32nd International Conference of Agricultural Economists
2-7 August 2024 I New Delhi I India

Towards Sustainable Agri-Food Systems: Assessment of Climate Risk and its impact on Rice Productivity for Indian States

Nishi Yadav[1]

1: Indian Institute of Technology, Guwahati.

Corresponding author email: nishi_yadav@iitg.ac.in

Abstract

Sustainability is threatened by the changing climate, especially in the agricultural sector. The consequences of this changing climate can have strong repercussions on food security by affecting productivity through hazards like droughts and floods. The study employs a climate risk assessment, considering hazards, exposure, and vulnerability, aligning with SDG 13's goals. The study creates a climate risk index for 26 major states of India which correspond to different agro-climatic zones. The study also explores the relationship between climate risk and rice productivity in Indian states using a panel data regression analysis. The results show that states such as Assam, Arunachal Pradesh, Himachal Pradesh, and Tamil Nadu are most susceptible to climate risks. Whereas states such as Bihar, Uttarakhand and Jharkhand are least susceptible to climate risk. The regression analysis results show a negative relationship between climate risk and rice yield, indicating that an increase in climate risk can severely affect rice productivity and India's food security. Since India is the second largest exporter of rice, climate risk can have global consequences. The results indicate immediate region-specific adaptation measures and advocate for sustainable mitigation practices.

JEL Codes: Q01, Q22, Q540, C33.

1. Introduction

Sustainability is defined as the ability of the present generation to meet its own needs without compromising those of future generations (UN, 1987). It is considered critical, particularly in the context of agriculture. Achieving sustainability in agriculture involves ensuring food security while safeguarding non-renewable resources and maintaining a consistent food supply over extended periods (Pretty, 2008). Climate change stands out as a significant factor that can impact sustainability. It affects agricultural productivity, heightens the risk of hazards such as droughts and floods, increases susceptibility to pests and diseases, increases food wastage, and degrades soil quality all of which simultaneously hampers the food security of a nation.

Even with these challenges, farmers employ adaptation practices to mitigate the effects of climate change. These practices include adjusting irrigation in response to reduced rainfall, modifying sowing and harvesting schedules based on anticipated climatic shifts, exploring alternative job opportunities, and utilizing additional fertilizers, among other mitigation strategies (Raghuvanshi et al., 2018; Tripathi & Mishra, 2017; Kumar and Sidana, 2019). However, existing studies analyzing the impacts of climate change often overlook these mitigation methods. Consequently, there is a need for a more comprehensive approach to analyze risks arising from climate change to achieve sustainable agri-food systems. Climate risk assessment is one such tool that allows us to incorporate both the adaptation and mitigation methods implemented by governments and individuals affected by climate change. Climate risk is represented as the probability or likelihood of hazardous events occurring or trends multiplied by the impacts of these events (IPCC, 2014). It is dynamic and depends entirely on socio-economic conditions and mitigation methods (Helbeing, 2013). According to the IPCC (2014), risk arises out of climate-related hazards in the presence of exposure and vulnerability of humans and ecological systems.

Therefore, climate risk comprises three aspects, i.e., hazards, exposure, and vulnerability (IPCC, 2012). A few studies have theoretically assessed climate risk (Simpson et al., 2021; Adger et al., 2018). These assessments include identifying and planning a theoretical climate risk assessment framework. The limitation of such frameworks is that they are too complex and may not always have the supported data needed to carry out the research.

Risk assessment is the qualitative or quantitative estimation of risks. In 2012, Lavell et al. (2012) stated that risk assessment is only the beginning of an efficient framework for reducing risk occurring due to climate change. Risk assessment has been carried out for different regions such as Italy (Mysiak et al., 2018) Europe (Greiving et al., 2013), China (Li et al., 2021), Ghana (Antwi-Agyei et al., 2012), Bangladesh (Haque et al., 2021), South Asia (Amarnath et al., 2017). Climate risk assessment has been carried out by international agencies and national governments (Greiving et al., 2013; King et al., 2013; Mohanty & Wadhawan, 2021). The Climate Risk Index by Germanwatch (2021) lists the countries facing high risks of climate change. However, it only considers macro indicators. It focuses on extreme weather events such as storms, floods, and heatwaves, which fail to account for the micro-level socio-economic factors (Eckstien et al., 2021).

Climate change poses a significant risk to crop yields in India, further exacerbating the challenges faced by the agricultural sector (IPCC, 2022). The unpredictable climate patterns and extreme events directly impact crop production, affecting both the quantity and quality of a crop as temperature and moisture-sensitive as rice. Rice is the primary staple food for over half of India's population, providing the energy and nutrition required for their daily sustenance. It is the second-largest producer of rice globally, after China, and contributes significantly to food security in the country (Krishniah and Rani, 2000). The abundance of literature is a testament to this fact (Baig et al., 2021; Guntukula, 2019; Singh and Sharma, 2018; Sarker et al., 2012**;** Aufhammer et al., 2012). However, the impact of climate risk on rice yield has been scarcely studied. Understanding the specific risks associated with climate change on a regional level is crucial for developing effective adaptation strategies and managing food security across regions.

A climate risk assessment and its impact on rice yield helps identify potential threats to crop production, enabling farmers, policymakers, and researchers to implement strategies that enhance the resilience of agri-food systems which aligns with the goals of achieving SDG 2 and SDG 13 directly (UN, 2015). Specifically, this initiative contributes significantly to SDG 2.3 (doubling agricultural productivity) and 2.4 (sustainable food production and resilient agricultural practices) of SDG2 (Zero Hunger), by enhancing food security through the identification and mitigation of climate-related threats to agricultural productivity. Furthermore, it also aligns with SDG 13.1 (to strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries), 13.2 (to integrate climate change measures into national policies and planning), 13.3 (improving awareness and capacity on climate change mitigation, adaptation, impact reduction, and early warning) of SDG 13 (Climate Action), as it actively engages in assessing and responding to climate risks within the agricultural sector, promoting resilience and adaptive practices. This approach supports the broader agenda of fostering environmentally responsible and resilient food systems, thus contributing to the interconnected goals of the 2030 agenda for Sustainable Development and is a step towards building sustainable agri-food systems. In addition, the study advocates for the efficient use of resources, reduction of waste, and adoption of environmentally friendly practices, aligning with the objectives of SDG 12 to ensure sustainable consumption and production patterns.

