Responses and Actions taken on Reviewers' Comments

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

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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.

Responses to comments from Referee #1

I have read your manuscript and think it covers an interesting topic. It is clearly the result of a major research effort. Including vulnerability in drought risk analysis is a known challenge, and I agree with you that looking at multiple physical drivers as well as at transient vulnerability are important steps for holistic drought risk assessments. The aim of the study is clearly stated and results are described in detail. However, the research is quite complex and so I think an extra effort is needed to make in understandable for readers of NHESS. I see some conceptual issues, but they may have been caused by a lack of understanding of the method due to its incomplete or undetailed description. In general, I think more of the method could be in the main manuscript and more details to the method (currently lacking) can be described in the supplementary material. Below, I will elaborate on the main points that I think can help improve/clarify the manuscript. In addition, I think the manuscript would benefit from a review by an English language editor, as there are multiple grammar mistakes in the manuscript and I see various possibilities for vocabulary improvements.

We thank the reviewer for the positive and constructive feedback on our work. We have now provided more details and description about the methods and they will be included in the revised manuscript and the revised supplementary material. Further, we have proof-read the manuscript and corrected for grammar and language wherever necessary. We have addressed the comments provided by you in the below sections.

I haven't listed all grammar / vocabulary mistakes, but here are a few examples from the abstract:

e.g. L7 ”a” major threat

e.g. L10 This study investigates and evaluates the change in projected drought risk under future climatic and socio-economic conditions by combining vulnerability and hazard information at a country-wide scale for future climatic and socio-economic conditions

e.g. L18 “are found to be high risk under all scenarios”

We will consider all the above suggestions from the reviewer and revise them in the manuscript.

e.g. L15-17: Sentence is too long, it is unclear what is meant with “worst-case” scenario

We have now simplified the sentence as **“**In the worst-case scenario for drought hazard (RCP2.6-Far future), there is a projected decrease in the area under high or very high drought hazard classes in the country by approximately 7%. Further, the worst-case scenario for drought vulnerability (RCP6.0-SSP2-Near future) shows a 33% rise in the areal extent of high or very high drought vulnerability classes.”

I think maybe “The West Utter Pradesh, Haryana, …., regions” are meant rather than “regions of West Utter Pradesh,…”

The sentence will be rewritten as “The West Uttar Pradesh, Haryana, West Rajasthan and Odisha regions are found to be high risk under all scenarios.”

In general, in the manuscript there are many sentences that are difficult to understand (too long and/or with too complex structure).

We will take care of the complex sentences and simplify them in the revised manuscript.

Below, I add some general comments and questions structured following the study aims, highlighting the most pressing questions with respect to the method.

1. Multivariate drought hazard projection using Multivariate Standardized Drought Index (MSDI) that considers concurrent deficits in precipitation and soil moisture for future warming scenarios.

a) L81: “*However, droughts can often manifest as a complex interplay of multiple influencing variables necessitating a multivariate approach for characterization of drought hazard (Sahana et al., 2020). For the agrarian country of India, agro-meteorological drought hazard projections should consider deficits in precipitation or soil moisture or both*” I agree looking only at PR is too narrow. It is indeed interesting to look at both, but as far as I understand the method, only events with both a SM-deficit and a PR-deficit are considered. Is this approach justified? I can think of cases where a SM-deficit alone is enough to cause a drought impact – I feel the hazard method does not sufficiently take into account the propagation of drought through the hydrological cycle, which involves attenuation and lag effects. The manuscript displays different results than other papers: how can it be evidenced that the presented method is better and the results are more reliable than those of other studies?

We would like to clarify that the Multivariate Standardized Drought Index (MSDI) is equally capable of capturing deficits individually in precipitation or soil moisture, or their joint deficit, considering dependence between these two variables. This is a unique advantage of MSDI (Hao and AghaKouchak, 2014) over other univariate indices. This clarification will be included in the revised manuscript. Further, we have added Supplementary Figure S5 (given below) that shows how the MSDI is capable of representing the onset, propagation and termination of drought. In this figure, considering -0.8 as the threshold for drought trigger, it seen that whenever either the SPI or the SSI falls below this threshold, MSDI covers the critical trajectory and offers a conservative characterization of drought, thereby capturing attenuation and lag effects. Finally, our country-wide drought hazard map for the baseline period from the present study (Figure 3) matches well with hazard maps developed from other multivariate indices such as the SPEI (Gupta et al., 2020), as compared to those developed from the univariate SPI (Vittal et al., 2020). This comparison with other papers will be included in the revised manuscript.

