<u>Responses and Actions taken on Reviewers' Comments</u>

Journal: Natural Hazards and Earth System Sciences

Manuscript Reference No.: nhess-2022- 18

Title: Evolution of multivariate drought hazard, vulnerability and risk in India under climate change.

Authors: Venkataswamy Sahana, Arpita Mondal

We thank the Reviewer for reviewing our manuscript and providing valuable feedback that have helped improve the quality of the work significantly. In this document, we provide a point by point response and actions taken on the comments and suggestions from the reviewers.

<u>Responses to comments from Referee #2</u>

Summary

1) This paper presents a drought risk assessment for India for a baseline period and for two RCPs and two SSPs. The methodology used seems appropriate for the data used and spatial scale considered. The authors found that drought risk was primarily comprised of the drought vulnerability component, rather than the hazard, these results were shown effectively using bivariate maps. Overall, I found this an interesting paper with results and outcomes that could be useful for drought planning and mitigation at the high level in India. However, I found that the clarity of the paper could be improved and made more expansive making it easier to follow and reproduce elsewhere. Specific examples are discussed below. I recommend that this paper is revised before publication to clarify key methodological points highlighted below.

We thank the reviewer for the positive and encouraging comments. We have addressed the reviewer concerns and provided explanation and clarity on the methods.

Major comments

2) I found the description of the methods to calculate the DHI and DVI in the supplementary information unclear, with not enough detail provided on the steps and processes with no further information provided (some examples listed below regarding weighting and standardisation). I would like to see the methods in the main body of the paper expanded. I recommend that all the whole methodology is moved to the main body of the paper, rather than the fundamental steps being in the supplementary information. I would also suggest that Figure 1 in the main

body of the paper is expanded, with more detail and steps added to fully capture the methodological steps described in the paper – this is further discussed below.

We will move the methods on hazard and vulnerability computation to the main manuscript. Further, an example on the drought hazard calculation depicting the weights and ratings for a randomly chosen location is given in Table S2. We have included more details about the methods in Figure 1.

Drought hazard assessment

Drought hazard forms an important component of drought risk assessment. Here, we assess the country-wide drought hazard based on the deficiencies in precipitation and soil moisture. Therefore, the multivariate standardized drought index (MSDI) of the non-parametric form is computed using the bivariate case of Gringorten plotting position formula (Gringorten, 1963). The steps involved in the calculation of MSDI is presented below.

1. The joint probability distribution of the 1-month time scale precipitation (R) and soil moisture (S) is given by

$$P\ (R\ \leq\ r, S\ \leq\ s) = p \qquad \text{... (1)}$$

where p represents the joint probability of the precipitation and soil moisture.

2. For the sample size n, the count of occurrence of the pair (r_i, s_i) for $r_i \leq r_k$ and $s_i \leq s_k$ is denoted as m_k. This count is used to derive the empirical joint probability for the bivariate case with the Gringorten plotting position (Gringorten, 1963) as

$$P(r_k, s_k) = \frac{m_k - 0.44}{n + 0.12} \qquad \text{... (2)}$$

3. The above empirical joint probability is then standardized to obtain the multivariate index MSDI.

$$MSDI =\ \varphi^{-1}(P) \qquad \text{... (3)}$$

where φ is the standard normal distribution function. Since the empirical distributions use ranks of data instead of actual values, the sample size should be sufficiently large.

The method of drought hazard assessment followed in the present study is based on Kim et al. (2015). Hazard is measured as the product of magnitude and the associated frequency of occurrence of an event. The MSDI time series at each region is categorized into four groups similar to Mckee et al. (1993). These categories are assigned weights according to the magnitude of MSDI value. Higher weights will be assigned to worst (high negative) MSDI values, and vice versa. Further, each weight category is divided into different clusters based on the frequency of occurrence of MSDI values. The total number of clusters for ratings in each MSDI category is determined using the prominent k-means data clustering algorithm. Higher ratings will be assigned to the cluster with high frequency values, and vice versa. The weightage and rating scheme is depicted graphically in Figure 1. In the k-means clustering technique, distance between the data points is computed using the squared Euclidean distance metric. To avoid the convergence to local minima, the k-means algorithm is run with 100 random initial seeds with 10000 iterations. The Calinski-Harabasz Index (CHI) (Caliński and Harabasz, 1974) is used to determine the optimum number of clusters and is given by

$$CHI = \frac{n-K}{K-1} \times \frac{BGSS}{WGSS} \quad \text{... (4)}$$

where n= number of data points, K= number of clusters, $BGSS = \sum_{k=1}^{K} n_k \left|\left|G^{\{k\}} - G\right|\right|^2$ is the between the group scatter, $G^{\{k\}}$ = centroid of the kth cluster, G = centroid of all the observations, $WGSS = \sum_{k=1}^{K} WGSS^{\{k\}}$ is within the group scatter and $WGSS^{\{k\}} = \sum_{i \epsilon I_k} \left|\left|M_i^{\{k\}} - G^{\{k\}}\right|\right|^2$, where $M_i^{\{k\}}$ are the observations. The k-means clustering algorithm is driven for 1 to n clusters. The number of clusters that gives highest value of CHI is the optimum number of clusters. These optimum number of clusters is used for assigning ratings. The categorized weightages and computed ratings are used to calculate the drought hazard for every region as below.

$$DH = \sum_{i=1}^{t} weights_i \times ratings_i \quad \text{... (5)}$$

where t is the length of MSDI time series. Although the weightages and ratings are intrinsically linked, the above scheme assures drought hazard quantification based on magnitudes and frequencies. The DH values from Eq 5 are standardized as shown below to obtain DHI that varies between 0 and 1.