Therefore, given the above, this study aims to:

I. Quantify climate risk for the Indian states by forming a climate risk index and calculating sub-indices such as Hazard, Exposure, and Vulnerability.

II. Study the impact of climate risk on rice yield across the Indian states.

2. Data sources and Methodology

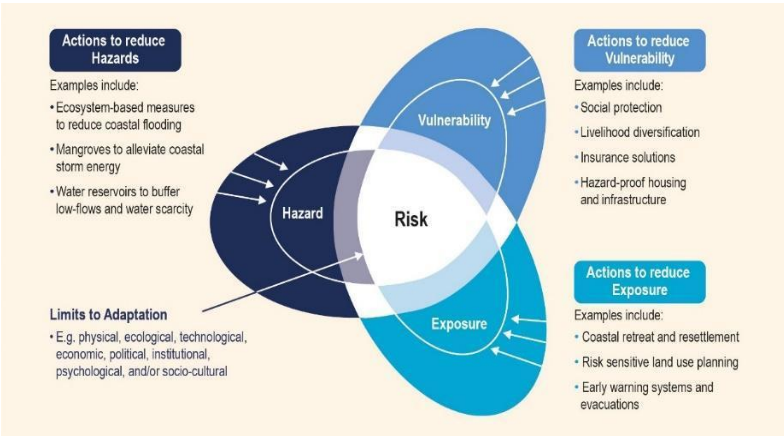
2.1. Data Sources

The current study uses secondary data. The data is extracted from various government sources. Daily Rainfall data was extracted from the IMD website. The data for indicators such as the percentage of people dependent on agriculture, net sown area, livestock per capita, agricultural credit availed, and average size of landholding was collected from ICRISAT state-level database which was collected from government and agricultural censuses. The data for forest area was taken from the website of Forest Survey of India, state of forest reports. The data for illiterate landholders, machinery used for agriculture, marginal and small landholders, and a few missing values of other indicators was extracted from Input survey conducted by the Agricultural Ministry of India. The data for fertilizers was extracted from the Indiastat database. The data for rice yield was extracted from the Handbook of Statistics on Indian States, RBI. The time period for the index was decided to be 2001-2015, due to three reasons. First, the last agricultural census was conducted for the 2015-2016 period. Second, for variables such as livestock, credit availed consistent data before 2000 could not be found. Third, in the year 2000 three states were formed, Chhattisgarh from Madhya Pradesh, Uttrakhand from Uttar Pradesh and Jharkhand from Bihar, which made it important to include them in the study. Therefore, the time period was decided to be 2001-2015, the index can be renewed when new data becomes available.

2.2. Methodology for Climate Risk Assessment

The methodology for the study is adapted from the IPCC Risk Assessment framework, which expresses risk as an amalgam of hazard, exposure, and vulnerability (IPCC, 2014). To study climate risk, a climate risk index is developed by combining three risk indices namely the hazard index, exposure index, and vulnerability index.

Fig1: IPCC risk framework (IPCC, 2014)



To calculate the Hazard Index a different methodology has been applied from the Exposure and Vulnerability indices. In the present study, we assess the drought hazard, as the majority of India is affected by drought. According to the IMD climate atlas around 87% of the Indian districts are suffering from extreme drought situations. Standardized precipitation index (SPI) is a popular tool to monitor and measure drought hazard across all regions. SPI is highly recommended by World Meteorological Organisation for drought monitoring across the globe and has been used in the present study to measure drought hazards (WMO, 2012).

The SPI was developed to incorporate different timescales in the analysis of water availability and water use (McKee et al, 1993). The different timescales reflect the impacts of drought on different water resources required by decision-makers. For instance, the 1 or 2-month SPI is useful for meteorological drought, while the 1 to 6-month SPI is useful for agricultural drought. The 6-month SPI has been used in the present study as a 6-month SPI can be useful in showing the precipitation over distinct seasons and may also provide information about anomalous stream flows and reservoir levels (EDO, 2020). Elevated SPI values signify precipitation levels above the median, while lower values indicate precipitation below the median. Drought conditions are present when the SPI is -1.0 or lower, and these conditions cease when the value turns positive. We used IMD daily gridded data for 32 years from 1990-2021 to calculate the SPI for the states of India (Pai et al., 2015). To do so first the precipitation data from IMD is extracted and then fitted to the shape files of the Indian states using ArcGIS software. The monthly rainfall is then extracted and entered into the SPI software generated by the National Drought Mitigation Center (NDMC). The results are produced in the form of monthly SPI values for the zones based on the scale given in Table 1.

Table 1: SPI Classification

SPI Value	***Classification***
≥ 2.0	Extremely Wet
1.5 to 1.99	Severely Wet
1.0 to 1.49	Moderately Wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2 and less	Extremely Dry

Source: WMO, SPI user guide, 2012

In this study, drought hazard is measured as the likelihood of drought occurring as drought manifests when there is a substantial decline in precipitation levels compared to the long-term average. Therefore, our focus is primarily directed towards assessing the occurrences of moderately, severely and extremely dry events, since these are indicative of drought conditions. They are also given weights according to the severity of the event. Therefore, moderately dry events are given the weight of 1, severely dry events are given the weight of 2 and extremely dry events are given the weight of 3 (Shahid and Behrawan, 2008). The probability of a drought hazard in a particular state is determined by multiplying the total occurrences of moderately dry, severely dry, and extremely dry events by their respective weights and then dividing this sum by the total number of events in a year i.e. 12.

$$P(D) = \frac{1\times(Moderately\ dry)+2\times(Severely\ dry)+3\times(Extremely\ dry)}{12} \quad \ldots(1)$$

The final hazard index will have zero probability of drought occurring in a state in any particular year of the 15 year study period. So the probability for the same has been taken as 0.0001 when taking geometric mean for Climate Risk Index.