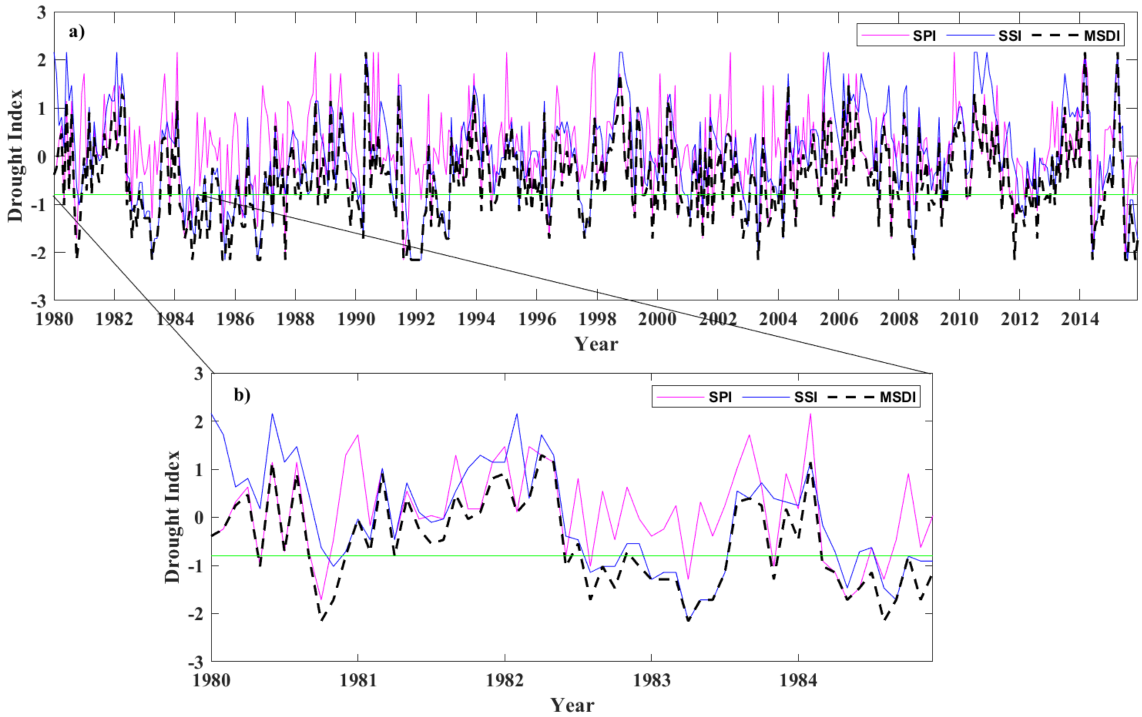

Figure S5: Time series of SPI, SSI and MSDI for Marathwada region for 1980 – 2015 (a). Time window for 1980-1984 is expanded in (b). MSDI effectively captures the drought initiation, propagation and termination by correctly characterising drought events whenever either SPI, or SSI, or both fall below a chosen threshold (green horizontal line).

b) L81: "*The above two datasets are regridded to a common spatial resolution of 0.5° lat.× 0.5° lon. and rescaled to monthly frequencies for the historical drought hazard assessment.*" Could you please explain in the supplementary material how this is done?

Re-gridding of the observed datasets to 0.5° lat.× 0.5° lon resolution is carried out using the Triangulation-based linear interpolation method (Watson and Philip, 1984). This information will be included in the Supplementary material.

Is there an increased spatial variability included by this re-gridding to counteract an averaging effect?

Further, monthly time series of spatial variation in terms of standard deviation of precipitation and soil moisture from their observed and rescaled datasets is now shown in Figure S6 (given below). It is observed that the rescaling of datasets from their parent resolution to 0.5° lat.× 0.5° lon results in no additional variability.