$$DHI = \frac{DH - DH_{min}}{DH_{max} - DH_{min}} \quad \text{... (6)}$$

The weighing and rating scheme to calculate DHI for a randomly chosen grid is given in Table S1. ”

Table S1. Weighting and rating scheme for DHI calculation for a randomly chosen grid (11˚ lat, 75˚ lon)

MSDI	Class	Weight	Frequency of occurence	Rating
-0.99 to 0.99	Mild	1	0.71-0.82	6
			0.60-0.68	5
			0.49-0.57	4
			0.37-0.46	3
			0.26-0.348	2
			0.18-0.24	1
-1 to 1.49	Moderate	2	0.150-0.15	4
			0.13-0.13	3
			0.098-0.098	2
			0.07-0.07	1
-1.5 to -1.99	Severe	3	0.04-0.04	1
-2 or less	Extreme	4	0.016-0.016	1

Drought vulnerability assessment

Drought vulnerability forms another important component of drought risk assessment. Several aggregation techniques have been employed in the past studies to combine the drought vulnerability indicators to assess drought vulnerability. However, we use the robust method – TOPSIS (Hwang and Yoon, 1981) owing to its lesser rank reversal probabilities (Sahana et al., 2021). The steps involved in drought vulnerability assessment is outlined as below.

1. Standardization of numerical drought vulnerability indicators (irrigation index, water body fraction, groundwater availability, population density and GDP) is carried out such that their values vary between 0 and 1.

$$Std.Indicator = \frac{Indicator - Indicator_{min}}{Indicator_{max} - Indicator_{min}} \quad \ldots (7)$$

   Suitable weights are assigned to categorical drought vulnerability indicators (LULC, slope and soil texture), following Thomas et al. (2016) and Sahana et al. (2021) (Table S2). This gives the decision matrix n_{ij}, where $i = 1,2, \ldots n$ represents the number of regions and $j = 1,2, \ldots m$ represents the number of drought vulnerability indicators.

2. The above decision matrix n_{ij} is associated with the indicator weights w_j obtained from the Analytic Hierarchy Process (AHP) method (Sahana et al., 2021). This gives the weighted decision matrix v_{ij}

$$v_{ij} = w_j n_{ij} \quad \ldots (8)$$

3. Positive (A^+) and Negative (A^-) Ideal solution is calculated for each of the indicators.

$$A^+ = (v_1^+, v_2^+, \dots v_m^+) = [(\max v_{ij} | j \in I), (\min v_{ij} | j \in J)] \qquad \dots (9)$$

$$A^- = (v_1^-, v_2^-, \dots v_m^-) = [(\min v_{ij} | j \in I), (\max v_{ij} | j \in J)] \qquad \dots (10)$$

where I and J are associated with the benefit and cost criteria respectively. Here population density, LULC, slope and soil texture that bear positive correlation with the drought vulnerability are considered as benefit criteria. On the other hand, irrigation index, groundwater availability, waterbody fraction and GDP that bear negative correlation with drought vulnerability are considered as cost criteria.

4. Positive (d_i^+) and negative (d_i^-) separation measures for each region i are computed based on A^+ and A^- (also shown in Figure 1)

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2} \qquad \dots (11)$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2} \qquad \dots (12)$$

5. Relative closeness (R_i) of each region to the Positive Ideal Solution is calculated as

$$R_i = \frac{d_i^-}{d_i^- + d_i^+} \qquad \dots (13)$$

R_i signifies vulnerability of region i to drought. R is further standardised to vary between 0 and 1 to obtain drought vulnerability index (DVI)

$$DVI = \frac{R - R_{min}}{R_{max} - R_{min}} \qquad \dots (14)$$

Table S2. Weightages for categorical vulnerability indicators used for vulnerability assessment (Thomas et al. 2016; Sahana et al. 2021)

Vulnerability indicator	**Classification**	**Weight**	**Normalized Weight**
Land use	Water Body	0	0
	Barren	1	0.04
	Scrub	3	0.12
	Forest	4	0.15
	Agriculture	8	0.31
	Habitation	10	0.38
Soil	Silty Clay	2	0.032
	Clay	3	0.048
	Silty Clay Loam	4	0.063
	Clay Loam	5	0.079

	Silt Loam	7	0.111
	Loam	9	0.143
	Sandy Clay Loam	10	0.159
	Sandy Loam	11	0.175
	Loamy Sand	12	0.190
Slope (%)	0-1	1	0.048
	1-4	2	0.095
	4-6	4	0.190
	6-10	6	0.286
	>10	8	0.381

