation

6. Drought monitoring

In this research, drought analysis was carried out using the standardised precipitation index (SPI). McKee et al. (1993) developed SPI for the identification and monitoring of droughts through recorded precipitation data. Different time scales (1, 3, 6, 12, 24 and 48-months) can be used to compute the SPI index; the longer time scales relate to hydrological drought while, the shorter ones may represent agricultural drought. Although SPI is more suited to monitoring meteorological and hydrological droughts than agricultural droughts, it is flexible enough to inform on some aspects of agricultural droughts. Due to its simplicity of calculations, decent reliability, and ability to address a variety of drought-related issues, and because it just needs rainfall data as input, it is a popular index for monitoring different kinds of drought. Essentially, SPI is the standard deviation index of a given precipitation deficiency. Positive SPI values indicate higher than median precipitations, and negative values indicate less than median ones. Its values are generally between ± 2.0. Table 1 shows the SPI thresholds defined by McKee et al. (1993). A drought event starts when the SPI values are continuously negative and reach an intensity of -1.0. The drought event ends when the SPI values return to positive. Based on normalised SPI values, an event is considered normal, moderate, severe, or extreme.

Table 1. SPI drought severity classes for wet and dry periods

SPI Classes	SPI Value
Extremely wet	> 2
Severely wet	1.5 - 1.99
Moderately wet	1 - 1.49
Normal	-0.99 - 0.99
Moderately dry	-1.49 - -1
Severely dry	-1.99 - -1.5
Extremely dry	< -2

The computation of SPI is conducted using a software programme developed at the University of Nebraska and downloadable from the website of the National Drought Mitigation Center which provides comprehensive information and a complete formulation for SPI calculation. The SPI in each time scale is the difference between precipitation on the time series (X_i) and the mean value $\vec{X}$, divided by the standard deviation (S):

$$SPI = \frac{x_i - \bar{x}}{s} \quad (3)$$

It quantifies observed precipitation as a standardised departure from a selected probability distribution function that models the precipitation data. The precipitation data are typically fitted to a gamma or Pearson Type III distribution or applied to a rank-based non-parametric method to find their empirical cumulative probabilities and then transformed to a normal distribution.

The severity and duration of SPI were evaluated using 30 years of monthly rainfall data from 22 stations in arid and semi-arid regions of Isfahan province, Iran. Drought characteristics, including severity, duration, and frequency, identified based on SPI at a 3-month time scale, were used as indicators of exposure to drought for different counties in the study area. The selection of the 3-month time scale was due to the importance of agricultural drought in the study area.

7. The uncertainty analysis

Emission scenarios and GCMs are among the most important sources of uncertainty in climate change studies. Creating the probable decision space for the future requires using an efficient method of uncertainty analysis. On the other hand, samples should be excellent examples of the target community. For this purpose, the bootstrap technique was applied to estimate the confidence interval (Fakhri et al., 2014). Using this method, drought characteristics for the future period were estimated at a 95% confidence level. The drought characteristics, including frequency, severity, and duration, were investigated using linear correlation for the past-time horizon and also for the future period, through analysing the uncertainty band arising from agreement and disagreement between models.

Result and Discussion

Some constraints limit the investigation of the drought index. The first one is the lack of observed data, as well as the non-regular data distribution in some stations. The second problem is the short-term recorded dataset, which can lead to a lack of consideration of extreme events compared to the long-term return period. In this regard, we attempt to provide a methodology for regions without recorded hydrological data and also for regions with a short period that is capable of investigating climatic change scenarios for the future. In the first step, the drought severity, frequency, and duration characteristics were calculated for the past period from the SPI index for each county. The calibration and validation processes were conducted next. As agriculture is among the first sectors to experience economic damage from exposure to drought, the agricultural drought vulnerability for each county was calculated at the next step based on the model presented in Section 2.4. Finally, the expected effects of climate change on counties' agricultural drought vulnerability were assessed based on the projected climatic variability for the future period.

1. The results of SPI index

Fig. 3 shows the efficiency of the SPI index in the estimation of the drought events that occurred in 2000, 2008, and 2010. As the only input variable for the SPI index is rainfall, the annual and monthly changes in rainfall were investigated more precisely to provide a better understanding of the study area (Fig. 4). The minimum and maximum amounts of annual rainfall are 40 mm and 349 mm, respectively. The fluctuation of rainfall is considerable in the yearly time series and shows a significant reducing trend with respect to time in such a way that the amount of long-term average rainfall for this station is 123 mm. Monthly precipitation also shows severe fluctuations during different seasons. The highest amount was in March with 22 mm, and the lowest was in September with near zero value. The presented monthly and annual fluctuations are two important indicators, indicating the extreme vulnerability of the region to drought.

2. Spatial analysis of drought characteristics

In this study, the occurrence of drought was investigated based on severity, duration, and frequency characteristics over a 3-month timescale. The resulting SPI values at corresponding drought categories were mapped for each county, for drought severity, duration, and frequency per year in Isfahan province using the inverse distance weighting (IDW) interpolation method in Arc GIS. The IDW method was chosen for all data interpolation processes as it provides a reasonable level of accuracy in data prediction and is much less time-consuming in comparison to other interpolation methods, such as Kriging. Fig. 5 shows the severity, duration, and frequency characteristics of drought for each county.

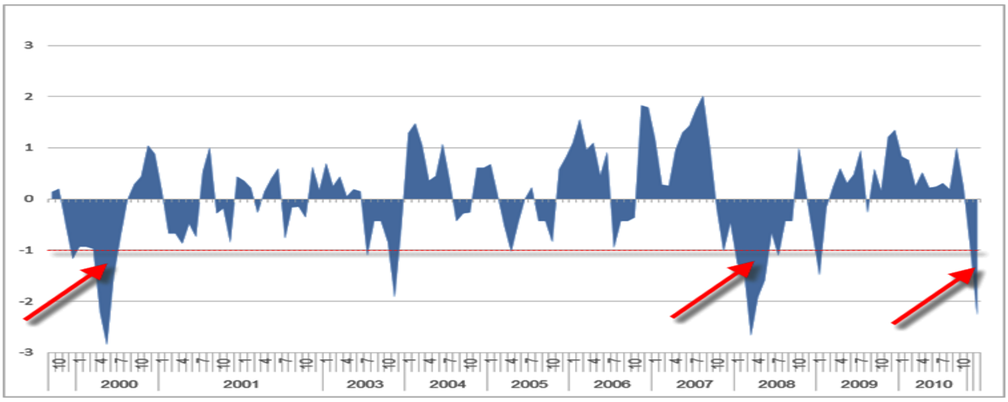


Fig 3. Description of past drought events in Isfahan province based on SPI index

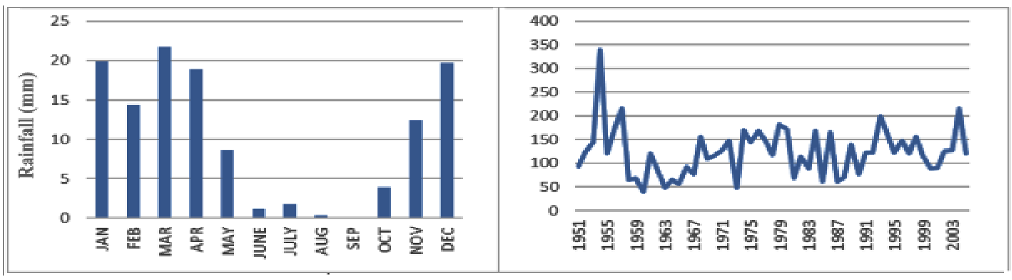


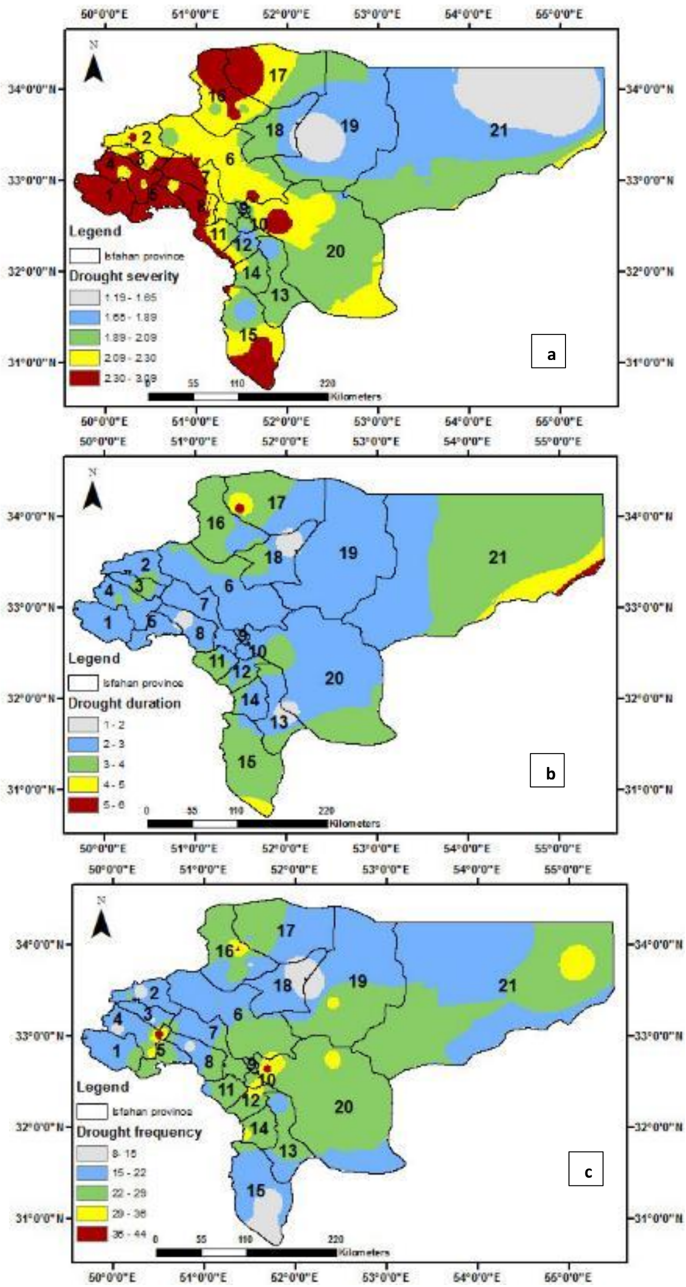
Fig 4. The annual and monthly time series of rainfall in Isfahan synoptic station