The methodology for Exposure and Vulnerability indices entails forming a composite index based on the OECD Handbook of constructing Composite Indicators (Nardo et al., 2008). The following steps were followed:

- Deciding indicators

For this present study, we considered indicators for the agricultural sector that may be at risk of exposure to climatic hazards to measure exposure. Therefore, net cropped area, roads per capita, and population dependent on agriculture as the indicators for exposure index.

To assess the vulnerability of a natural or socio-economic system, two key factors are taken into account: sensitivity (S) and lack of adaptive capacity (AC). Sensitivity refers to how susceptible a system is to harm from the initial impact of a hazard or stressor, while adaptive capacity is the system's ability to successfully respond to climate change and variability (IPCC, 2014). Higher sensitivity leads to greater vulnerability and lower adaptive capacity results in increased vulnerability. Therefore, to assess the vulnerability of the agricultural sector the indicators decided were gross irrigated area (AC), area under horticulture (AC), livestock per capita (AC), women in agriculture (AC), credit availability (AC), land under forest area (AC), number of small and marginal farmers (S) and number of illiterate farmers(S) (Dasgupta et al., 2019).

- <u>Filling missing values</u>

Data availability was a hindrance to the study. It was found that the data was not available for many indicators for a few years. To find a solution to this problem the missing values for the indicators were completed using the linear interpolation method.

Linear interpolation is a commonly used method for estimating values between two known data points. It assumes a linear relationship between the data points and uses this relationship to estimate intermediate values. Linear interpolation is used because it is straightforward to implement and can provide reasonably accurate estimates when the data points are evenly spaced and the relationship between them is linear.

- <u>Normalizing indicators</u>

As different indicators have different units of measure, with varying scales, therefore, before any data aggregation, it is essential to normalize our data. This makes the data comparable across indicators and can be easily aggregated. For this purpose, we use the Min-Max method of normalization. This method transforms the variables into a range of [0,1].

For indicators that are positively related to climate risk i.e., the following formula is used:

$$\text{Normalized value} = \frac{\textit{Actual indicator value} - \textit{Minimum indicator value}}{\textit{Maximum indicator value} - \textit{Minimum indicator value}} \qquad \ldots(2)$$

For indicators that are negatively related to climate risk, i.e., the following formula is used:

$$\text{Normalized value} = \frac{\textit{Maximum indicator value} - \textit{Actual indicator value}}{\textit{Maximum indicator value} - \textit{Minimum indicator value}} \qquad \ldots(3)$$

- <u>Determining weights</u>

Weights were determined using Principal Component Analysis. However, the index ranking and trends for all the states did not reflect any change after accounting for weights in the study.

The only change was seen in the values of the indices, which decreased in its absolute value and therefore to keep easy readability of the index it was decided to keep equal weights for all the indicators.

- <u>Aggregating the indicators to find Exposure and Vulnerability indices</u>

Arithmetic mean is taken to calculate both exposure and vulnerability indices after calculating normalized values.

- <u>Calculating the Climate Risk Index</u>

To form the climate risk index, geometric mean of all three indices has been taken. The geometric mean is a suitable method when dealing with indices that have a multiplicative relationship, such as in the case of climate risk, where the overall risk is a function of the interaction between hazard, vulnerability, and exposure. By taking the geometric mean of the three indices, we can obtain an overall index that captures this relationship. The geometric mean approach assumes that the three indices are equally important.

$$\text{Climate risk index} = \sqrt[3]{\text{hazard index x vulnerability index x exposure index}} \qquad \ldots(4)$$

2.3.**Methodology for the impact of Climate risk on Rice yield**

Diagnostic Tests: The first step in an analysis is to carry out a few diagnostic tests to make sure that the model follows the basic assumptions of linear regression. Firstly, we carried out the Hausman test to find out which model was more suitable for our panel data, and fixed effects were chosen after the test. Secondly, the Modified Wald test for groupwise heteroscedasticity was carried out. Since a presence of heteroscedasticity was found in the model we have used robust standard errors in the fixed effects model. Woolridge test was performed to detect the presence of autocorrelation. Serial autocorrelation is found in the model; robust standard errors are used for the same. Lastly, the Levin–Lin–Chu unit-root test was used to check for stationarity (Tan, 2021). Mechanisation per capita was found to be non-stationary and for that the first difference of mechanisation per capita is used as the indicator

Panel data regression using a fixed effects model was carried out using Stata. Rice yield was taken as the dependent variable and climate risk as the independent variable. Further, mechanization, fertilizer use, and the average size of landholdings were taken as the control variables.

Model Specification:

$$Yield_{it}= \beta 0+\beta 1CR_{it}+ \beta 2\ Mech_{it}+ \beta 3AOLS_{it}+ \beta 4Fert_{it}+\alpha_i+u_{it} \qquad \ldots(5)$$

Equation 5 represents the basic structure of the model. Where, $Yield_{it}$: represents the rice yield in state i at time t. CR_{it} is the climate risk in state i at time t, reflecting climatic conditions and socioeconomic conditions. $Mech_{it}$ is the level of mechanization in state i at time t, indicating the degree of agricultural machinery usage. $AOLS_{it}$ stands for the average size of operational landholdings in state i at time t. $Fert_{it}$ represents per-hectare fertilizer consumption in state i at time t. u_{it} is the error term, capturing unexplained variations in rice yield. The model aims to assess how variations in climate risk, mechanization, landholding size, and fertilizer consumption impact rice yield in the Indian context.

There was an endogeneity issue in the data set and fertilizer per hectare was found to be an endogenous variable. Therefore, to solve for endogeneity, lag for fertilizer per hectare has been taken as an instrumental variable. We have used the two stage least squares within estimator model to account for the endogeneity in our model. Where two simultaneous equations are used to account for endogeneity.

The first stage equation becomes:

$$x_{it}=\beta 1x_{it-1}+\beta 2w_{it}+ci+v_{it} \qquad \ldots(6)$$

In equation 6, $\beta 1$ represents the coefficient of interest on the lagged value, x_{it-1} used as an instrument. $\beta 2$ represents the coefficients of other exogenous variables w_{it}. v_{it} is the error term in the first stage regression.