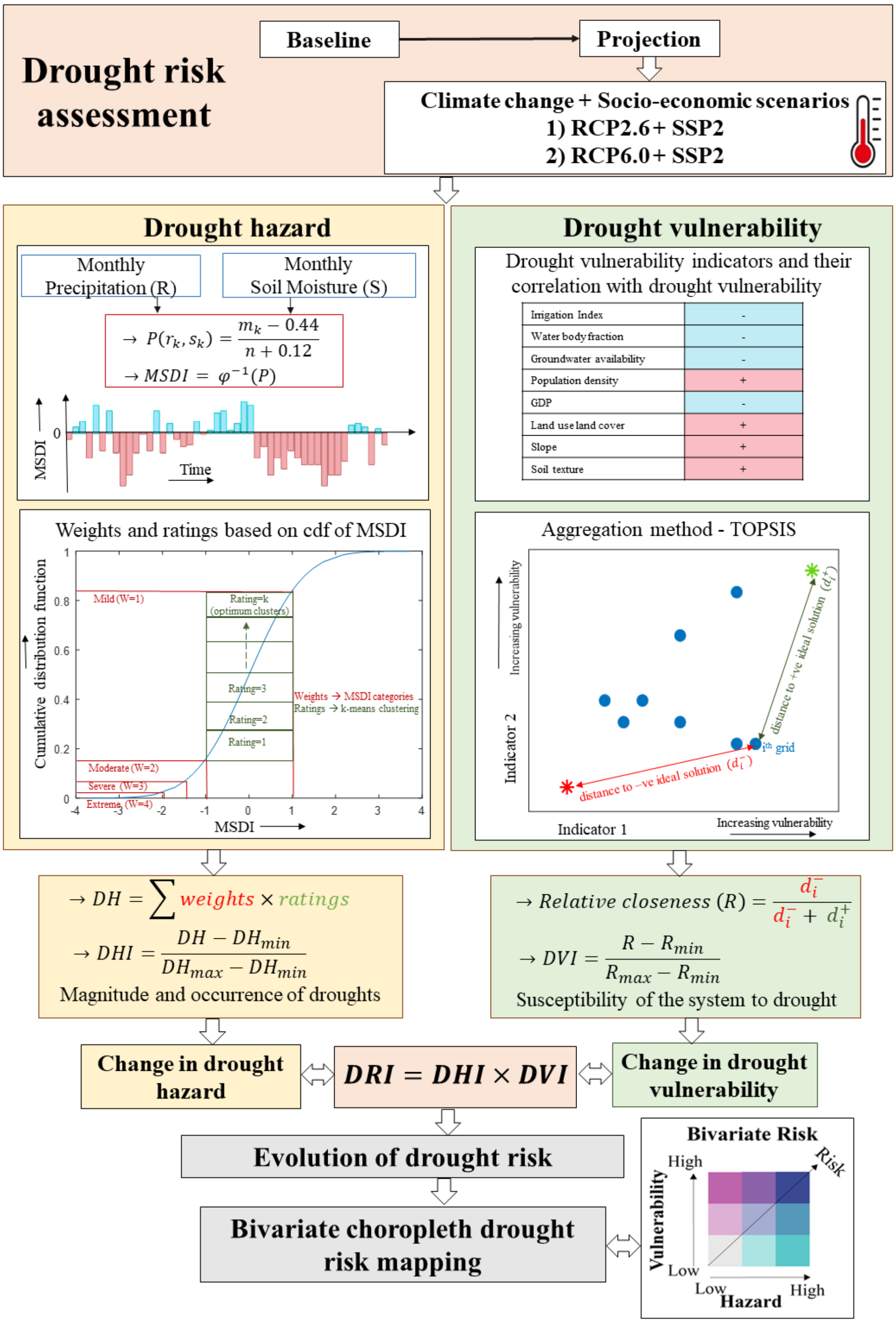

Figure 1. Framework to assess drought risk evolution. Monthly rainfall and monthly soil moisture is used to compute multivariate standardized drought index (MSDI). Weights and ratings system of MSDI is adopted to further compute drought hazard index (DHI). Multi-criteria decision making technique – TOPSIS is used to calculate drought vulnerability index (DVI) considering eight drought vulnerability indicators. The product of DHI and DVI is the drought risk index (DRI). Drought risk assessment is carried out for baseline period (1980-2015), near future (2021 2050) and far future (2061-2100) for various climate and socio-economic scenarios.

3) Use of terminology – literature usually talks about vulnerability factors – i.e. the factors that make a person or location vulnerable to drought impacts. Also regarding vulnerability terminology, you mention components of vulnerability in the introduction (L35-38), how do the indicators (or factors) you used map onto these? This could be included in Table 1. Did you consider using for example, WorldPop data such that the vulnerability assessment could be disaggregated by sex?

Table 1 is revised to represent sensitivity, adaptive capacity and exposure components of the drought vulnerability indicators in terms of their socio-economic, physical and infrastructural aspects. We agree with the reviewer that the study would be comprehensive with the inclusion of other socio-economic indicators. However, for a densely-populated and rapidly-developing nation such as India, acquisition of reliable datasets on these indicators is often challenging. Most importantly, unavailability of projections of these indicators over the Indian region limits their use in this study, since our primary goal is to compare baseline drought risk with that under future projected climate change. This discussion will be included in the revised manuscript.

Table 1. Drought vulnerability indicators used for drought vulnerability assessment. The sources for indicators in baseline period and projected period along with their relevance and correlation with drought vulnerability is presented. Representative indicators to arrive at the drought vulnerability indicators for projected period are also listed.