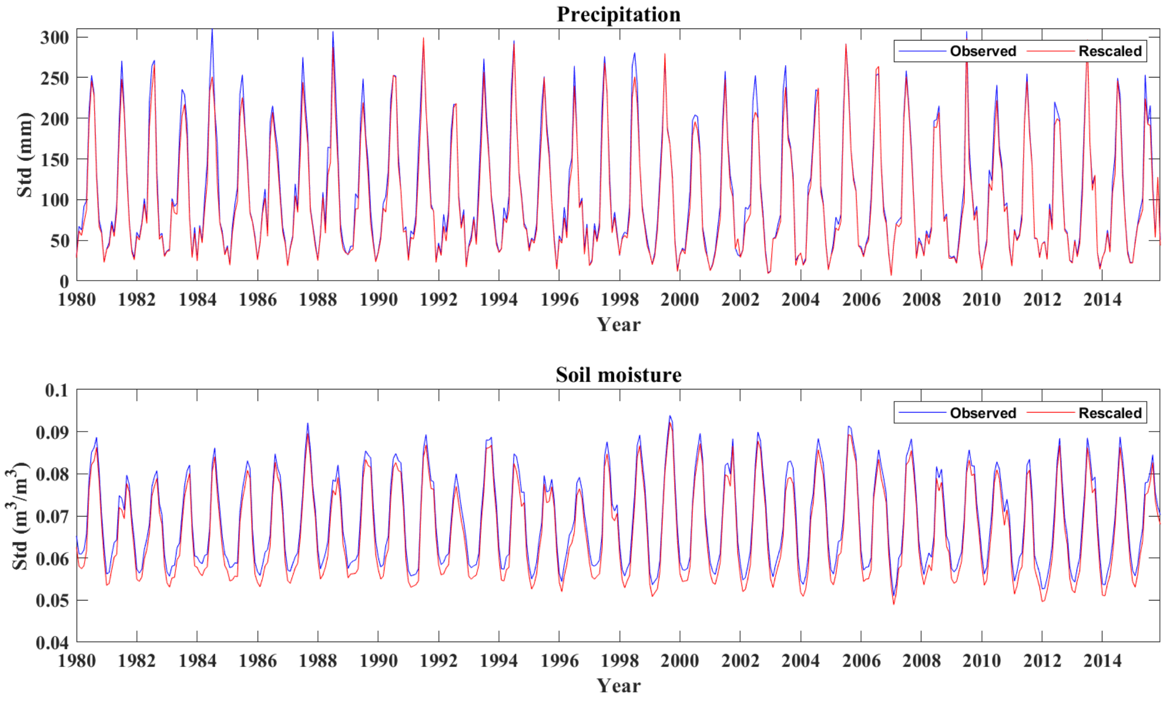

Figure S6. Standard deviation of the country-wide cumulated observed and rescaled datasets of precipitation (top panel) and soil moisture (bottom panel).

c) L75 + 83: "*The drought hazard assessment for baseline period (1980-2015) requires observed hydroclimatic variables*" + "*In order to evaluate the projected drought hazard over India, the projected precipitation and soil moisture data at a spatial resolution of 0.5° lat.× 0.5° lon. is obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (Warszawski et al., 2014). The historical (1980-2005) and projected (2006-2099) data from available GCMs namely ….*" How did you deal with the overlapping time period between observed and modelling data? Was, for example, the Delta Method (projecting the difference between modelled historic and projected onto the observed data; or; projecting to difference between observed and modelled historic onto the projected data) applied? I do not find information on how the final hazard dataset is constructed – so I suggest adding this to the supplementary material.

Here, historical (1980-2015) hazard maps are generated only from observed datasets - IMD for precipitation and MERRA for soil moisture. The projected near (2021-2060) and far (2061-2099) future hazard is obtained from the GCMs. We do not use the Delta Method or any such procedure to compare and 'correct' data from the GCMs, since the ISIMIP uses precipitation data that has already been downscaled and bias-corrected with respect to global level observed precipitation from EartH2Observe observations, WFDEI and ERA-Interim data. Further, for obtaining projections of soil moisture, ISIMIP employs the global vegetation model, LPJmL, that is capable of representing fine resolution physical processes using carbon, water and energy balance equations (Schaphoff et al., 2018) under a changed climate, thereby, offering a significant improvement over simplistic data-based approaches such as the Delta Method. This information will be included in the revised manuscript under the Section 2.1.1.

It would be nice to show with some figures how the ISIMIP data and the used observed IMD Pr and MERRA SM data compare?

Further, based on the reviewer's suggestion, we carry out an additional analysis for evaluation of ISIMIP simulations with respect to observed precipitation and soil moisture data, and present the results of such evaluation in Figure S7 in the revised manuscript (given below). The performance of all the ISIMIP models are comparable with that of the observed data, except for the soil moisture during monsoon months. The lowered soil moisture estimates from LPJmL model (ISIMIP experiments) simulations compared to the MERRA-Land soil moisture observations for the monsoon months could be due to overestimation of LPJmL's simulated runoff (Zaherpour et al., 2018).