As presented in Fig (5), the distributions of characteristics show variability. The counties that are most affected by drought severity are located in the western zone (such as Fereydoun Shahr, Chadegan, and Najafabad), while the least affected ones are in the east. The spatial analysis of drought duration indicates that eastern counties, a part of north and south (especially in Naeen, Semirom, Kashan, and Aran-va-

Bidgol) have experienced the longest drought duration, while the central region has faced the shortest (Fig. 5). By jointly looking at both characteristics, the severity and duration of the drought are affecting the majority of counties, such as Kashan, Aran-va-Bidgol, and Semirom.

Northern and western regions (Kashan, Barkhar-va-Meimeh and Fereydan) have more frequent droughts than other areas, and Natanz and the west of Ardestan counties have less. Generally speaking, the drought frequency is lower in the east of the study area.

Since the drought damage differs between counties, the comparison of vulnerability should be undertaken at the level of counties.



Names of counties	ID
Fereydoun Shahr	1
Golpayegan	2
Khansar	3
Fereydan	4
Chadegan	5
Barkhar-va-Miemeh	6
Najafabad	7
Tiran-va-Karvan	8
Khomeini Shahr	9
Felavarjan	10
Lenjan	11
Mobarakeh	12
Shahreza	13
Semirom Sofla	14
Semirom	15
Kashan	16
Aran-va-Bidgol	17
Natanz	18
Ardestan	19
Isfahan	20
Naeen	21

Fig 5. Drought (a) severity, (b) duration, and (c) frequency per year in Isfahan province, Iran

3. Calculating agricultural vulnerability

Exposure maps for intensity, frequency, and severity characteristics of drought were extracted based on observed data. Then, by considering the ratio between total land and agricultural area, the agricultural drought vulnerability for each county was evaluated based on the vulnerability model presented in Eq. 1.

Fig (6) shows the vulnerability to drought in different counties. Though considering total area, drought vulnerability differs for each characteristic, showing more homogeneity for only agricultural areas. The vulnerability of agriculture to drought in the counties of Isfahan and Barkhar-va-Meimeh was as its maximum (Black line),

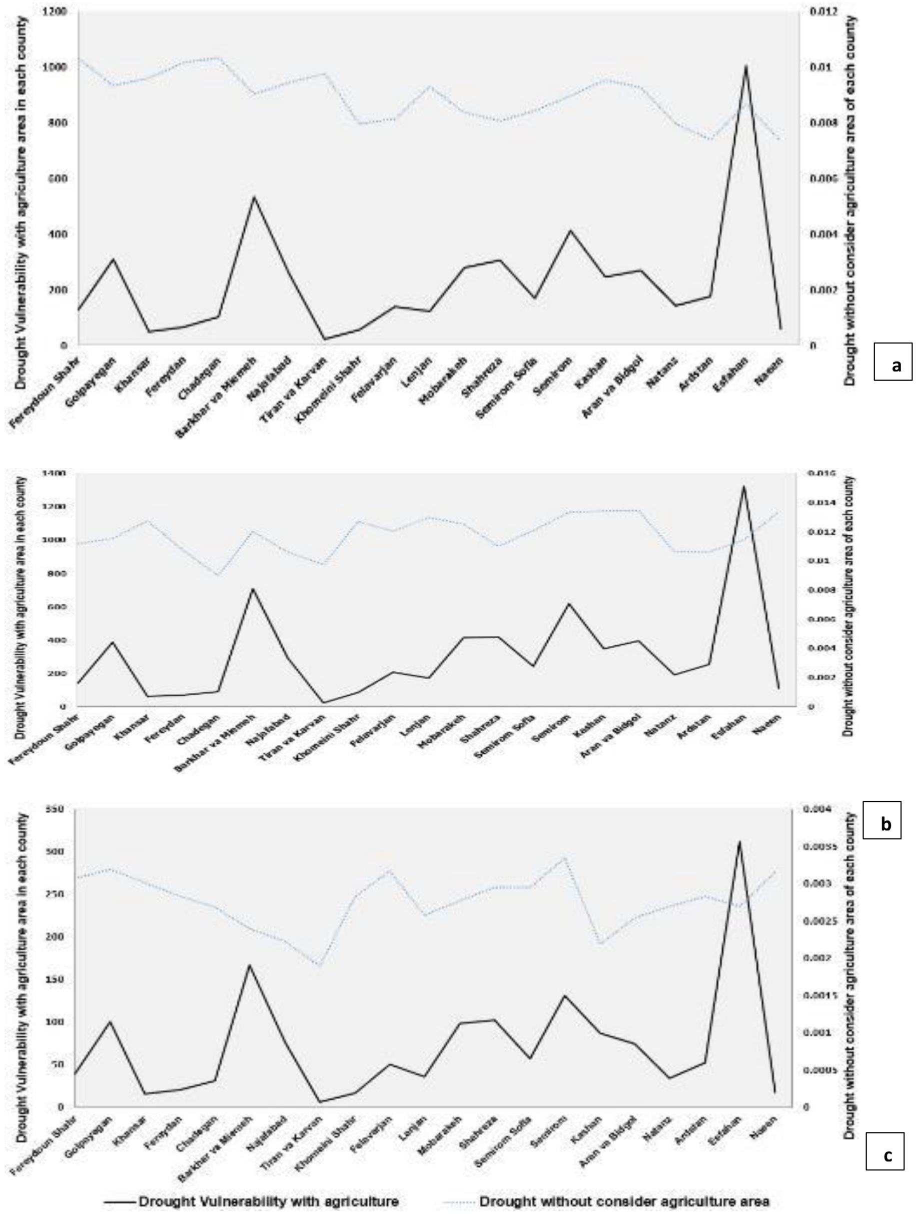


Fig 6. Drought vulnerability of (a) severity, (b) duration, and (c) frequency with and without consideri agriculture in each county

while these counties in the total area have a low vulnerability (Fig 6). It is evident that when the agriculture area of each county is applied, the trend of drought will change. Moreover, while some counties have less total area, they have more agricultural areas, in contrast to some other counties with more total area and fewer agricultural areas. In these counties (such as Tiran-va-Karvan, Khomeini-Shahr, and Naeen), the agricultural area can have a significant impact on drought vulnerability.

In counties of Isfahan province, by the heppening of drought in a county with more agricultural areas and gardens, people in the center, west and south are more faced with damages (Fig. 1) and this circumstance is more critical for counties that have lessened areas, such as Khomeini Shahr and Felavarjan. Exposure with damages means that people who live in agricultural areas will gradually abandon agriculture and turn to other careers. In occupations in the west and south, agriculture is a popular job for people and thus, during drought, it has more vulnerability. In Felavarjan county, people are employed in agriculture and gardening, and after Khomeini Shahr, this county is the smallest town in this matter. Likewise, farmers in Isfahan and Felavarjan counties are cultivating rice, which requires plenty of water to grow, and the drought events in the past years have caused a considerable reduction in its production. Therefore, these counties are much more sensitive to drought than other areas.

4. Calibration, validation, and uncertainty analysis of the CRU data based on observation data

In this study, 50 grids of CRU data with a 0.5-degree resolution for Isfahan province were used. For calibration, the CRU data were analysed based on observation data at the Isfahan station. The accuracy of the proposed methodology was evaluated using an observational and simulated rainfall performance evaluation over a 50-year-long period at Isfahan station. The results, presented in Table 2, indicate acceptable accuracy in May to excellent accuracy in June. Regarding CRU acceptable calibration results at Isfahan station, at the stage of validation, the vulnerability of agricultural drought characteristics was considered for each county using observation and CRU data for a common period of 1951 to 2005, and then the results were normalised.

Table 2. The result of Nash-Sutcliffe efficiency index for the validation period

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.97	0.82	0.87	0.91	0.50	0.99	0.85	0.63	0.98	0.73	0.93	0.89

Fig (7) shows the results of validation as well as the uncertainty band for each county. Regarding Fig. (7), the uncertainty of agricultural drought vulnerability is different between counties. The highest uncertainty is related to Felavarjan, Mobarakeh, Esfahan, and Ardestan, due to the high level of farming area in these counties. The lowest uncertainty was related to Khansar, Fereydan and Tiran-va-Karvan. Furthermore, the most significant difference between observed data and the 95 PPU band, was found in Isfahan and Barkhar-va-Meimeh, and the lowest difference was related to Fereydan and Tiran-va-Karvan, respectively.