<table>
<tr><th rowspan="2">Data</th><th rowspan="2">Relevance to drought vulnerability</th><th rowspan="2">Correlation with drought vulnerability</th><th rowspan="2">Past studies using this data</th><th colspan="5">Observed</th><th colspan="2">Projected</th></tr>
<tr><th>Source</th><th>Period</th><th>Spatial resolution</th><th>Units</th><th>Details</th><th>Source</th><th>Representative Indicator</th></tr>
<tr><td>Population density</td><td>Demographic attribute for assessing social vulnerability and exposure.</td><td>Positive</td><td>(Carrão et al., 2016; Rajsekhar et al., 2015)</td><td>NASA Socioeconomic Data and Applications Centre (SEDAC) (http://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density)</td><td>2010</td><td>1 km</td><td>person/km^2</td><td>• Population density estimates are based on the national censuses and population registers.
• Given as population count by area.</td><td rowspan="5">Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b experiments) data archive (Warszawski et al., 2014)</td><td>Population (SSP2)</td></tr>
<tr><td>GDP</td><td>Economic welfare for assessing economic vulnerability as well as adaptive capacity.</td><td>Negative</td><td>(Carrão et al., 2016; Naumann et al., 2014; Wu et al., 2017)</td><td>(Ghosh et al., 2010)</td><td>2006</td><td>1 km</td><td>millions of dollars</td><td>• Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime imagery by NOAA to calculate total GDP (Ghosh et al., 2010)</td><td>GDP (SSP2)</td></tr>
<tr><td>Irrigation Index</td><td>Adaptive capacity component. High irrigation ratio implies high adaptive capacity and lower drought vulnerability.</td><td>Negative</td><td>(Murthy et al., 2015; Wu et al., 2017)</td><td>Web based land use statistics information system https://aps.dac.gov.in/LUS/Index.htm</td><td>2010</td><td>District</td><td>-</td><td>• Data published by Directorate of Economics & Statistics, Department Agriculture, Cooperation & Farmers Welfare.
• Land use statistics information system is designed and developed by Agriculture Informatics Division, National Informatics Centre, Ministry of Communication & IT, Govt. of India, New Delhi.
• Given as the ratio of irrigated area to cropped area.</td><td>Irrigation water consumption, Irrigation water withdrawal (RCP2.6 –SSP2 & RCP6.0-SSP2)</td></tr>
<tr><td>Water bodies fraction</td><td>Water resources (streams/rivers) and water infrastructure (dams/reservoirs) for assessing the physical vulnerability, and provides adaptive capacity.</td><td>Negative</td><td>(Naumann et al., 2014)</td><td>Bhuvan-Indian Geo Platform</td><td>2010</td><td>3'</td><td>-</td><td>• Advanced Wide Field Sensor (AWiFS) satellite imagery is used by NRSC to extract the water bodies fraction.</td><td>Surface runoff, Total runoff, Total water storage (RCP2.6 –SSP2 & RCP6.0-SSP2)</td></tr>
<tr><td>Groundwater</td><td>Adaptive capacity component to cope with drought.</td><td>Negative</td><td>(Pandey et al., 2010)</td><td>Dynamic Ground Water Resources of India, Central Ground Water Board Ministry of Water Resources, Report on July 2011, (CGWB, 2014)</td><td>2011</td><td>District</td><td>ham</td><td>• Groundwater resources assessment based on the State and Central groundwater boards of India.
• Net groundwater availability estimates are based on the annual replenishable groundwater resources and the natural discharge during non-monsoon season.</td><td>Groundwater runoff, Total water storage (RCP2.6 –SSP2 & RCP6.0-SSP2)</td></tr>
<tr><td>Land Use Land Cover (LULC)</td><td>Accounts for social vulnerability to drought due to exposure.</td><td>Positive</td><td>(Pandey et al., 2010; Thomas et al., 2016)</td><td>The USGS Land Cover Institute (LCI) (https://landcover.usgs.gov/global_climatology.php)</td><td>2001-2010</td><td>0.5 km</td><td>-</td><td>• The Collection 5.1 Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) product for the period 2001-2010 isused by Broxton et al. (2014) to develop global land cover.</td><td>NASA Earthdata from ORNL DAAC (Chini et al., 2014) (https://doi.org/10.3334/ORNLDAAC/1248)</td><td>Fractional Land Use Land Cover data (RCP2.6 & RCP6.0)</td></tr>
<tr><td>Digital Elevation Model (DEM)</td><td>Spare time for water retention bestows higher adaptive capacity in flat slope parts. Accounts for physical vulnerability to drought.</td><td>Positive</td><td>(Ekrami et al., 2016; Pandey et al., 2010)</td><td>SRTM 90 m Digital Elevation Database v4.1 (http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1#download)</td><td>2007</td><td>90 m</td><td>m</td><td>• NASA Shuttle Radar Topography Mission elevation data derived from interferometric techniques.</td><td rowspan="2" colspan="2">Constant (same as observed)</td></tr>
<tr><td>Soil Type</td><td>Water holding capacity of soil based on the textural properties. Accounts for social vulnerability to drought due to exposure.</td><td>Positive</td><td>(Pandey et al., 2010; Thomas et al., 2016)</td><td>FAO Harmonized World Soil Database (HWSD) (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/)</td><td>2003</td><td>1 km</td><td>-</td><td>• Major contributors of the soil data for the Indian regions are All India Soil and Land use Survey (1965) and the International soil map of vegetation by India Council of Agricultural Research (FAO-UNESCO, 1977).
• Loamy soils are more vulnerable to drought compared to clayey soils.</td></tr>
</table>

A final question on the factors used, how do the vulnerability factors selected address the exposure component? Although a population may be vulnerable to the impact of drought, they may not be exposed to drought or may be exposed to a lower severity of drought hazard than in other locations, for example.

In this study, population density, land use and soil type constitute the exposure indicators for drought vulnerability assessment. We agree with the reviewer that a highly vulnerable population might be exposed to mild droughts or no droughts at all. These differences are precisely accounted in the overall drought risk estimates, since we characterize risk as a combination of vulnerability and hazard. For eg., if the hazard is low in a region, it is likely to be classified as 'low to moderate' in terms of drought risk, despite having high vulnerability. This discussion will be included in the revised manuscript.

4) The baseline period used (1980-2015) excludes the past six years, excluding significant drought events in 2016-2018 and 2021. Is there a way that updated precipitation data could be obtained and analysed to include these recent events?

We have used hydro-climatic and socio-economic variables for the period 1980-2015 to ensure overlap between drought hazard and vulnerability indicators for the baseline period. The overall risk estimates may be misleading if the exposure, adaptive capacity and sensitivity indicators are overlayed on hazard events of dissimilar timelines. Further, our analysis takes into account the major drought episodes of 1982, 1984, 1986, 1987, 1989, 1991, 2000, 2002 and 2015 as identified by earlier study (Sahana et al., 2020). Among them, the major drought episodes of 2002 and 2015 had severely impacted multiple sectors of the country. For example, agricultural contributions to GDP dipped by 3.1% along with heavy agricultural income losses in the 2002 drought event (DownToEarth, 2015), while the 2015 drought event affected over 330 million people (BBC India, 2016), and reservoir levels dropped to minimal values (The Times of India, 2016). These events contribute to the hazard assessment in this study. Additional inclusion of subsequent droughts of 2016-2018 and 2020 is unlikely to significantly alter our conclusions.