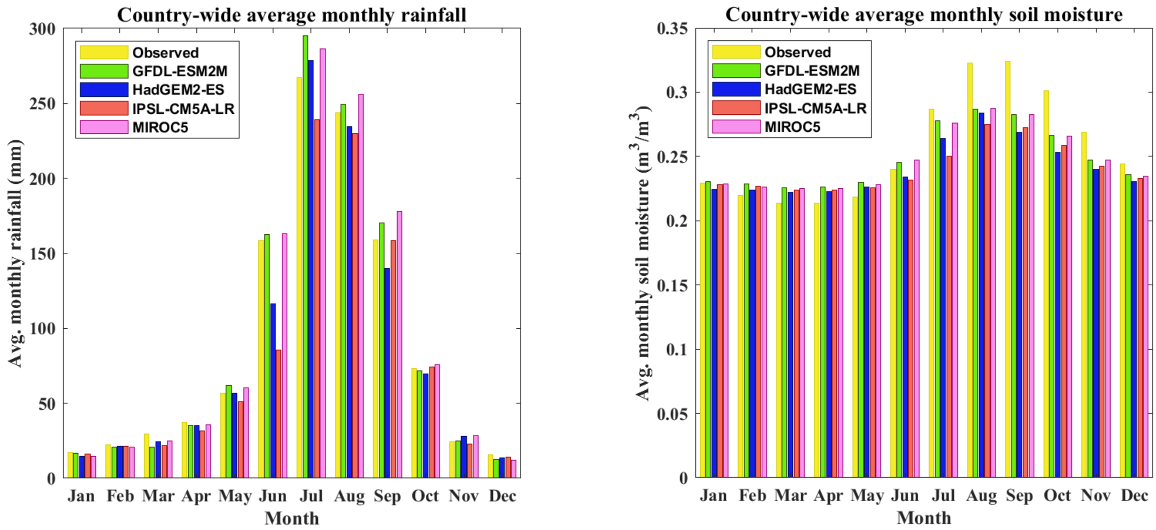

Figure S7: Observed and ISIMIP-model simulated climatology of country-wide average monthly precipitation and soil moisture for the period 1980-2005.

d) L93 "*The spatial pattern of annual mean surface soil moisture for India from the LPJmL impact model is consistent with the satellite-based Essential Climate Variable soil moisture* *product (Gu et al., 2019)*." Is this ECV similar to the MERRA Land data used? Or how is it connected to the data used?

We have performed an additional analysis to compare the LPJmL soil moisture dataset with MERRA. Therefore, we remove the statement regarding comparison of LPJmL soil moisture dataset with respect to ECV. We will refer to our Figure S7 and include the following discussion in the revised manuscript. "The performance of LPJmL simulated rootzone soil moisture (1980-2005) is comparable with that of the MERRA soil moisture (Figure S7), except for the monsoon months. The lowered soil moisture estimates from LPJmL model (ISIMIP experiments) simulations compared to the MERRA-Land soil moisture observations for the monsoon months could be due to overestimation of LPJmL's simulated runoff (Zaherpour et al., 2018).

e) L95 "*Although the simulated soil moisture data underestimates the monsoon months' soil moisture (June, Jul, Aug, Sep) during the historic period (1980-2005), we did not perform the bias correction, since we intend to capture the variability in the soil moisture rather than their magnitudes for drought index calculation*" – can you please add graphs / maps to show this in the supplementary please?

We will include Figure S7 (given in Comment #1c) in the revised Supplementary material.

f) In the Supplementary Material (drought hazard assessment and S1): Is the co-occurrence – covariance of Pr and SM modelled per ensemble member after which the mean of the DH value is calculated? Or are ensemble mean / median PR and SM used to calculate the DH value?

The ensemble mean of monthly precipitation and soil moisture from different GCMs is computed. Further, these ensemble mean monthly precipitation and soil moisture time series is used to calculate the MSDI and DHI values.

What are rk and sk in formula 2 – are they thresholds for droughts in SM and PR?

r_k and s_k denote the actual precipitation and soil moisture values for k^{th} observation. In Gringorten plotting position method, the number of occurrences (m_k) of precipitation and soil moisture pair below r_k and s_k from the whole set of observations is used to calculate empirical joint probability for k^{th} observation.

g) In the Supplementary Material (drought hazard assessment): Until "*The MSDI series at each region is categorized into four groups similar to Mckee et al. (1993).*" I could follow the description, then it becomes unclear à please add more detail (e.g., on the weighing and rating: I do not understand why nor how this is done) and please add some examples to showcase and justify the method.

We rewrote the methodology for drought hazard assessment and will be included in the main manuscript. An example on the calculation of drought hazard is also added.

"The method for 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

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

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.

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

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.

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

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

h) Supplementary “*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.”* -> which categories? And how does dividing based on occurrence probabilities differ from McKee et al? That is what they do, too, no? I do not understand why both are needed since they (intensity and probability) are intrinsically linked.

The division of MSDI series into different drought groups based on Mckee et al. (1993) gives the magnitude of drought events alone. However, hazard is a measure of magnitude of the event as well as its associated frequency. Therefore from the available MSDI series, it is required to discretize magnitude (weights) and occurrence probability (ratings) (Kim et al., 2015), though they are intrinsically linked. This will be clarified in the methods section.