The second stage regression equation therefore is:

$$y_{it}=\beta 1x_{it}+\beta 2w_{it}+c_i+u_{it} \qquad \ldots(7)$$

In equation 7, $\beta 1$ is the coefficient of interest measuring the effect of x_{it} on y_{it} after addressing endogeneity using the instrumental variable approach. $\beta 2$ represents the coefficients of other exogenous variables w_{it}. u_{it} is the error term in the second stage regression.

For the current study the 2 stage-stage linear equations are:

$$NPK_{it}= \beta 1NPK_{it-1}+ \beta 2\text{climate risk}_{it}+ \beta 3ASoL_{it}+ \beta 4\text{mechanization}_{it}+c_i+v_{it} \qquad \ldots \quad (8)$$

$$\text{Rice Yield}_{it}=\beta 1\text{climate risk}_{it}+\beta 2NPK_{it}+ \beta 3\text{mechanization}_{it}+ \beta 4ASoL_{it}+c_i+u_{it} \qquad \ldots \quad (9)$$

In equation 8 and 9, Climate risk is the climate risk index value in state i and year t. It is measured collectively by hazard, exposure and vulnerability indices and it takes a value between 0 and 1. NPK is the fertilizer per hectare in state i and year t. NPK_{it-1} represents the instrumental variable, which is the lag of fertilizer consumption per hectare. $ASoL_{it}$ is the average farm size in state i and year t. $\text{Mechanisation}_{it}$ is mechanisation per hectare in state i and year t. C_i represents state specific fixed effects. And finally yield_{it} is the yield of particular crop in state i and year t.

3. Results and Discussion

3.1. Hazard Index

The hazard index shows the probability of a drought hazard occurring during the study period for the Indian states using historical precipitation patterns. According to the analyses, Arunachal Pradesh (62) faces the highest number of dry or drought events during the 30-year period followed by Meghalaya (57). The least number of drought events are seen in Gujarat (20), refer to Figure:2. States exhibiting a high likelihood of drought hazards demand prioritized implementation of disaster risk reduction strategies. In these regions, proactive measures such as water conservation and harvesting practices should be promptly introduced. Furthermore, specific adaptation measures tailored to the unique characteristics of each region must be executed. For instance, in states with a higher probability of drought, the focus could be on the development of resilient and water-efficient crop varieties, investment in water storage infrastructure, and promotion of community-led water management initiatives. This targeted approach ensures that mitigation efforts address the specific challenges posed by drought in each state, contributing to a more effective and region-specific disaster response.

Figure 2: The number of dry events across all the states for the 30 year period.

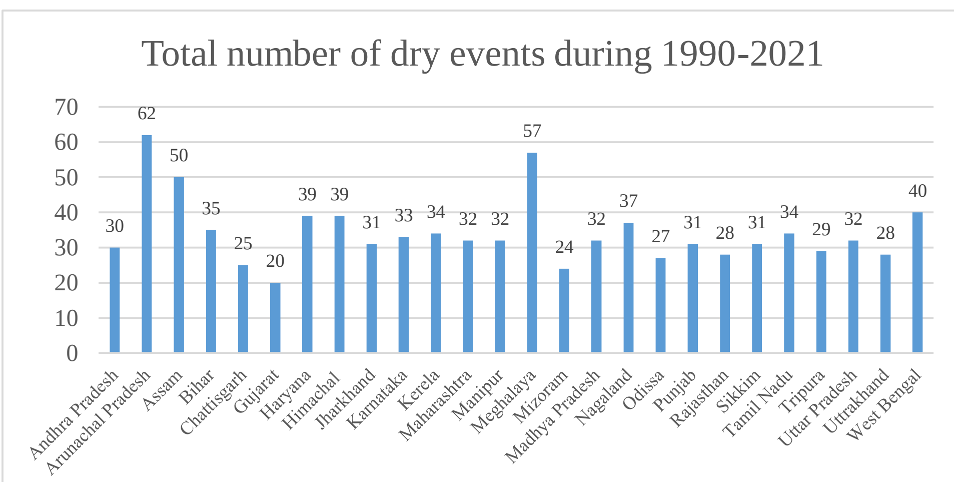


Table 2: Annual Drought Hazard Index for the Indian States:

Hazard Index	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Andhra Pradesh	0.333	1.167	0.583	0.083	0.167	0.000	0.000	0.000	0.750	0.000	0.083	0.083	0.000	0.333	0.167
Arunachal Pradesh	0.500	0.000	0.000	0.000	0.000	1.333	0.667	0.750	1.250	0.083	1.000	1.833	0.583	0.000	0.000
Assam	0.167	0.000	0.000	0.000	0.000	1.167	0.167	0.250	1.167	0.083	1.333	1.083	1.250	0.500	0.250
Bihar	0.333	0.000	0.000	0.000	0.500	0.333	0.000	0.000	1.250	0.500	0.083	0.083	0.250	0.000	0.333
Chattisgarh	0.500	1.000	0.000	0.083	0.000	0.083	0.000	0.000	1.333	0.250	0.000	0.000	0.000	0.000	0.417
Gujarat	0.333	0.917	0.000	0.250	0.000	0.000	0.000	0.000	0.000	0.167	0.000	0.667	0.000	0.167	0.000
Haryana	0.500	1.167	0.000	0.167	0.000	0.333	0.250	0.333	0.417	0.667	0.000	1.000	0.000	0.750	0.000
Himachal	0.917	1.000	1.333	1.417	0.000	0.000	0.000	0.000	0.500	0.083	0.167	0.417	0.000	0.083	0.000
Jharkhand	0.083	0.000	0.000	0.000	0.750	0.083	0.000	0.083	1.167	1.667	0.083	0.250	0.000	0.000	0.000
Karnataka	0.750	1.583	1.917	0.250	0.167	0.000	0.083	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.250
Kerela	0.167	0.917	1.000	0.333	0.000	0.000	0.000	0.000	0.250	0.000	0.000	0.750	0.333	0.000	0.167
Maharashtra	0.417	0.250	0.083	0.167	0.000	0.000	0.000	0.500	0.417	0.000	0.083	0.833	0.000	0.333	1.000
Manipur	0.250	0.000	0.583	0.000	0.000	0.250	0.250	0.000	0.083	0.000	0.000	0.250	0.667	1.000	0.417
Meghalaya	0.083	0.000	0.000	0.000	0.000	1.500	0.583	0.500	1.750	0.333	1.583	1.417	0.167	0.250	0.167
Mizoram	0.000	0.000	0.000	0.000	0.083	0.333	0.333	0.250	0.000	0.000	0.000	0.417	1.000	0.917	0.083
Madhya Pradesh	0.667	0.750	0.000	0.083	0.000	0.083	0.833	0.250	0.417	0.333	0.083	0.083	0.000	0.333	0.000
Nagaland	0.250	0.250	0.000	0.000	0.000	0.667	0.250	0.083	0.500	0.000	0.000	0.667	0.833	0.833	0.417
Odissa	0.583	1.000	0.083	0.083	0.000	0.000	0.000	0.000	0.833	0.500	0.000	0.167	0.000	0.000	0.333
Punjab	0.750	1.417	0.000	1.167	0.000	0.000	0.000	0.083	0.000	0.750	0.000	0.000	0.000	0.917	0.000
Rajasthan	0.667	1.750	0.083	0.500	0.000	0.000	0.000	0.167	0.667	0.333	0.000	0.333	0.000	0.000	0.000
Sikkim	0.500	0.000	0.000	1.000	0.500	0.167	0.000	0.000	0.000	0.000	0.917	0.167	0.000	0.167	0.250
Tamil Nadu	0.583	2.250	2.333	1.083	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.000
Tripura	0.000	0.000	0.083	0.000	0.000	0.500	0.250	1.000	0.000	0.000	0.083	0.583	0.833	0.667	0.250
Uttar Pradesh	0.250	0.583	0.000	0.000	0.000	0.500	0.167	0.333	1.000	0.167	0.000	0.083	0.000	0.917	1.000
Uttrakhand	0.000	0.000	0.000	0.167	0.000	0.083	0.083	0.083	2.250	0.250	0.000	0.833	0.000	0.000	0.417
West Bengal	0.167	0.000	0.000	0.000	0.083	0.333	0.000	0.083	1.000	0.250	0.250	1.917	0.333	0.417	0.250

From the above results we see that the hazard index for drought events shows considerable variation over the years within each state. Some years have high index values, indicating more severe drought conditions, while others have low or zero values. Certain years stand out as having particularly high drought hazard index values across multiple states. For example, 2001, 2006 and 2012 appear to be years with significant drought conditions in several states. Tamil Nadu and Himachal Pradesh has consistently high drought hazard index values in the early years (2001-2004). Meghalaya, Arunachal Pradesh and Assam show higher probability to drought in the later years of the study period. There may be regional patterns in the drought data, where neighboring states experience similar trends. For example, states in southern India such as Tamil Nadu, Karnataka, Kerala, and Andhra Pradesh often show high indices around the same years. Many states exhibit significant year-to-year fluctuations in their drought hazard indices. This indicates that drought conditions are not consistent annually and can vary dramatically from one year to the next.

3.2.Exposure Index

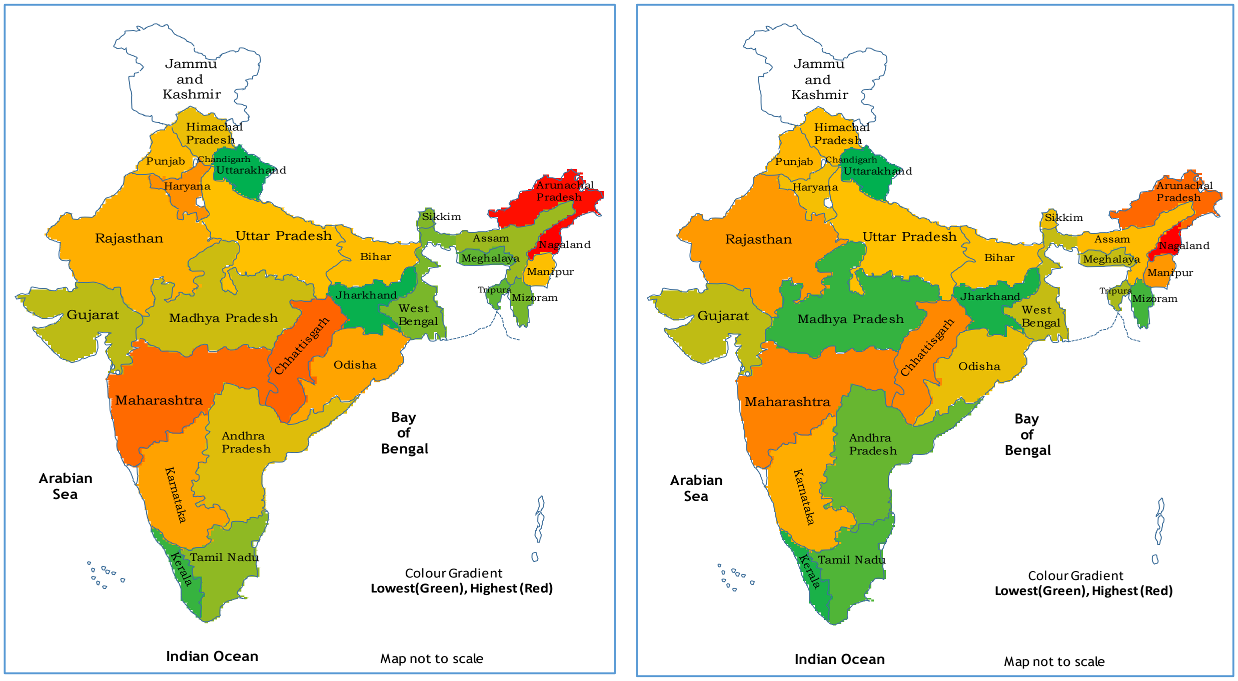
The Exposure Index for different Indian states provides an assessment of their susceptibility to climate risks and hazards in the agriculture sector, with higher values indicating increased exposure of the population over multiple years. States like Nagaland, Arunachal Pradesh, and Chhattisgarh consistently exhibit relatively higher exposure, suggesting elevated susceptibility to climate risks. In contrast, states like Uttarakhand, Jharkhand, and Kerala consistently display lower exposure, indicating potentially better resilience to climatic challenges, see Table 4.