5) L140-142: the first sentence here states that variability of the two scenarios increased over time, but the second states that the baseline period is more variable than the projected period. I am not sure how both of these statements can be true, nor am I convinced I can see these difference in the time series for precipitation or soil moisture. Please clarify this point further.

Figure 2 is updated to include the time series of precipitation and soil moisture for the baseline period as well (1980-2015). It is observed that the variability of both the variables in the projected period increases with time. However, it is evident from Figure 2, that the variability in the hydro-climatic variables in the baseline period is high compared to the projected period.

Figure 2. Datasets used for drought risk assessment. a) Projected hydro-climatic variables such as monthly precipitation and monthly soil moisture are used for drought hazard assessment. b) Projected drought vulnerability indicators such as irrigation index, water body fraction, groundwater availability, population, GDP and land use land cover, along with static drought vulnerability indicators such as slope and soil texture are used for drought vulnerability assessment. Datasets for projected period are divided into near future (2021-2060) and far future (2061-2100) to check the evolution of drought risk.

This also applies to Table 3 and the text in L199-205, and Table 4 and text L232-233.

Table 3 and Table 4 represent the transition of drought vulnerability/risk from one class of vulnerability/risk from baseline to another class of vulnerability/risk in the future. In general, socio-economic development is a slow process, and takes time to reflect in terms of significant changes in the socio-economic indicators (Dellink et al., 2017). Further, majority of the drought vulnerability/risk studies across the globe have adopted static vulnerability assessment that represent drought vulnerability snapshot in time (Hagenlocher et al., 2019). Therefore, we used the static vulnerability indicators for the year 2010, 2060 and 2099 to quantify drought vulnerability for the baseline, far future and near future period respectively. In the case of drought risk assessment, the drought hazard capturing the droughts in baseline (1980-2015), near (2021-2060) and far (2061-2099) future period is combined with drought vulnerability at 2010, 2060 and 2099 respectively. This will be clarified in the revised manuscript.

Figure 7 is mentioned only on two lines at the end of Section 3.3.1, could this summary be referred to in the previous discussions of hazard, vulnerability and risk as it is a more intuitive figure to understand than tables shown in Tables 2, 3 and 4.

Figure 7 will be referred for the discussion on hazard, vulnerability and risk projections. Section 3.1.2 – "Of all the future drought hazard scenarios considered, the RCP2.6-Far scenario revealed the largest area (2.8%) under high and very high hazard classes (Figure 7)." Section 3.2.2 – "As high as 42.9% area transits from lower vulnerability classes to higher vulnerability classes under RCP6.0-SSP2 Near future, with 93% area of the country under high and very high drought vulnerability class (Figure 7)." Section 3.3.1 – **"**In the worst case drought risk scenario (RCP6.0-SSP2 Far future), it is observed that 2.7% area of the country is under high and very high drought risk class (Figure 7)."

6) L233-238: Here you state that the RCP6.0-SSP2 Far future scenario is not the worst case for drought vulnerability, but was the most severe for drought risk due to the hazard component (L233-235). Then on L236-238 in the discussion of Figure 6, you state that drought vulnerability makes up the majority of the drought risk for the same scenarios. Please could you clarify these seemingly contradictory statements. I do not disagree with the point that we need more holistic drought risk assessment though.

Risk is an outcome of interaction between hazard and vulnerability, and is also a function of time. The fact that worst case scenarios are different for drought hazard and drought vulnerability, indicates dissimilar behavior of drought hazard and vulnerability indicators in inducing drought risk. For eg. population density is high in the near future period (2060) as compared to the far future (2100), while precipitation is continuously increasing in the projected period. A combination of such different hazard and vulnerability behavior in a given time period is effectively captured through comprehensive risk analysis. Therefore, though RCP6.0-SSP2 Far future scenario is not the worst-case scenario for drought vulnerability compared to RCP6.0-SSP2 Near future, interaction of high hazard with moderate to high vulnerability resulted in worst drought risk scenario in the case of RCP6.0-SSP2 Far future. However, in general, when the change in drought risk for all the future scenarios are compared with the baseline, it is observed that area falling under drought risk due to drought vulnerability is increased (Figure 6). Therefore, though seemingly contradictory, the statements pointed out by the reviewer reflect realistic and to a large extent, expected drought risk behavior. Clarification on the above discussion will be included in the revised manuscript.

7) Section 3.3.2: At what spatial scale is this information useful to policy makers? You could consider whether the gridded data used here is relevant to that of decision makers.

The drought hazard, vulnerability and risk projection maps from the present study, developed at 0.5° lat.× 0.5° lon spatial resolution are comparable with blocks/district level area. Therefore, these maps can assist the block-level administrators to know region-specific causative factors inducing severe drought risk both in baseline and projected period, besides the indigenous components governing the drought risk. Also, these maps can inform the state or federal disaster management authorities concerning the climate action plans. The change in drought risk at different projected periods can modulate adaptation and mitigation strategies and can be included in decision support system for drought management. Since drought risk is found to be mainly driven by societal factors, action plans should be directed to improve socio-economic conditions. Groundwater conservation, conjunctive use of surface and groundwater, farmer participation in crop insurance, water saving farm practices and technologies are some important measures that can be adopted for raising the socio-economic standards. Further, the framework of our study is applicable for state-wise drought risk assessment with reliable hydro-climatic and socio-economic indicators. Such an assessment is can recommend measures for watershed management, irrigation and agricultural practices and reorganizing water demand and supply management at a local scale.