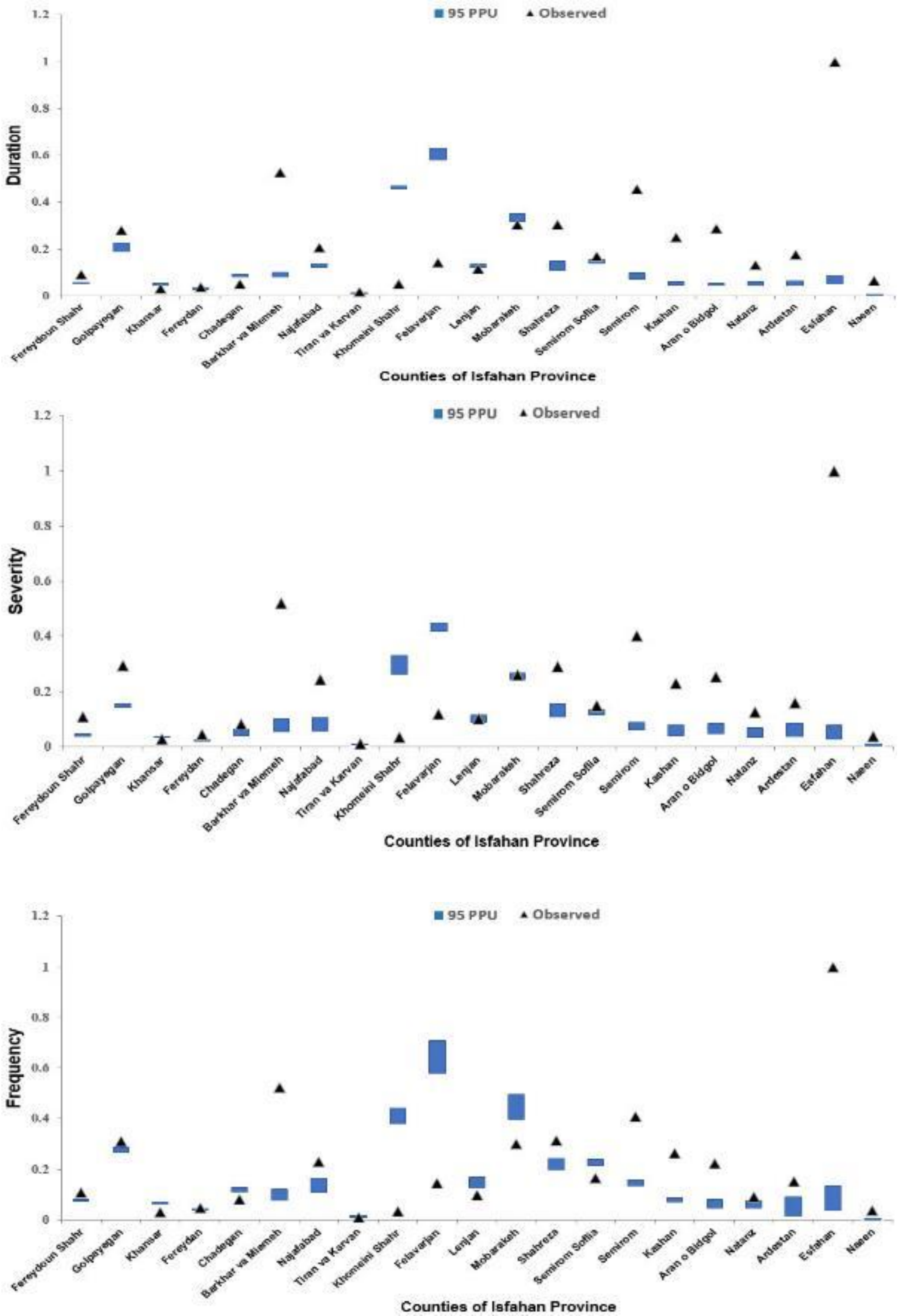


Fig 7. Comparison of 95PPU ranges of drought vulnerability of severity (a), duration (b) and frequently (c) characteristics in counties, with CRU data for the period of 1951–2005 (In these figures, blue band is the range of CRU)

5. Effects of climate change on drought characteristics in the future period

Results with a value higher than 0.5 for the Nash-Sutcliffe efficiency index (in the calibration and validation) approve the effectiveness of the proposed methodology. To be able to take into account events with long return periods, the duration of the statistical period was extended to a long period of 100 years. Drought characteristics based on CRU data for the twentieth century were calculated. These characteristics were assessed for the twenty-first century under different sources of uncertainty due to emission scenarios and AOGCM models.

Fig. 8a shows the impact of climate change on drought severity. The A1 emission scenario, representative of the most critical condition for all GCM models, shows an increase in drought intensity. Some models represent a considerable difference, and some of them are more close to the result of the past period. Other scenarios have shown a decreasing trend in the incidence of drought intensity, and meanwhile, the most optimistic intensity is projected to occur under the B1 scenario.

Fig. 8b shows the impact of climate change on drought duration. The results presented

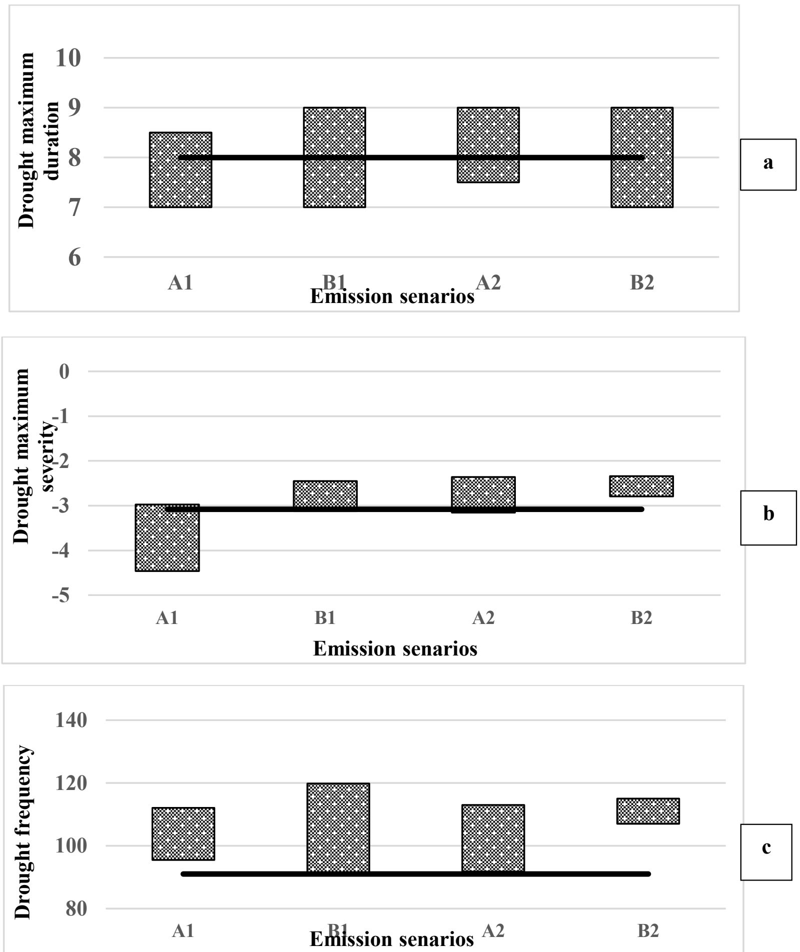


Fig 8. Assessment of drought duration, severity, and frequency characteristics under climate change

in this figure show disagreement between the results of different models in terms of projected drought duration. The most disagreement was related to B1, and B2 scenarios, and the lowest was observed in the group with an emission scenario.

Fig. 8c indicates that all four scenarios are projecting an increasing trend for drought frequency characteristics in the future period. B1 and B2 scenarios show the widest and thinnest ranges of uncertainty bands, respectively. Although the uncertainty of the B2 scenario is less that of other scenarios, its considerable difference from the observed values of the past period implies the criticality of the condition from the perspective of this scenario. All models have consensus in this respect.

6. Agricultural drought vulnerability under the effects of climate change in the future period

In this section, the vulnerability of the agriculture sector was investigated under the effect of climate change under different emission scenarios, related to the fourth and fifth assessment reports of the IPCC. The first step is to investigate the spatial distribution of drought characteristics, including intensity, duration, and frequency under A1, A2, B1, and B2 emission scenarios of the IPCC 4th assessment report. Investigation of these characteristics under 2.6, 4.5, 6.0, and 8.5 scenarios of the 5th assessment report is the next step. Then, the Bootstrap method was applied for both a 2.5% and 97.5% confidence interval to investigate the drought intensity, duration, and frequency characteristics for the future period and their spatial distribution in the province. The uncertainty band, along with historic base values, was calculated to investigate each characteristic at the county level. Figures 15 to 18 show the results.

6.1. Spatial analysis of agricultural drought vulnerability under the effects of climate change, according to AR4

Figures 9 to 11 represent the spatial distribution of duration, frequency, and intensity characteristics of drought for the base period and also under the effect of climate change considering A1, A2, B1, and B2 emission scenarios, at a confidence band of both 2.5% and 97.5%.

Fig. 9 shows that in the eastern part of the province, the duration of drought will increase under the effect of climate change at 97.5% confidence interval level; the most pessimistic scenarios are related to B1, and the most optimistic are related to A2 at 2.5% confidence interval level; all scenarios show an increase in drought duration for eastern counties, and also a decrease for western counties. According to Fig. 10, the probable effect of climate change in all emission scenarios, will cause an increasing trend in drought frequency, in the northeastern and southern parts. The maximum frequency is projected for the central part; the most pessimistic scenarios are related to the A2 emission scenario at the level of 97.5%, and the most optimistic scenario is related to the B1 scenario at the 2.5% confidence interval level. For both 2.5% and 97.5% confidence interval levels, the frequency of drought is projected to undergo a decreasing trend under the effect of climate change.