2. Drought vulnerability projection considering combinations of RCP and SSP scenarios, using a list of drought vulnerability indicators that represent exposure, sensitivity and adaptive capacity components.

a) The manuscripts' understanding of vulnerability (including exposure) does not fully match the understanding of this concept by the sources cited (IPCC AR5) and does not match L36 (although it is true other authors see exposure as part of vulnerability – so I suggest look up other scholars who also include exposure as part of the vulnerability quantification). Besides, with respect to the chosen vulnerability factors, I think multiple interesting other social, economic vulnerability indicators could have been selected (e.g., Meza et al 2020 https://nhess.copernicus.org/articles/20/695/2020/)

We agree with the reviewer that our characterization of drought vulnerability is not fully consistent with the IPCC (AR5)'s recommended definition of drought risk. Though the AR5 delineates exposure as separate component of the risk, we have included exposure to be an integral part of the vulnerability following Vittal et al. (2020), since such a definition is unlikely to affect the overall conclusions of risk assessment. Further, the vulnerability indicators chosen in the present study comprises of sensitivity, exposure and adaptive capacity indicators and this information is updated in Table 1.

We also agree that an extensive vulnerability assessment encompasses other social and economic vulnerability indicators such as those used by Meza et al. (2020). 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.

Data	Relevance to drought vulnerability	Correlation with drought vulnerability	Past studies using this data	Observed					Projected	
				Source	Period	Spatial resolution	Units	Details	Source	Representative Indicator
Population density	Demographic attribute for assessing social vulnerability and exposure.	Positive	(Carrão et al., 2016; Rajsekhar et al., 2015)	NASA Socioeconomic Data and Applications Centre (SEDAC) (http://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density)	2010	1 km	person/km^2	• Population density estimates are based on the national censuses and population registers. • Given as population count by area.	Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b experiments) data archive (Warszawski et al., 2014)	Population (SSP2)
GDP	Economic welfare for assessing economic vulnerability as well as adaptive capacity.	Negative	(Carrão et al., 2016; Naumann et al., 2014; Wu et al., 2017)	(Ghosh et al., 2010)	2006	1 km	millions of dollars	• Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime imagery by NOAA to calculate total GDP (Ghosh et al., 2010)		GDP (SSP2)
Irrigation Index	Adaptive capacity component. High irrigation ratio implies high adaptive capacity and lower drought vulnerability.	Negative	(Murthy et al., 2015; Wu et al., 2017)	Web based land use statistics information system https://aps.dac.gov.in/LUS/Index.htm	2010	District	-	• 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.		Irrigation water consumption, Irrigation water withdrawal (RCP2.6 –SSP2 & RCP6.0-SSP2)
Water bodies fraction	Water resources (streams/rivers) and water infrastructure (dams/reservoirs) for assessing the physical vulnerability, and provides adaptive capacity.	Negative	(Naumann et al., 2014)	Bhuvan-Indian Geo Platform	2010	3'	-	• Advanced Wide Field Sensor (AWiFS) satellite imagery is used by NRSC to extract the water bodies fraction.		Surface runoff, Total runoff, Total water storage (RCP2.6 – SSP2 & RCP6.0-SSP2)
Groundwater	Adaptive capacity component to cope with drought.	Negative	(Pandey et al., 2010)	Dynamic Ground Water Resources of India, Central Ground Water Board Ministry of Water Resources, Report on July 2011, (CGWB, 2014)	2011	District	ham	• 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.		Groundwater runoff, Total water storage (RCP2.6 –SSP2 & RCP6.0-SSP2)
Land Use Land Cover (LULC)	Accounts for social vulnerability to drought due to exposure.	Positive	(Pandey et al., 2010; Thomas et al., 2016)	The USGS Land Cover Institute (LCI) (https://landcover.usgs.gov/global_climatology.php)	2001-2010	0.5 km	-	• 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.	NASA Earthdata from ORNL DAAC (Chini et al., 2014) (https://doi.org/10.3334/ORNLDAAC/1248)	Fractional Land Use Land Cover data (RCP2.6 & RCP6.0)
Digital Elevation Model (DEM)	Spare time for water retention bestows higher adaptive capacity in flat slope parts. Accounts for physical vulnerability to drought.	Positive	(Ekrami et al., 2016; Pandey et al., 2010)	SRTM 90 m Digital Elevation Database v4.1 (http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1#download)	2007	90 m	m	• NASA Shuttle Radar Topography Mission elevation data derived from interferometric techniques.	Constant (same as observed)	
Soil Type	Water holding capacity of soil based on the textural properties. Accounts for social vulnerability to drought due to exposure.	Positive	(Pandey et al., 2010; Thomas et al., 2016)	FAO Harmonized World Soil Database (HWSD) (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/)	2003	1 km	-	• 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.		

b) Table 1: I do not always follow the reasoning regarding the relevance (I would not say population density and land use cover are proxies for social vulnerability) but more importantly: I would like to see some more information about how these indices are calculated (population density is pop sum / area; but how is the water bodies fraction calculated, or the irrigation index? How does the water holding capacity positively influence the vulnerability?).