8) L269-270: You say here that this study is an improvement for decision makers over existing drought risk assessment in India. Please briefly state what this improvement is.

Drought risk projection studies undertaken over the Indian region are based on drought hazard alone, and no consideration has been given to the drought vulnerability component. The present study quantifies the relative contribution of drought hazard and drought vulnerability to the overall drought risk projections under a comprehensive risk framework. Thus, our analysis can aid different stakeholders involved in drought management for adaptation and mitigation plans under changing climate and socio-economic conditions. This marks the significant improvement of our study over existing studies on drought risk assessment in India under climate change.

Supplementary information

9) The description of the categorisation of the MSDI at the bottom of page 2 is not clear and should be expanded – for example, it should be clearly stated which categories from McKee et al., - presumably extreme drought, severe drought, moderate drought etc., but you should include the thresholds and categories used in this study here. The meaning of the following two sentences ("Further, each category is organised into sub-groups based on the occurrence probabilities of the selected category. While the weightages are assigned to MSDI categories to account for drought magnitude, ratings are assigned to the sub-groups of each MSDI category to account for drought occurrence probability") are aren't sufficiently clear; the methodology of how weights were assigned should be described more clearly – for example, you start talking about ratings and clusters, and it is not clear what these are used for.

Our response to Reviewer #2, comment #2 addresses this comment.

10) The description of the drought vulnerability index is also overly complex and should be clarified by describing the process in words. You should also be specific for example on how exactly data were standardised and what is meant by 'suitable weights' – what makes them suitable, how have these be validated and checked.

Drought vulnerability assessment method will be moved to main manuscript with detailed explanation starting from data standardization. Weights for categorical indicators are shown in Table S2. Further, our response to Reviewer #2, comment #2 clarifies the concerns from this comment.

Minor issues

11) In several places e.g. L119 and in the supplementary information you mention that data have been standardised, please explain how these data are standardised (e.g. across time or space).

Drought risk values derived from $Risk = DHI \times DVI$ is standardized spatially to obtain DRI, such that the DRI values vary between 0 and 1.

$$DRI = \frac{Risk - Risk_{min}}{Risk_{max} - Risk_{min}} \quad \text{... (16)}$$

12) L99-100: '…and brought to a monthly time-scales.' This isn't clear – how and what metric? Total precipitation? Average soil moisture? Please expand on this comment.

The projected daily precipitation is cumulated over each month to get the monthly precipitation values and converted its units from kg m^{-2} s^{-1} to mm. The projected monthly soil moisture (average monthly soil moisture) from the model is converted from kg m^{-2} to m^3/m^3. This will be clarified in the revised manuscript.

13) L139: 'the country-accumulated data of these hydro-climatic variables…' please clarify how these data were accumulated

Data is summed over all grids.

14) L145: ' …many regions is less **severe** compared to the baseline period.' Word missing

We will make the correction as "…many regions is less severe compared to the baseline period."

15) L168-169: It is not clear whether this choice of low skill GCMs was in the current study or Koutroulis et al and Cook et al. – note that this same comment is also made on L209-210.

We will clarify the statement on L168-169 as "Such contradicting observations are possibly due to selection of low-skill GCMs (Aadhar and Mishra, 2020) in Koutroulis et al. (2019) & Cook et al. (2020)." and L209-210 as "Such contradicting observations in drought vulnerability is possibly due the choice of low-skill GCMs in Koutroulis et al. (2019)."

16) L193: Highest differences… → The biggest difference in…
17) L198: many region of the country **are** expected to
18) L211: …sub-division~~-wise~~…

Write up of comments #16, #17 and #18 will be corrected in the revised manuscript.

19) L211: Here you mention meteorological sub-divisions, what exactly does this mean, how were these defined?

Meteorological sub-divisions are the meteorologically homogenous regions identified by India Meteorological Department (Kelkar and Sreejith, 2020). This will be clarified in the revised manuscript.

20) L222: …expected to be under high risk to drought compared… → …expected to have a high drought risk compared…

Will be corrected in the revised manuscript.

21) A mix of tenses seems to be used throughout, this should be reviewed, ensuing that the past tense is used where appropriate.

Noted and will be revised.

22) In some places 'Far Future' is capitalised and others it is not – you should ensure this is consistent.

Noted and will be revised.

Tables and Figures

23) Table 1: Please also included the last date that the factors were updated and the date range that was available. Some of the descriptions of the datasets are unclear, for example, Water Bodies Fraction and Groundwater – it is not clear what these data actually are, and what they're measuring. It would be useful to include the unit of each factor where appropriate, e.g. for 'Groundwater', 'Water Bodies Fraction'

We have revised Table 1 to include all the details pointed out by the reviewer.

24) Table 2: I find these tables unintuitive and difficult to marry up with the description of results in the text. e.g. L149-15150: 'The future drought hazard assessment using the projected hydro-climatic variables revealed that more than 35% area of the country is expected to be under the low hazard class, as compared to 8% in the baseline period' – I can't seem to make any of the very low hazard boxes up to these numbers or the difference between them. You could consider adding a more detailed example walk through of what this table means. There is also no reference to or legend for the colour scheme used here.

We will refer to Figure 7 for these numbers as "The future drought hazard assessment using the projected hydro-climatic variables revealed that more than 35% area of the country is expected to be under the low hazard class, as compared to 8% in the baseline period (Figure

7)." Caption for Table 2 will be revised and explained as "Table 2. Transition of drought hazard from baseline period to projected period. The value in each cell represents the change in % area of the country from one hazard class to another. Red color shows transition, and blue represents no transition." A detailed explanation of the table will be included as "The hazard transition from the baseline to different scenarios is presented in Table 2. The upper triangle in the table represents % area transition from lower to higher hazard classes, the lower triangle represents % area transition from higher to lower hazard classes, and the diagonal elements represent % area with no transition."