Table 3: Exposure index for the Indian states

Exposure Index	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Andhra Pradesh	0.441	0.431	0.436	0.427	0.434	0.424	0.435	0.431	0.416	0.432	0.430	0.420	0.347	0.344	0.330
Arunachal Pradesh	0.568	0.564	0.561	0.558	0.555	0.553	0.550	0.532	0.526	0.516	0.405	0.540	0.509	0.507	0.535
Assam	0.390	0.407	0.437	0.423	0.435	0.440	0.455	0.435	0.431	0.427	0.448	0.427	0.452	0.456	0.434
Bihar	0.468	0.473	0.466	0.465	0.463	0.467	0.466	0.459	0.448	0.443	0.449	0.450	0.444	0.444	0.427
Chattisgarh	0.519	0.543	0.543	0.528	0.533	0.533	0.539	0.530	0.529	0.528	0.510	0.508	0.513	0.513	0.497
Gujarat	0.415	0.416	0.420	0.405	0.407	0.407	0.413	0.413	0.411	0.408	0.408	0.398	0.401	0.402	0.387
Haryana	0.493	0.482	0.481	0.470	0.471	0.466	0.468	0.464	0.458	0.454	0.450	0.438	0.433	0.436	0.422
Himachal	0.451	0.461	0.460	0.409	0.416	0.459	0.475	0.460	0.460	0.458	0.459	0.445	0.453	0.452	0.432
Jharkhand	0.276	0.286	0.281	0.302	0.287	0.279	0.281	0.281	0.268	0.260	0.269	0.278	0.277	0.277	0.279
Karnataka	0.483	0.488	0.483	0.485	0.487	0.492	0.502	0.486	0.487	0.485	0.474	0.455	0.461	0.463	0.451
Kerela	0.312	0.320	0.322	0.319	0.334	0.337	0.349	0.327	0.323	0.319	0.320	0.288	0.297	0.296	0.280
Maharashtra	0.515	0.515	0.518	0.508	0.510	0.508	0.511	0.508	0.507	0.509	0.509	0.507	0.521	0.521	0.504
Manipur	0.464	0.473	0.470	0.448	0.449	0.450	0.453	0.481	0.480	0.478	0.473	0.491	0.498	0.496	0.479
Meghalaya	0.343	0.345	0.345	0.366	0.371	0.370	0.381	0.359	0.360	0.381	0.379	0.360	0.383	0.397	0.390
Mizoram	0.361	0.356	0.349	0.328	0.324	0.318	0.322	0.318	0.315	0.309	0.303	0.287	0.291	0.286	0.307
Madhya Pradesh	0.427	0.413	0.402	0.400	0.411	0.406	0.411	0.383	0.393	0.400	0.406	0.371	0.353	0.349	0.297
Nagaland	0.575	0.576	0.578	0.619	0.591	0.594	0.620	0.671	0.684	0.686	0.693	0.685	0.696	0.699	0.661
Odissa	0.482	0.484	0.487	0.467	0.472	0.471	0.479	0.464	0.441	0.448	0.434	0.428	0.439	0.437	0.414
Punjab	0.469	0.447	0.452	0.441	0.440	0.438	0.440	0.459	0.458	0.457	0.460	0.451	0.455	0.453	0.441
Rajasthan	0.476	0.411	0.489	0.472	0.479	0.482	0.496	0.497	0.489	0.508	0.503	0.478	0.491	0.483	0.476
Sikkim	0.370	0.368	0.365	0.396	0.405	0.377	0.386	0.379	0.377	0.375	0.397	0.397	0.403	0.422	0.417
Tamil Nadu	0.380	0.362	0.361	0.362	0.366	0.360	0.358	0.349	0.340	0.339	0.346	0.320	0.328	0.331	0.315
Tripura	0.343	0.392	0.402	0.428	0.435	0.423	0.433	0.404	0.400	0.396	0.364	0.351	0.413	0.386	0.373
Uttar Pradesh	0.466	0.466	0.465	0.454	0.454	0.453	0.452	0.453	0.456	0.455	0.455	0.446	0.441	0.443	0.428
Uttrakhand	0.270	0.305	0.303	0.286	0.287	0.292	0.301	0.289	0.287	0.286	0.286	0.280	0.284	0.285	0.263
West Bengal	0.364	0.362	0.365	0.387	0.387	0.392	0.397	0.410	0.408	0.395	0.408	0.397	0.401	0.399	0.391

The trend of the Exposure Index across the years reveals certain states experience fluctuations in their Exposure Index values, indicating changing vulnerabilities over time. States such as Andhra Pradesh, Chhattisgarh, Gujarat, Tamil Nadu and Mizoram show a decreasing trend in the index values over time. Whereas States such as Assam, and Sikkim show an increasing trend. The exposure index has remained more or less consistent for the remaining states showing a consistent level of exposure throughout the years. States facing elevated exposure to climate risks require protective measures and should be accorded priority in policymaking. Policies should be tailored to address the specific vulnerabilities of these states, encompassing strategies such as climate-resilient infrastructure development, early warning systems, and community-based adaptation programs.