The drought vulnerability indicators chosen in this study, their sources, spatial and temporal distribution, units, method for data generation, relevance to the drought vulnerability, correlation with drought vulnerability, and previous studies who have employed such data for regional/national/global drought vulnerability studies are presented in Table S1 from Sahana et al. (2021). The population density is given as the population count by area, with its units as persons/km^2. Irrigation index is the ratio of total irrigated area to the total cropped area. Further, soil textural properties range from clayey to loamy, with clayey soils having higher water holding capacity compared to loamy soils. Hence loamy soils are more vulnerable to drought compared to clayey soils. Also, weightages for different categories of soil texture is presented in Table S2. All the above information is now updated in Table 1.

Besides, I see different sources used to the observed versus projected situation: how is consistency ensured?

Drought vulnerability indicators such as population density and GDP for the year 2010 from SSP2 pathway are comparable with their respective observed dataset, with small/negligible difference between the observed and SSP-simulated datasets (Figure S8). Further, drought vulnerability indicators such as groundwater availability, irrigation index and waterbody fraction for the projected period are not directly available. Hence, these indicators are proxied by their representative indicators (Table 1) using multiple linear regression (MLR). Consequently, irrigation ratio, groundwater availability and water body fraction for the projected period are derived based on relationships between them and the representative variables in the baseline period, and therefore consistency is ensured. The Land Use Harmonization (LUH) (Chini et al., 2014) dataset provides the fractional land use classes for the time period 1500-2100. The historical maps of crop and pasture data from HYDE 3.1 (Hurtt et al., 2011), and estimates of historical national wood harvest and of shifting cultivation are used as input for 1500-2005. Further, the projections of LULC for 2005-2100 are based on the Integrated Assessment Model (IAM) implementations of the RCPs. Each IAM for different RCPs are used as input to the Earth System Models (ESMs) for future carbon-climate projections. Therefore, LULC scenarios are based on RCPs. LUH is a credible dataset for LULC projection and has been previously used for drought risk projection in South-Asian region (Chou et al., 2019). Further, LULC projections can also be derived based on the land use models, using past LULC data and socio-economic factors driving the land use change. However, development of such models at country scale is beyond the scope of the present study. The above discussion will be included in the supplementary section.

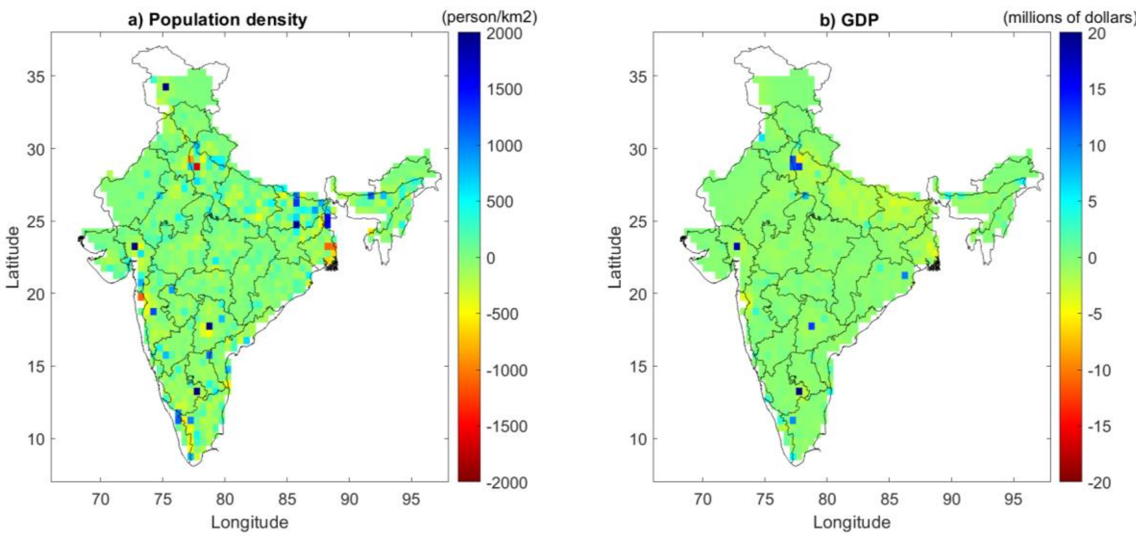

Figure S8. Difference between the observed and SSP2 pathway dataset at the year 2010 for a) Population density and b) GDP.

c) In the supplementary material: Please repeat the weights of Thomas and Sahana for the vulnerability indicators

Done.