Fig. 11 shows the severity of droughts under the effect of climate change, based on emission scenarios for AR4. It can be seen that in all scenarios, the severity of drought events will increase. In general, for all scenarios, the drought severity will increase in the eastern part of the province, while the western part of the province will experience a decreasing trend.

6.2. Spatial analysis of agricultural drought vulnerability under the effect of climate change, according to the fifth assessment report

Based on this assumption that the uncertainties in the fifth assessment report have been reduced, the drought characteristics of frequency, severity, and intensity were also analysed based on the fifth assessment report of the IPCC.

Fig. 12 shows the spatial distribution of agricultural drought vulnerability based on drought duration for the AR5 scenario at a level of 2.5 % and a 97.5 % confidence interval. The most pessimistic projection is related to the 2.6 emission scenario at the level of 97.5 %, and the most optimistic one is related to the 2.6 emission scenario at the level of a 2.5% confidence interval. In contrast to the results of the fourth report, the results extracted based on the fifth report, suggest that the northern and west-northern parts of the province will be affected by the duration characteristic, more than the eastern part.

Fig. 13 shows the spatial distribution of agricultural drought vulnerability under climate change, based on the frequency of drought for AR5 scenarios at 2.5% and 97.5% confidence intervals. The most pessimistic scenario is related to the 2.6 emission scenario at the level of 97.5%, and the most optimistic one is related to the 4.5 emission scenario at the 2.5% confidence interval level. In contrast to the results suggested by AR4, results based on AR5 suggest that western parts of the province will be affected by the frequency characteristic more than the eastern part.

Fig. 14 shows the spatial distribution of agricultural drought vulnerability based on drought severity for the AR5 scenario at 2.5% and 97.5% confidence intervals. The most pessimistic scenario is related to the 2.6 emission scenario at the level of 97.5%, and the most optimistic scenario is related to the 4.5 and 2.6 scenarios at the 2.5% confidence interval level. Based on this characteristic, the western parts of the province will be exposed to more frequent drought events, and these parts of the province will be more vulnerable in comparison to the base period. These results have a significant difference from the results derived from AR4.

6.3. Uncertainty bound of agricultural drought vulnerability for each county under the effects of climate change based on the fourth report

Figs. 15 and 16 show uncertainty bounds for agricultural drought vulnerability related to drought characteristics of intensity, duration, and frequency under the effect of climate change for A1, A2, B1, and B2 emission scenarios based on AR4 for each county of Isfahan province. The most uncertainty in all three characteristics and all emission scenarios in terms of agricultural drought vulnerability is related to Isfahan and then Barkhar-va-Meimeh. The maximum numerical value in terms of drought severity and duration was also observed in these counties. Tiran-va-Karvan counties show the lowest agricultural drought vulnerability based on all three drought characteristics.

In some counties, the future uncertainty bound for drought severity, frequency, and duration is greater than the historical average. In contrast, some counties show a lower value. But, for most counties, the duration is within the uncertainty bound range. As can be seen in Figs. 15 and 16, the most significant difference in uncertainty bound associated with the base and future periods, is related to the severity characteristic. Regarding emission scenarios, the B2 scenario shows the lowest uncertainty bound for all drought characteristics.

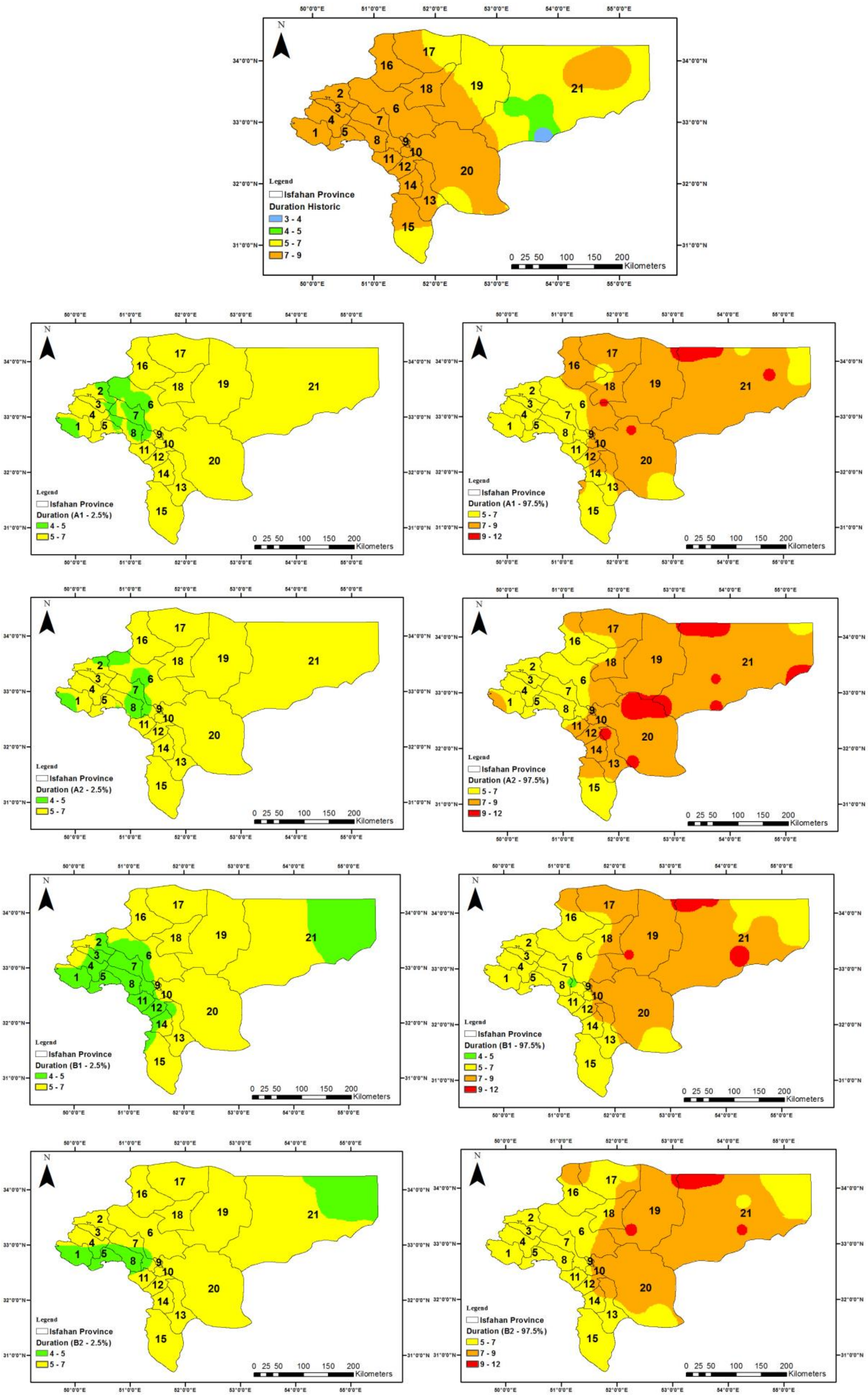


Fig 9. Assessment of drought duration under the effect of climate change based on AR4 report (A1 – 2.5% means A1 scenario in 2.5% uncertainty level)