Fig 3: The map of India showing Exposure Index for the years 2001 and 2015, respectively



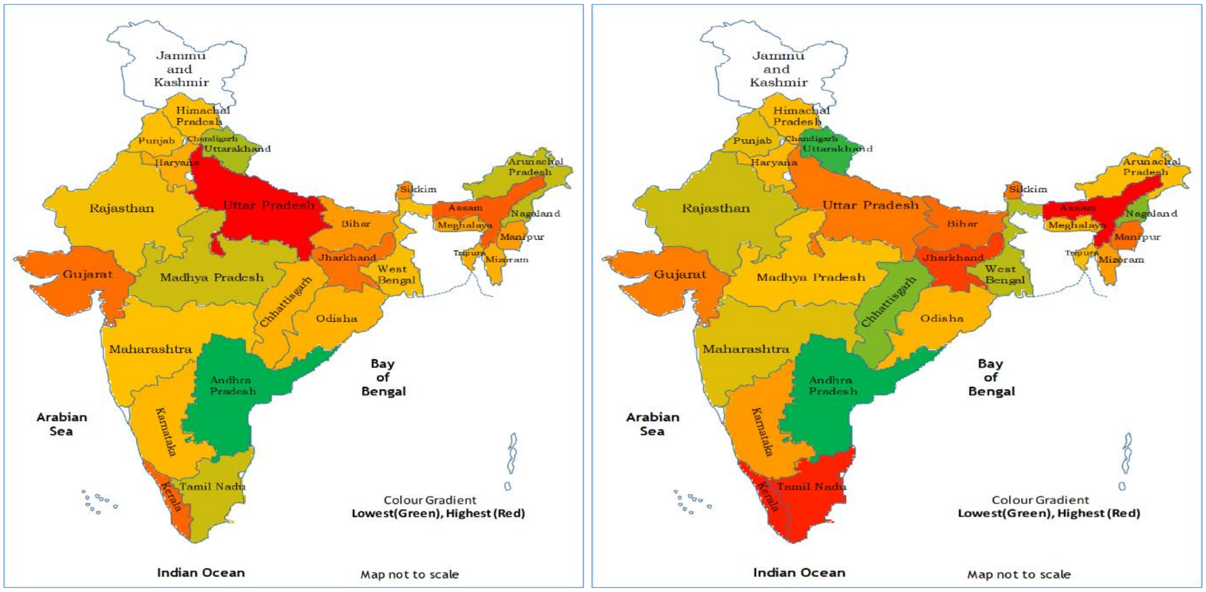
3.3. Vulnerability Index

The Vulnerability Index, reflecting the vulnerability of Indian states in the agriculture sector to climate risks, exhibits diverse trends and variations over the years. States like Arunachal Pradesh, Tamil Nadu, Andhra Pradesh, Assam, and Bihar show a general upward trend, indicating an increasing vulnerability from 2001 to 2015. In contrast, Uttar Pradesh experienced a fluctuating trend, with a peak in 2003 followed by a gradual decline. Some states, including Kerala and Uttarakhand, demonstrate a relatively stable or decreasing vulnerability, suggesting effective adaptation strategies. Chhattisgarh exhibits a decline in vulnerability, reflecting positive developments in climate resilience. West Bengal, Nagaland, Punjab, and Rajasthan showcase mixed trends, with periods of increased vulnerability interspersed with stability. States like Assam, Jharkhand, Kerela, and Bihar have however shown a high vulnerability across the years. The trend of the vulnerability index for all the states seems to be rising for the years and then decreases or becomes stable over the years, see table 4.

Table 4: Vulnerability index for the Indian states

Vulnerability index	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Andhra Pradesh	0.351	0.399	0.444	0.491	0.518	0.551	0.568	0.580	0.612	0.623	0.611	0.589	0.528	0.519	0.480
Arunachal Pradesh	0.475	0.520	0.574	0.618	0.627	0.607	0.606	0.615	0.615	0.616	0.603	0.601	0.591	0.576	0.530
Assam	0.645	0.680	0.723	0.766	0.789	0.780	0.784	0.801	0.813	0.813	0.801	0.773	0.749	0.718	0.659
Bihar	0.561	0.611	0.645	0.695	0.716	0.718	0.723	0.732	0.762	0.751	0.729	0.704	0.685	0.649	0.588
Chattisgarh	0.528	0.568	0.616	0.642	0.646	0.646	0.647	0.657	0.663	0.660	0.649	0.624	0.599	0.567	0.505
Gujarat	0.620	0.646	0.679	0.695	0.692	0.694	0.680	0.699	0.704	0.716	0.702	0.677	0.655	0.621	0.574
Haryana	0.536	0.562	0.580	0.595	0.592	0.588	0.598	0.605	0.627	0.628	0.624	0.602	0.584	0.564	0.533
Himachal	0.512	0.551	0.581	0.609	0.629	0.633	0.634	0.643	0.652	0.651	0.640	0.621	0.596	0.570	0.532
Jharkhand	0.613	0.664	0.716	0.744	0.760	0.763	0.763	0.771	0.784	0.779	0.767	0.742	0.718	0.686	0.617
Karnataka	0.523	0.565	0.612	0.653	0.679	0.679	0.676	0.676	0.684	0.679	0.667	0.652	0.627	0.596	0.555
Kerela	0.630	0.676	0.705	0.738	0.731	0.722	0.712	0.719	0.742	0.719	0.702	0.683	0.650	0.659	0.639
Maharashtra	0.511	0.550	0.587	0.616	0.626	0.637	0.644	0.652	0.664	0.677	0.662	0.647	0.621	0.589	0.523
Manipur	0.559	0.590	0.601	0.630	0.635	0.649	0.653	0.666	0.681	0.679	0.669	0.658	0.629	0.628	0.586
Meghalaya	0.544	0.570	0.602	0.615	0.615	0.631	0.631	0.642	0.654	0.654	0.659	0.638	0.604	0.571	0.537
Mizoram	0.533	0.565	0.592	0.637	0.652	0.659	0.670	0.686	0.701	0.710	0.707	0.670	0.641	0.615	0.552
Madhya Pradesh	0.480	0.515	0.535	0.547	0.576	0.603	0.609	0.616	0.635	0.645	0.626	0.609	0.582	0.556	0.529
Nagaland	0.471	0.500	0.519	0.559	0.580	0.587	0.576	0.589	0.584	0.581	0.555	0.557	0.545	0.534	0.506
Odissa	0.529	0.589	0.608	0.625	0.622	0.629	0.633	0.647	0.673	0.682	0.660	0.637	0.611	0.581	0.536
Punjab	0.514	0.517	0.509	0.493	0.491	0.491	0.493	0.501	0.518	0.524	0.525	0.518	0.511	0.500	0.525
Rajasthan	0.505	0.528	0.582	0.607	0.610	0.615	0.621	0.635	0.647	0.660	0.644	0.626	0.612	0.581	0.519
Sikkim	0.571	0.606	0.634	0.656	0.650	0.653	0.654	0.656	0.666	0.678	0.676	0.664	0.647	0.639	0.581
Tamil Nadu	0.480	0.529	0.569	0.589	0.597	0.601	0.604	0.603	0.617	0.615	0.627	0.640	0.649	0.655	0.636
Tripura	0.531	0.562	0.593	0.629	0.658	0.657	0.653	0.664	0.692	0.679	0.656	0.668	0.634	0.568	0.531
Uttar Pradesh	0.764	0.782	0.790	0.770	0.730	0.732	0.732	0.733	0.770	0.754	0.741	0.724	0.702	0.654	0.578
Uttrakhand	0.459	0.517	0.554	0.565	0.587	0.601	0.601	0.607	0.521	0.625	0.613	0.573	0.534	0.523	0.490
West Bengal	0.508	0.540	0.578	0.621	0.643	0.652	0.655	0.667	0.703	0.678	0.668	0.640	0.607	0.572	0.516