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

3. Drought risk projection integrating hazard and drought vulnerability information.

a) In general, there is no validation of the presented risk approach since the past risk analysis (1980-2015) is not compared with observed risk / reported impacts. This should be done in order to give credibility to the method, or – if impossible – be addressed in the discussion section.

Validation of the drought risk map for the baseline period (1980-2015) has been carried out by Sahana et al. (2021) (see Suppl. Figure S3 of Sahana et al., 2021), based on the disaster data in terms of number of people affected. It is noted that parts of Rajasthan, Madhya Pradesh, Maharashtra, Orissa and Tamil Nadu, Kerala, Chattisgarh, Haryana, Himachal Pradesh, Chandigarh, Assam and Nagaland that are under moderate to severe drought risk category, have experienced moderate to worst drought disaster. The above information on validation of drought risk will be included in the revised manuscript.

b) L119 "*Drought risk values computed using Eq 1 are further standardized to obtain the Drought Risk Index (DRI).*" Can you please elaborate how this is done? Two standardized indices are multiplied so I do not see the need to standardize the result again – this introduces some loss of information?

Standardization of drought risk at each grid is carried out using

$$DRI = \frac{Rsik - Risk_{min}}{Risk_{max} - Risk_{min}} \quad \dots(16)$$

Standardization is performed such that the values are distributed between 0 and 1, so as to classify different risk categories. This information will be included in the revised manuscript.

c) The effect of climate change is taken into account in two ways: by changing vulnerability (multiple vulnerability indicators are based on average water availability) and by changing occurrence. I think this is interesting but it is a pity that social vulnerability factors, influenced by socio-economic development, are not taken into account – this might have changed the vulnerability trend hence risk trend. Would it be possible to account for this?

The population density and GDP indicators, considered in the present study, accounts for social vulnerability, and the change in these indicators are accounted for vulnerability projections. Therefore, we do not agree that our study does not take into account social vulnerability factors. However, we do 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.

d) The classification of very low to very high and transition plots are interesting but it is unclear how these classes are defined. Moreover, there are regions with a very high historic hazard that change to low hazard – this is remarkable since this is not immediately clear from the average SM - PR maps in figure S2. Can you please explain this difference?

In each of the hazard, vulnerability and risk maps, the indices representing them are classified into five categories based on equal classification scheme: 0-0.2 (very low), 0.2-0.4 (low), 0.4-0.6 (medium), 0.6-0.8 (high) and 0.8-1 (very high). In the transition matrix we compute the percentage area of the country that transitioned from one hazard/vulnerability/risk class to other. This quantifies the effect of climate change/socio-economic condition/both respectively.

From Figure 2a, S1 and S2, we see that precipitation and soil moisture for the projected period show an increasing trend. Further, it is to be noted that the hazard assessment using MSDI is based on the long term mean and variability of these drought indicators under a probabilistic analysis framework, and not necessarily the magnitudes of precipitation and soil moisture. Here we see that the projections of these indicators exhibit lower variability compared to the baseline period (Figure 2a). Therefore, it is observed that many regions undergo transition from high hazard to low hazard. This information will be updated in the revised manuscript.