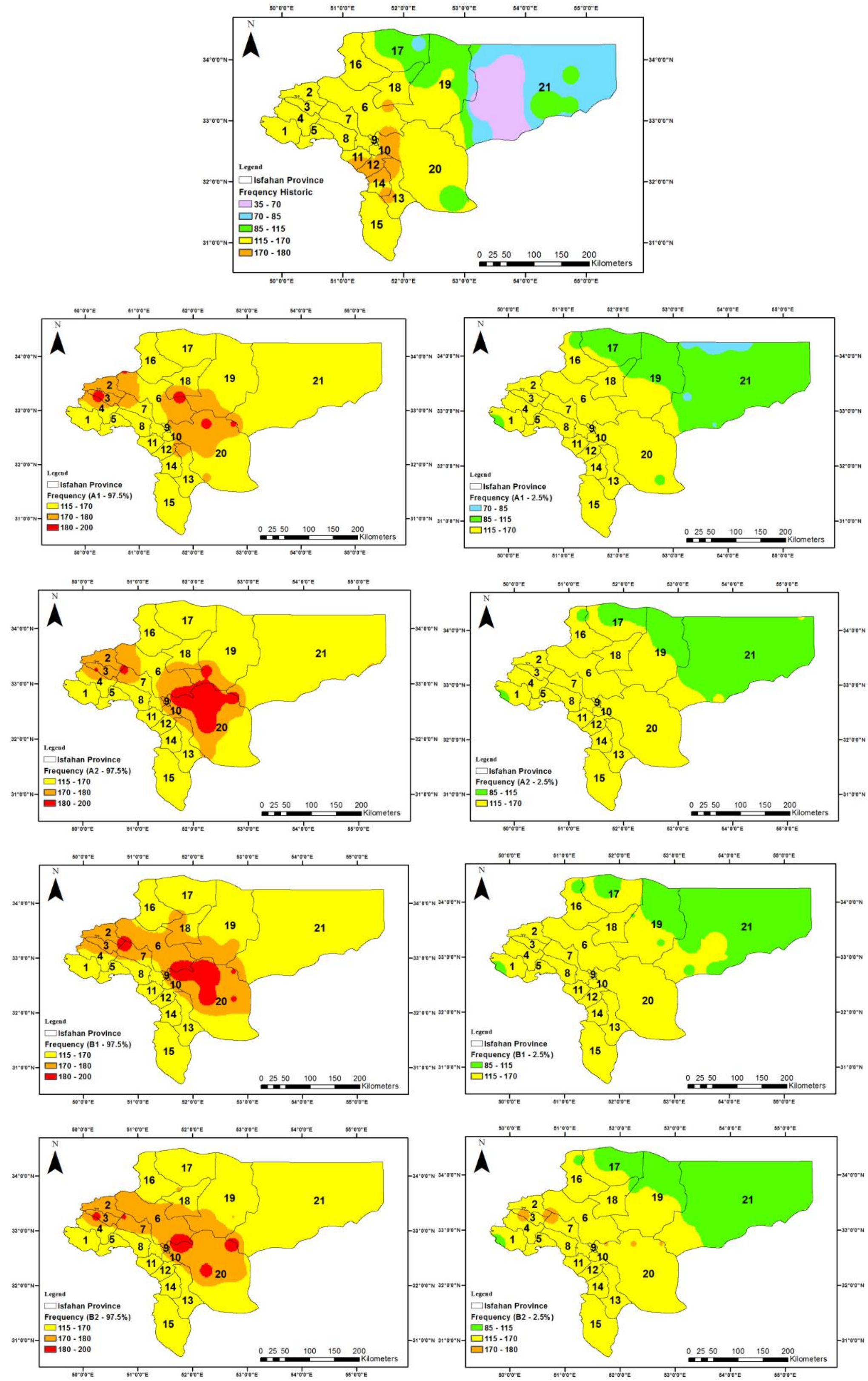


Fig 10. Assessment of drought frequency under the effect of climate change based on AR4 report

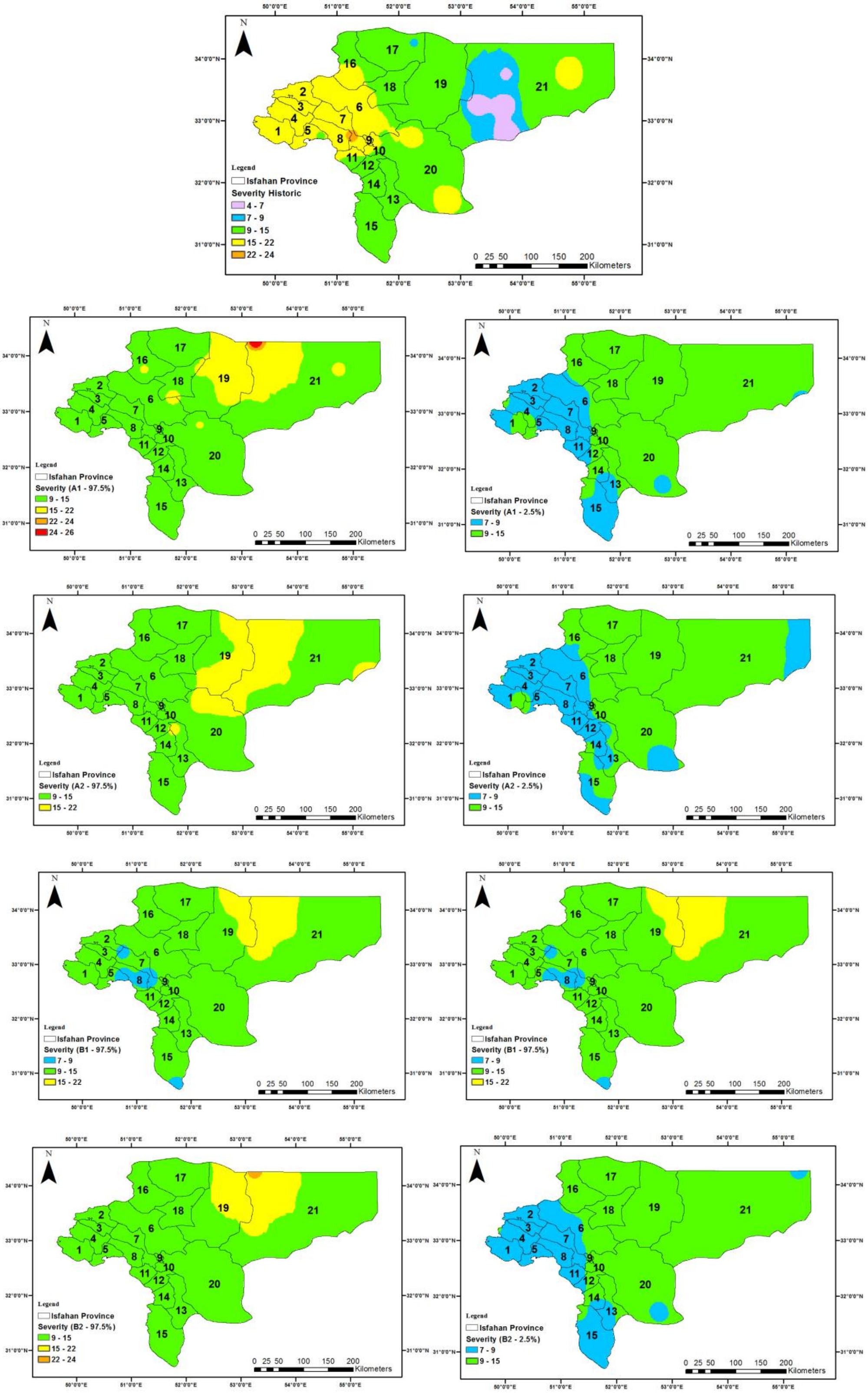


Fig 11. Assessment of drought severity under the effect of climate change based on AR4 report

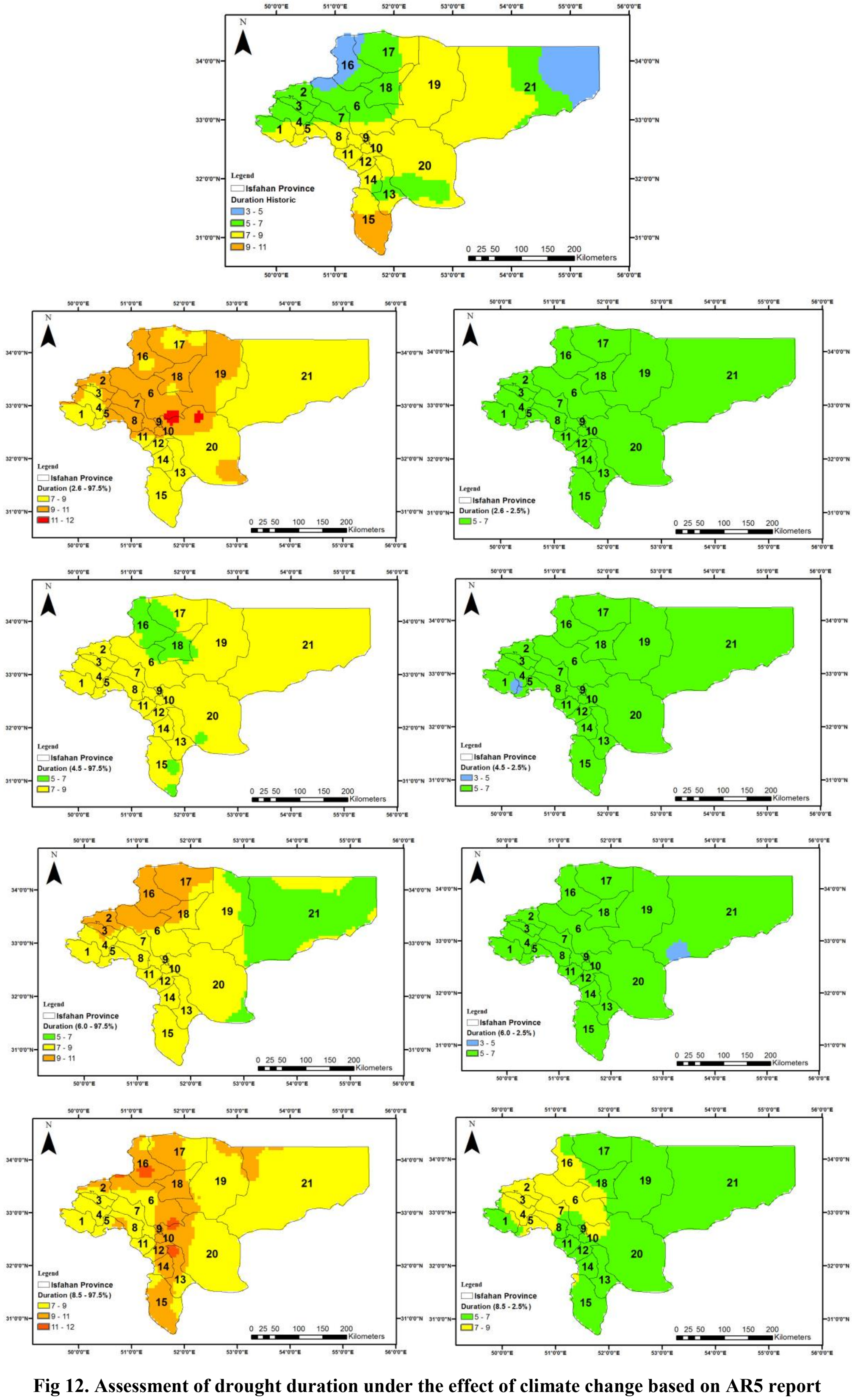


Fig 12. Assessment of drought duration under the effect of climate change based on AR5 report