25) Table 3 & 4: I assume these are all showing SSP2 scenarios, please clarify in the caption.

Tables will be updated indicating the SSP2 scenarios.

26) Figure 1: it would be helpful to refer to this figure in the description of methods included in the Supplementary Information. The DHI and DVI should be directly referenced in this figure to clarify when these are calculated in the processing chain – including mention of the baseline period.

In the revised methodology we will refer to Figure 1 in the calculation of DHI and DVI as "The weightage and rating scheme is depicted graphically in Figure 1." and "Positive (d_i^+) and negative (d_i^-) separation measures for each region i are computed based on A^+ and A^- (also shown in Figure 1)."

27) Figure 4: There are some parts that are white, yet white is not mentioned in the legend.

White regions represent no data region. Legend for Figure 4 will be revised accordingly.

28) Figure 5: I recommend adding another colour to the legend here to highlight the higher risk areas (such as a dark red or similar). Do the classes used represent any specific categories of risk?

Color of the legend is changed as per the suggestion. The classes here represent very low, low, medium, high and very high risk categories.

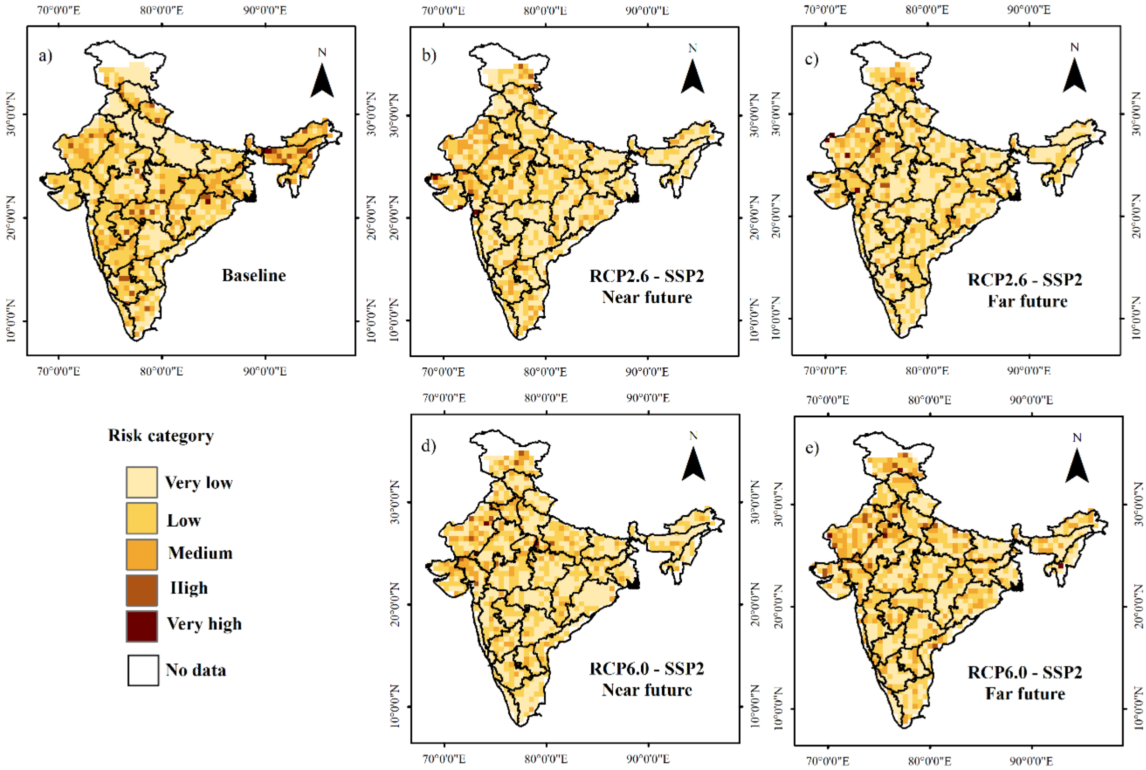

Figure 5. Multi-model ensemble drought risk maps for the scenarios a) baseline, b) RCP2.6-SSP2 Near future, c) RCP2.6-SSP2 Far future, d) RCP6.0-SSP2 Near future, e) RCP6.0-SSP2 Far future.

References:

Aadhar, S. and Mishra, V.: On the Projected Decline in Droughts Over South Asia in CMIP6 Multimodel Ensemble, J. Geophys. Res. Atmos., 125(20), 1–18, doi:10.1029/2020JD033587, 2020.

BBC India. India Drought: '330 Million People Affected’. Retrieved from. https://www.bbc.com/news/world-asia-india-36089377., 2016

Broxton, P. D., Zeng, X., Sulla-Menashe, D. and Troch, P. A.: A global land cover climatology using MODIS data, J. Appl. Meteorol. Climatol., 53(6), 1593–1605, doi:10.1175/JAMC-D-13-0270.1, 2014.

Caliński, T. and Harabasz, J.: Communications in Statistics - Theory and Methods, Commun. Stat., 3(1), 1–27, doi:10.1080/03610927408827101, 1974.

Carrão, H., Naumann, G. and Barbosa, P.: Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability, Glob. Environ. Chang., 39, 108–124, doi:10.1016/j.gloenvcha.2016.04.012, 2016.

Chini, L. P., Hurtt, G. C. and Frolking, S.: Harmonized Global Land Use for Years 1500 -2100, V1, , doi:10.3334/ORNLDAAC/1248, 2014.

Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E. and Anchukaitis, K. J.:

Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios, Earth's Futur., 8(6), 1–20, doi:10.1029/2019EF001461, 2020.

Dellink, R., Chateau, J., Lanzi, E. and Magné, B.: Long-term economic growth projections in the Shared Socioeconomic Pathways, Glob. Environ. Chang., 42, 200–214, doi:10.1016/j.gloenvcha.2015.06.004, 2017.

DownToEarth. Drought forever. Retrieved from. https://www.downtoearth.org.in/blog/drought-forever-44976., 2015

Ekrami, M., Marj, A. F., Barkhordari, J. and Dashtakian, K.: Drought vulnerability mapping using AHP method in arid and semiarid areas: a case study for Taft Township, Yazd Province, Iran, Environ. Earth Sci., 75(12), 1–13, doi:10.1007/s12665-016-5822-z, 2016.

FAO-UNESCO: Soil map of the world., 1977.

Ghosh, T., Powell, R. L., Elvidge, C. D., Baugh, K. E., Sutton, P. C. and Anderson, S.: Shedding Light on the Global Distribution of Economic Activity, Open Geogr. J., 148–161, 2010.

Gringorten, I. I.: A plotting rule for extreme probability paper, J. Geophys. Res., 68(3), 813–814, doi:10.1029/JZ068i003p00813, 1963.

Hagenlocher, M., Meza, I., Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S. and Sebesvari, Z.: Drought vulnerability and risk assessments: State of the art, persistent gaps, and research agenda, Environ. Res. Lett., 14(8), 083002, doi:10.1088/1748-9326/ab225d, 2019.

Hwang, C.-L. and Yoon, K.: Methods for multiple attribute decision making, in Multiple attribute decision making, pp. 58–191, Springer., 1981.

Kelkar, R. R. and Sreejith, O. P.: Meteorological sub-divisions of india and their geopolitical evolution from 1875 to 2020, Mausam, 71(4), 571–584, 2020.

Kim, H., Park, J., Yoo, J. and Kim, T. W.: Assessment of drought hazard, vulnerability, and risk: A case study foradministrative districts in South Korea, J. Hydro-Environment Res., 9(1), 28–35, doi:10.1016/j.jher.2013.07.003, 2015.

Koutroulis, A. G., Papadimitriou, L. V., Grillakis, M. G., Tsanis, I. K., Warren, R. and Betts, R. A.: Global water availability under high-end climate change: A vulnerability based assessment, Glob. Planet. Change, 175(August 2018), 52–63, doi:10.1016/j.gloplacha.2019.01.013, 2019.

Mckee, T. B., Doesken, N. J. and Kleist, J.: The relationship of drought frequency and duration to time scales, Eight Conf. Appl. Climatol., 179(January), 17–22, doi:citeulike-article-id:10490403, 1993.

Murthy, C. S., Laxman, B. and Sesha Sai, M. V. R.: Geospatial analysis of agricultural drought vulnerability using a composite index based on exposure, sensitivity and adaptive capacity, Int. J. Disaster Risk Reduct., 12, 163–171, doi:10.1016/j.ijdrr.2015.01.004, 2015.

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A. and Vogt, J.: Exploring drought vulnerability in Africa: an indicator based analysis to be used in early warning systems, Hydrol. Earth Syst. Sci., 18(5), 1591–1604, 2014.

Pandey, R. P., Pandey, A., Galkate, R. V., Byun, H.-R. and Mal, B. C.: Integrating Hydro-Meteorological and Physiographic Factors for Assessment of Vulnerability to Drought, Water

Resour. Manag., 24(15), 4199–4217, doi:10.1007/s11269-010-9653-5, 2010.

Rajsekhar, D., Singh, V. P. and Mishra, A. K.: Integrated drought causality, hazard, and vulnerability assessment for future socioeconomic scenarios: An information theory perspective, J. Geophys. Res., 120(13), 6346–6378, doi:10.1002/2014JD022670, 2015.

Sahana, V., Sreekumar, P., Mondal, A. and Rajsekhar, D.: On the rarity of the 2015 drought in India: A country-wide drought atlas using the multivariate standardized drought index and copula-based severity-duration-frequency curves, J. Hydrol. Reg. Stud., 31, 100727, doi:10.1016/j.ejrh.2020.100727, 2020.

Sahana, V., Mondal, A. and Sreekumar, P.: Drought vulnerability and risk assessment in India : Sensitivity analysis and comparison of aggregation techniques, J. Environ. Manage., 299, 113689, doi:10.1016/j.jenvman.2021.113689, 2021.

The Times of India. Only 24% of Water Left in India's 91 Key Reservoirs. Retrieved from. https://timesofindia.indiatimes.com/india/Only-24-of-water-left-in-Indias-91-keyreservoirs/articleshow/51818462.cms, 2016

Thomas, T., Jaiswal, R. K., Galkate, R., Nayak, P. C. and Ghosh, N. C.: Drought indicators-based integrated assessment of drought vulnerability: a case study of Bundelkhand droughts in central India, Nat. Hazards, 81(3), 1627–1652, doi:10.1007/s11069-016-2149-8, 2016.

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O. and Schewe, J.: The inter-sectoral impact model intercomparison project (ISI-MIP): Project framework, Proc. Natl. Acad. Sci. U. S. A., 111(9), 3228–3232, doi:10.1073/pnas.1312330110, 2014.

Wu, J., Lin, X., Wang, M., Peng, J. and Tu, Y.: Assessing agricultural drought vulnerability by a VSD Model: A case study in Yunnan Province, China, Sustainability, 9(6), 1–16, doi:10.3390/su9060918, 2017.