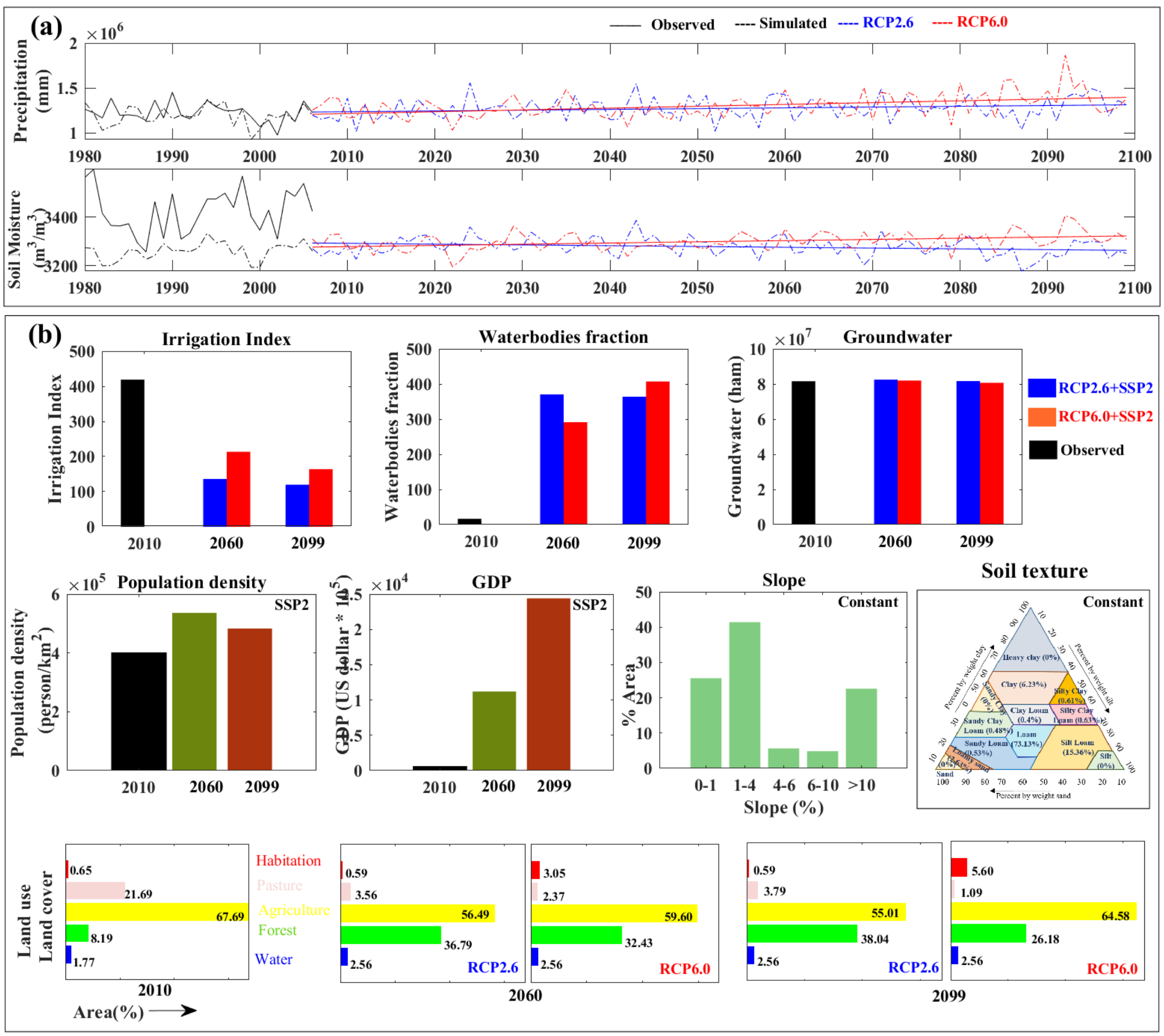

Figure 2. Datasets used for drought risk assessment. a) Projected hydro-climatic variables such as monthly precipitation and monthly soil moisture are used for drought hazard assessment. b) Projected drought vulnerability indicators such as irrigation index, water body fraction, groundwater availability, 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.

e) Fig2: I do not understand why land cover changes based on RCPs? Shouldn't this be SSP? Besides, I wonder why baseline (1980-2015) isn't shown? Now it is indicated as "2010" but that seems inconsistent with the method section.

The projections of LULC for 2005-2100 are based on the Integrated Assessment Model (IAM) implementations of the RCPs, and not based on SSPs (Chini et al., 2014). Further, in the revised manuscript, we will include a discussion on why baseline LULC time series is not shown in Figure 2, as follows. "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." For correct representation of vulnerability indicators, we will replace their time series with bar graphs for the years 2010, 2060 and 2099 (Figure 2b, see comment #3d).

4. Development of bivariate choropleth plots under future scenarios to quantify the individual roles of climate and societal changes in driving drought risk

a) This is a good way of visualising the results; but I would suggest to change the colour classes since now on e.g., the RCP6.0 near future, barely any variance is visible.

The RCP6.0 Near future results in mostly high vulnerability and low hazard regions. It is to be noted that the low variability in this scenario is due to data and not necessarily due to selected color scheme, since parts of Bihar and Telangana are distinctive with moderate vulnerability and moderate hazard. For a better comparison of the future scenarios with the baseline period, we would retain the existing bivariate color scheme.

5. Identification of regions and zones that are expected to be under worst drought risk conditions in the near and far future

a) (Make sure that in the discussion, the results are compared with papers who have a similar conception of vulnerability – or discuss the difference – because that might also be the cause of the diverging results)

We will include the following discussion in Section 3.3.1. "The drought risk estimates for the baseline period from the present study compares well with regional-scale drought risk studies in India such as those for Andhra Pradesh (Murthy et al., 2015), Bearma basin (Thomas et al., 2016), Maharashtra (Swami and Parthasarathy, 2021). However, the water availability projections for India by Koutroulis et al. (2019) show decreasing drought risk with time, as opposed to the increasing drought risk from the present study. The choice of climate change scenarios and climate models by Koutroulis et al. (2019) could be a possible reason for such difference."

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