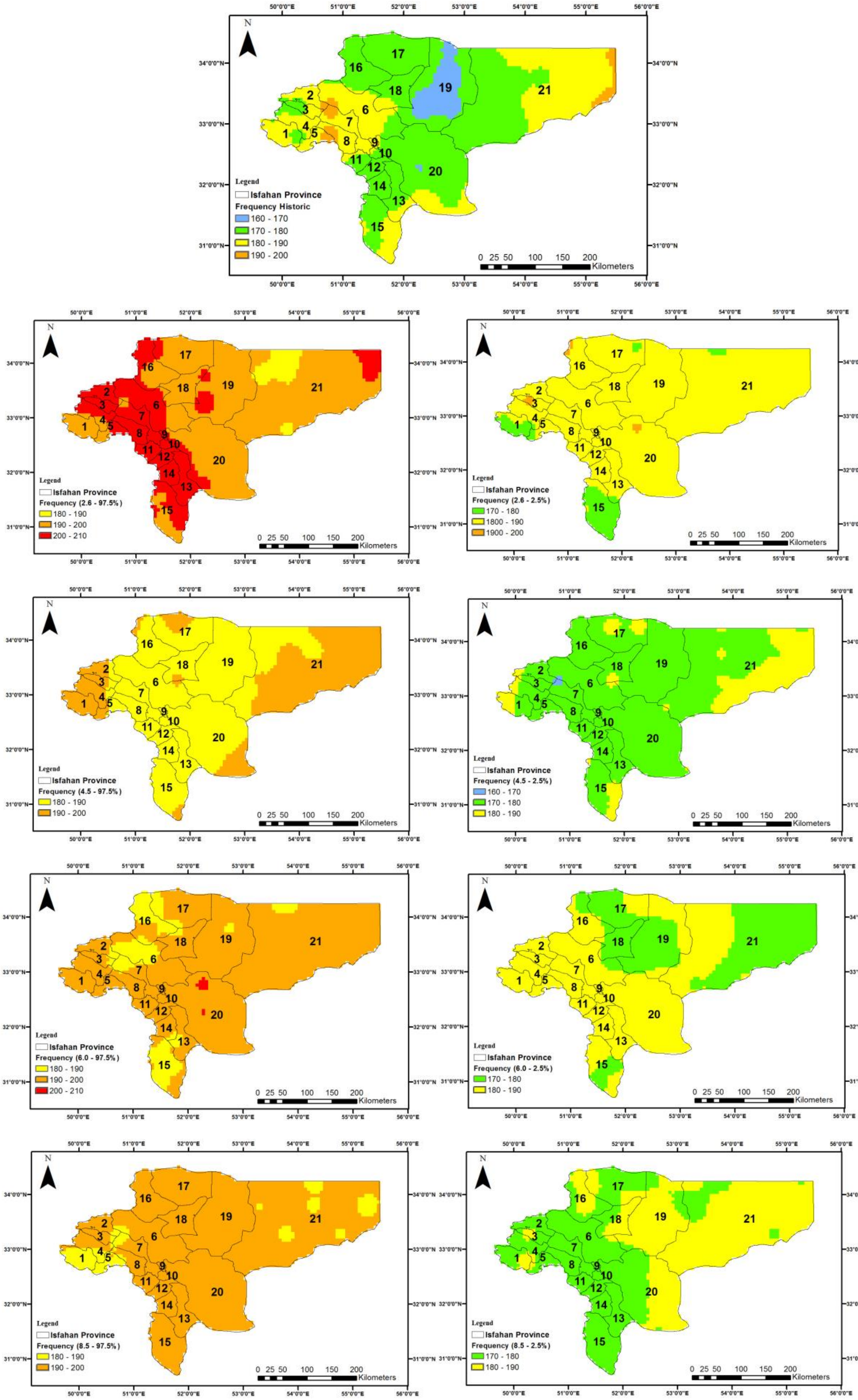


Fig 13. Assessment of drought frequency under the effect of climate change based on AR5 report

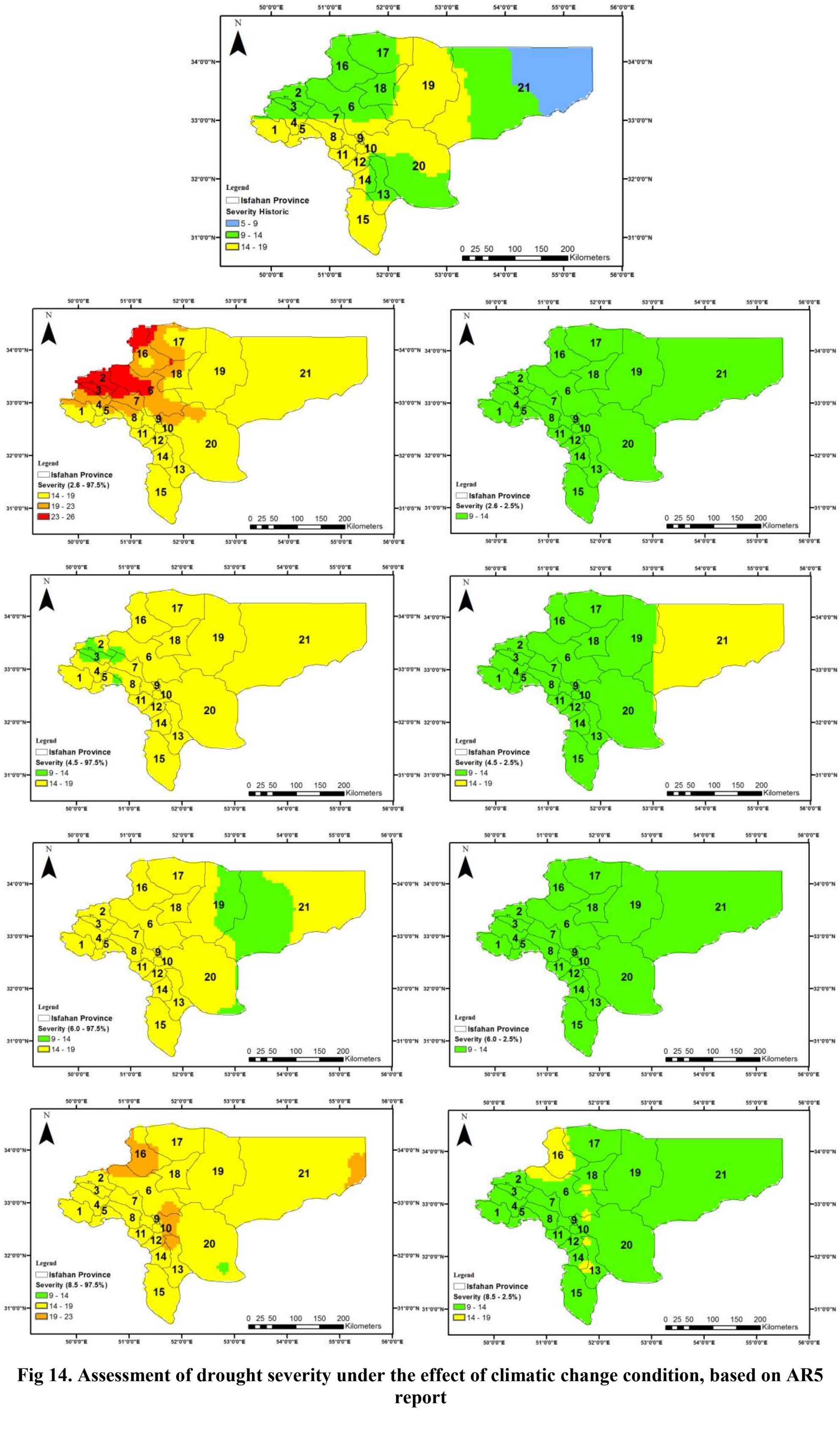


Fig 14. Assessment of drought severity under the effect of climatic change condition, based on AR5 report

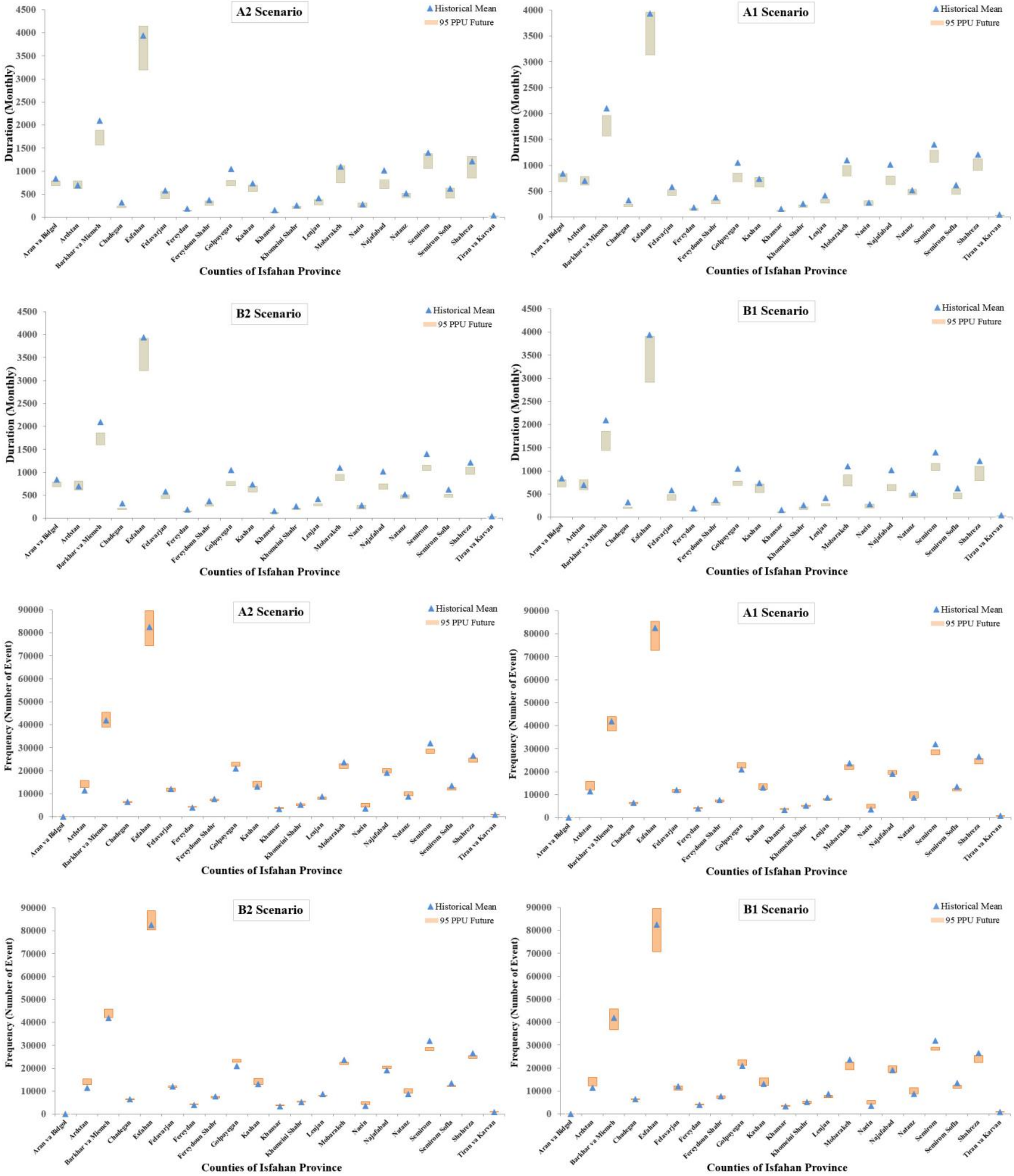


Fig 15. Comparison of 95PPU ranges of drought vulnerability for duration and frequently characteristics under the effect of climate change with AR4 emission scenarios in Isfahan counties

6.4. Uncertainty bound of agricultural drought vulnerability for each county, under the effects of climate change based on AR5

Figs. 17 and 18 show uncertainty bounds for drought characteristics of intensity, duration, and frequency, under the effect of climate change for emission scenarios of 2.6, 4.5, 6, and 8.5 based on AR5 for each county of Isfahan province. As the results from AR4, the most uncertainty in all three characteristics and all emission scenarios is related to Isfahan and then Barkhar-va-Meimeh. Maximum numerical values in terms of drought severity and duration were also observed in these two counties. Tiran-va-Karvan county shows the lowest agricultural drought vulnerability based on all three drought characteristics.

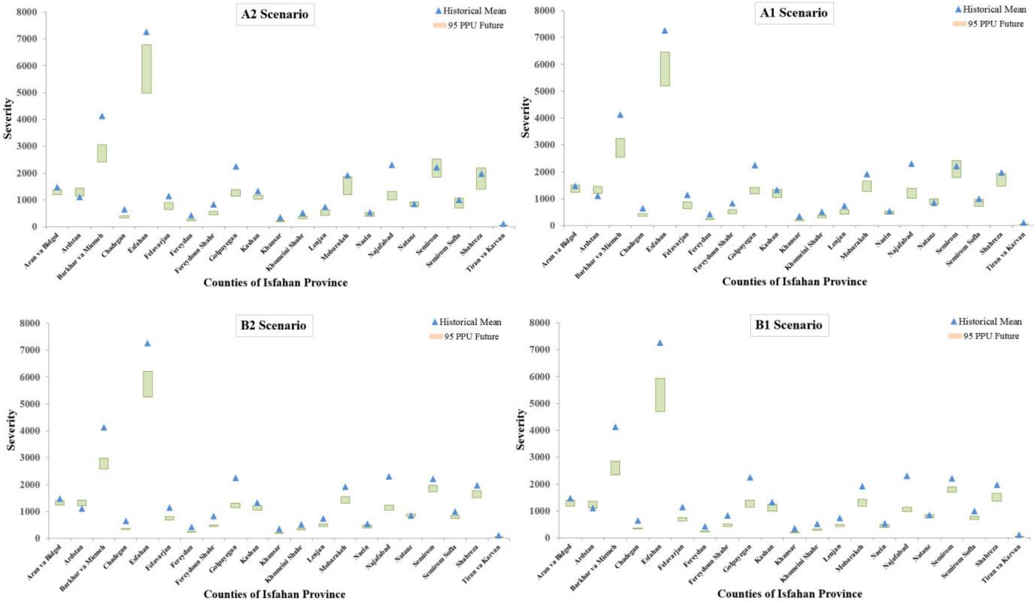


Fig 16. Comparison of 95PPU ranges of drought vulnerability for severity characteristic under the effect of climate change with AR4 emission scenarios in Isfahan counties

The most numerical value of the future uncertainty bound for drought duration is shown under the emission scenario of 2.6 while in contrast, the 4.5 scenario shows the lowest value.

In terms of drought frequency, the widest uncertainty bound belongs to the 8.5 and the lowest to the 4.5 emission scenarios. Also, the lowest difference between the historical average and the uncertainty bound is observed in the 4.5 emission scenario. For drought severity , the lowest uncertainty bound belongs to the 8.5 emission scenario, and the widest one is for the 2.6 scenario.

7. IPCC-AR6

The Intergovernmental Panel on Climate Change (IPCC) sixth Assessment Report (AR6) serves as a crucial scientific resource for investigating the impact of climate change on drought. Utilizing the precipitation projections outlined in AR6 enables researchers to comprehensively examine the implications of climate change on water resources and the occurrence of drought events. AR6 not only provides a robust foundation for understanding future precipitation patterns but also incorporates diverse uncertainty sources, such as greenhouse gas emission scenarios, climate model variability, and socio-economic factors. By considering these uncertainties, scientists can refine their analyses and offer a more nuanced understanding of the potential impacts of climate change on drought severity, frequency, and spatial distribution. The comprehensive and up-to-date information from IPCC AR6, therefore, serves as a valuable tool for researchers aiming to unravel the intricate connections between climate change and drought, ultimately contributing to informed decision-making and adaptive strategies for mitigating the consequences of a changing climate. The results presented in Table 3 show the amount of precipitation for 2020-2039 for Isfahan province under different uncertainty sources (39 models and 5 scenarios: median, low 10-90th percentile range and high 10-90th percentile range). Using the methodology presented in this

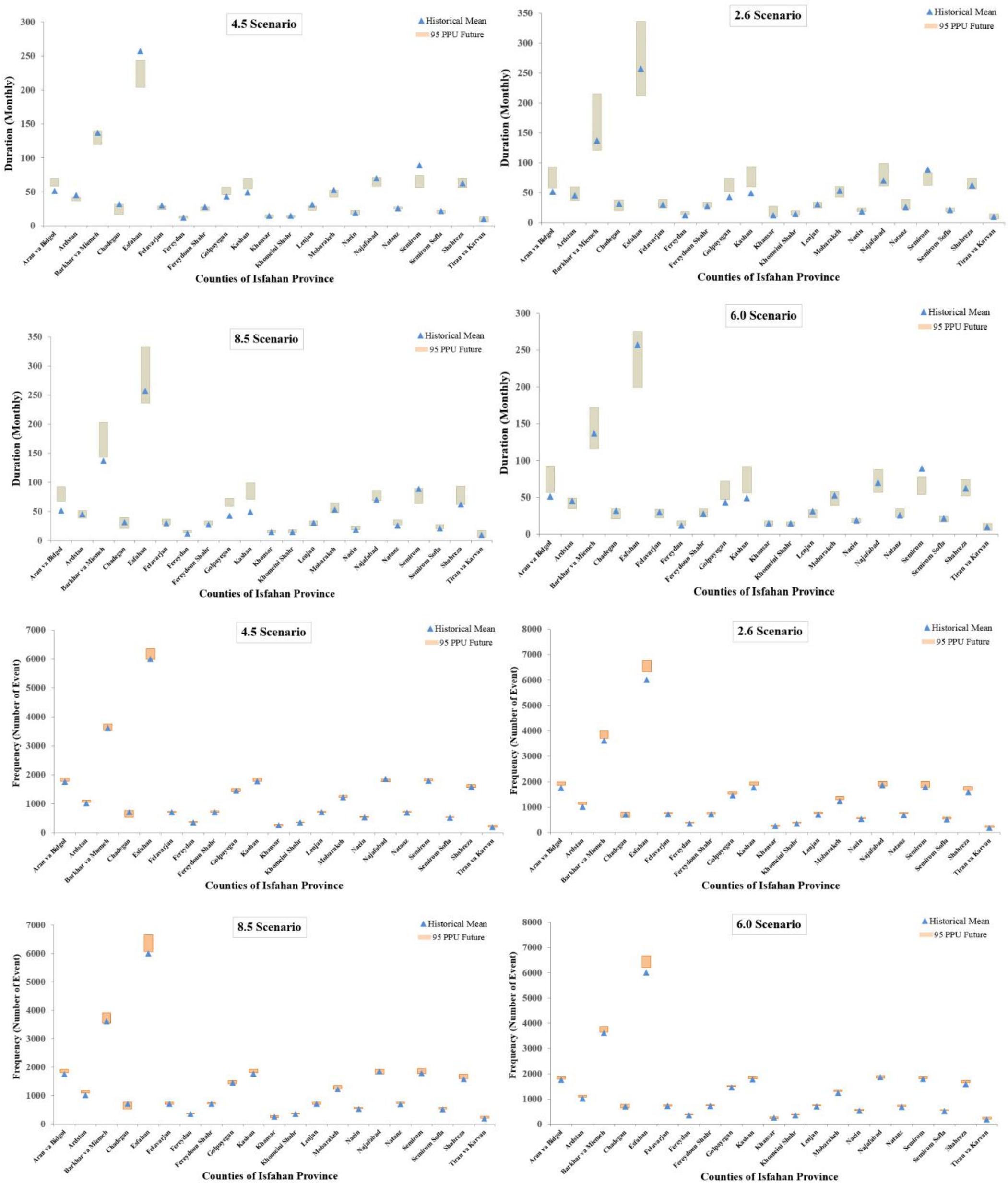


Fig 17. Comparison of 95PPU ranges of drought vulnerability of duration and frequently characteristics under the effect of climate change with AR5 emission scenarios in Isfahan counties

article, results similar to those presented in Table 3 can be extracted for each of the pixels in the study area, and the agricultural drought vulnerability can be analysed for each point. Similar to the near future (2020-2039), these results can be calculated and analysed for the middle (2040-2059 and 2060-2079) and distant future (2080-2099) as well.

Conclusions

The aim of this study was to perform analysis of the vulnerability for current and future climatic conditions, to depict drought conditions for current and future time horizons, while considering uncertainties arising from general circulation models and emission scenarios.

Assessing the vulnerability of different

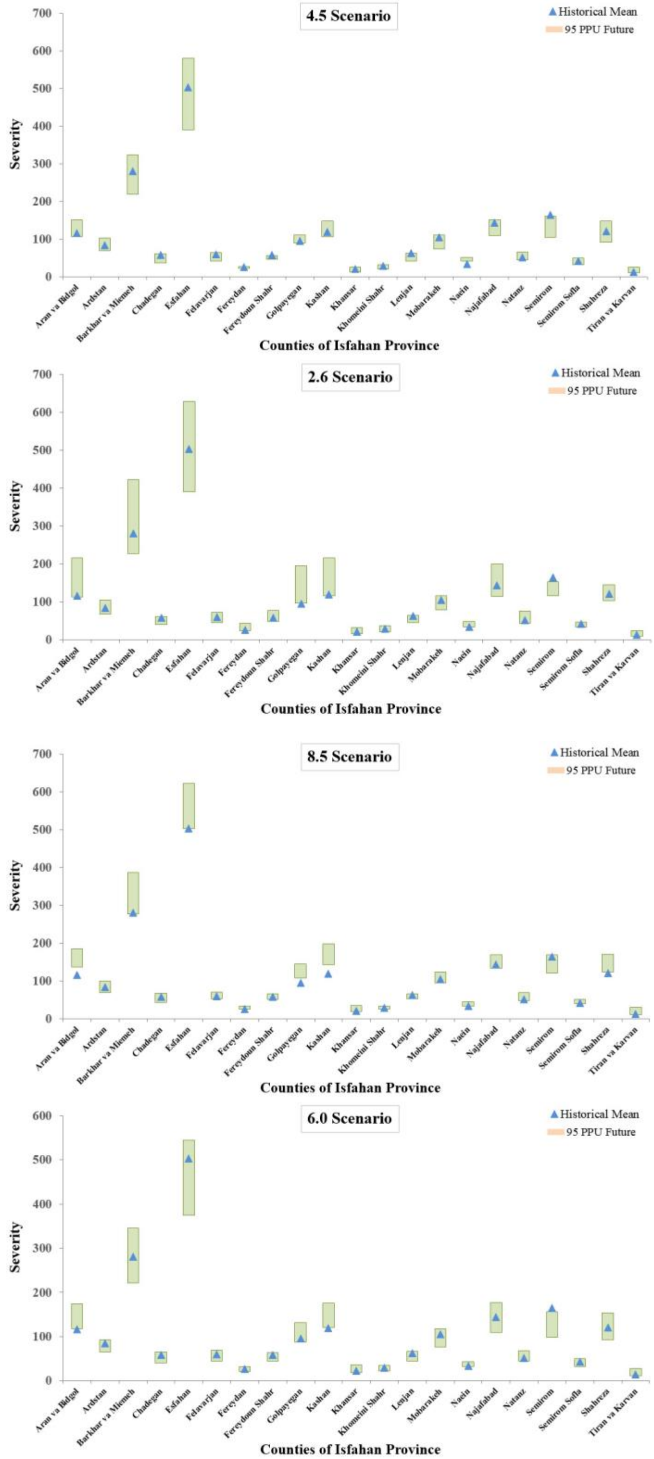


Fig 18. Comparison of 95PPU ranges of drought vulnerability of severity characteristic under the effect of climate change with AR5 emission scenarios in Isfahan counties

Table 3. projected climatology of precipitation for 2020-2039 for Esfahan provience scale under different uncertainty sources (models and scenarios)

Index	monthe	Historical Ref. Period, 1995-2014	2020-2039				
			SSP1-2.6	SSP2-4.5	SSP2-4.5	SSP3-7.0	SSP5-8.5
Median	Jan	26.92	29.41	29.51	29.51	28.46	29.16
	Feb	23.89	25.15	23.96	23.96	24.36	23.52
	Mar	27.66	29.02	29.59	29.59	29.15	26.82
	Apr	22.51	23.73	23.22	23.22	20.99	22.96
	May	8.52	9.41	9.18	9.18	8.95	9.05
	Jun	0.18	0.21	0.17	0.17	0.20	0.21
	Jul	0.00	0.00	0.00	0.00	0.00	0.00
	Aug	0.00	0.00	0.00	0.00	0.00	0.00
	Sep	0.00	0.00	0.00	0.00	0.00	0.00
	Oct	2.72	2.94	2.49	2.49	2.70	2.92
	Nov	15.17	14.98	15.93	15.93	14.54	15.35
	Dec	22.19	23.27	23.41	23.41	24.41	24.73
10-90th Percentile Range (low)	Jan	26.92	24.16	22.40	22.40	21.82	23.36
	Feb	23.89	19.35	18.77	18.77	19.73	17.93
	Mar	27.66	22.87	23.27	23.27	22.88	22.08
	Apr	22.51	18.41	17.27	17.27	17.03	17.27
	May	8.52	6.76	7.38	7.38	6.40	6.94
	Jun	0.18	0.08	0.07	0.07	0.06	0.07
	Jul	0.00	0.00	0.00	0.00	0.00	0.00
	Aug	0.00	0.00	0.00	0.00	0.00	0.00
	Sep	0.00	0.00	0.00	0.00	0.00	0.00
	Oct	2.72	1.60	1.46	1.46	1.39	1.43
	Nov	15.17	10.61	11.18	11.18	9.99	10.23
	Dec	22.19	18.05	17.90	17.90	20.49	17.88
10-90th Percentile Range (high)	Jan	26.92	33.05	33.46	33.46	34.37	37.24
	Feb	23.89	29.96	28.67	28.67	29.28	27.67
	Mar	27.66	34.78	34.47	34.47	34.40	32.80
	Apr	22.51	29.14	29.20	29.20	27.71	28.22
	May	8.52	11.61	11.46	11.46	11.27	11.77
	Jun	0.18	0.46	0.40	0.40	0.40	0.44
	Jul	0.00	0.00	0.00	0.00	0.00	0.00
	Aug	0.00	0.00	0.00	0.00	0.00	0.00
	Sep	0.00	0.00	0.01	0.01	0.01	0.00
	Oct	2.72	4.36	4.28	4.28	3.89	4.33
	Nov	15.17	20.08	19.72	19.72	20.89	21.90
	Dec	22.19	29.85	30.39	30.39	28.94	30.97

counties in Isfahan province in Iran, led to a ranking of the vulnerability of the counties. This ranking can support decision-makers in the identification of counties characterized by a high level of vulnerability.

Results showed that the agricultural vulnerability of drought in Isfahan and Barkhar-va-Meimeh was highest, while these counties had a low level of vulnerability in the total area. It was evident that, when the agricultural area of each county is applied, the trend of drought will change.

Moreover, some counties have more agricultural areas with less total area, in contrast to counties with a higher amount of total area. In these counties (such as Tiran-va-Karvan, Khomeini Shahr, and Naein), the agricultural area has a significant impact on drought vulnerability.

Based on these results in the studied area, each county with more agricultural area and gardens will experience the most crucial damage from exposure to drought because agriculture is among the first sectors to suffer from climate change and the resulting drought episodes.

Future improvements to the applied methodology can be obtained by incorporating applied indicators to create a spatial vulnerability map.

Finally, the proposed methodology represents a useful tool for decision-makers to rank priority areas and take appropriate management strategies.

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