Fig 4: The map of India showing Vulnerability Index for the years 2001 and 2015, respectively



3.4.Climate risk index

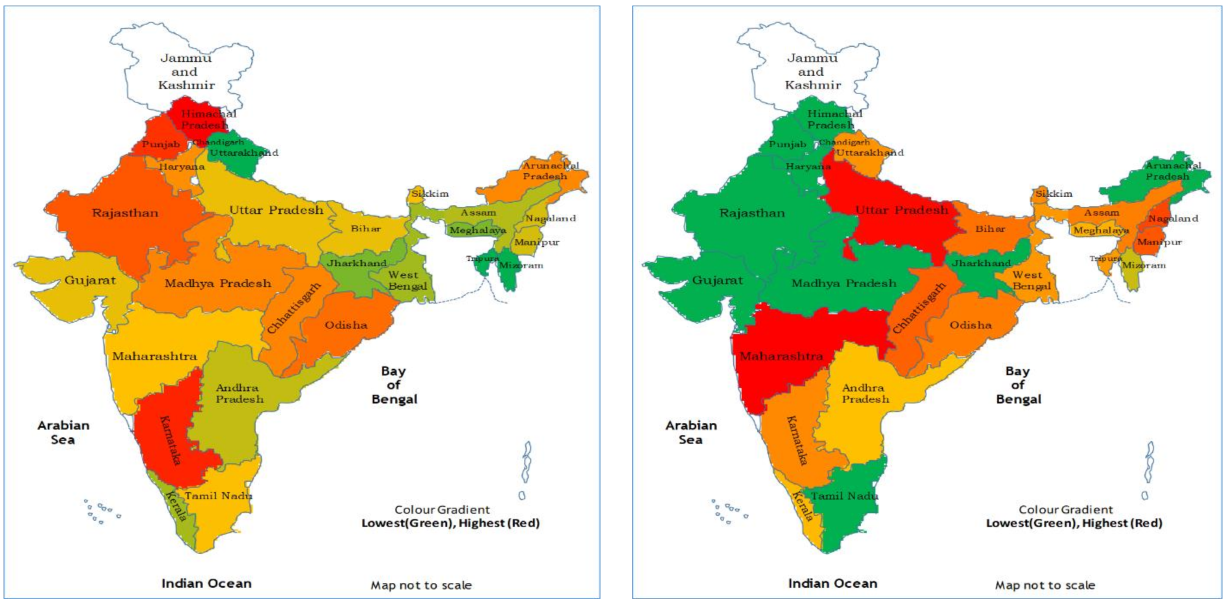
The Climate Risk Index provides insights into the exposure, and vulnerability of Indian states to climate-related hazards over the period from 2001 to 2015. Examining the trends reveals varying degrees of susceptibility across different states.

Table 5: Climate risk index for the Indian states

Climate Risk Index	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Andhra Pradesh	0.372	0.585	0.483	0.260	0.335	0.029	0.029	0.029	0.576	0.030	0.280	0.274	0.026	0.390	0.298
Arunachal Pradesh	0.513	0.031	0.032	0.033	0.033	0.765	0.606	0.626	0.740	0.298	0.625	0.841	0.560	0.031	0.030
Assam	0.347	0.030	0.032	0.032	0.032	0.737	0.390	0.443	0.742	0.307	0.782	0.710	0.751	0.547	0.415
Bihar	0.444	0.031	0.031	0.032	0.550	0.482	0.032	0.032	0.753	0.550	0.301	0.298	0.424	0.031	0.437
Chattisgarh	0.515	0.676	0.032	0.305	0.033	0.306	0.033	0.033	0.776	0.443	0.032	0.032	0.031	0.031	0.471
Gujarat	0.441	0.627	0.031	0.413	0.030	0.030	0.030	0.031	0.031	0.365	0.031	0.564	0.030	0.346	0.028
Haryana	0.510	0.682	0.030	0.360	0.030	0.450	0.412	0.454	0.493	0.575	0.030	0.641	0.029	0.569	0.028
Himachal	0.596	0.633	0.709	0.707	0.030	0.031	0.031	0.031	0.532	0.292	0.366	0.487	0.030	0.278	0.028
Jharkhand	0.242	0.027	0.027	0.028	0.547	0.261	0.028	0.262	0.626	0.696	0.258	0.372	0.027	0.027	0.026
Karnataka	0.574	0.758	0.828	0.429	0.381	0.032	0.305	0.032	0.032	0.032	0.032	0.031	0.031	0.030	0.397
Kerela	0.320	0.583	0.610	0.428	0.029	0.029	0.029	0.029	0.391	0.028	0.028	0.528	0.401	0.027	0.310
Maharashtra	0.479	0.414	0.294	0.374	0.032	0.032	0.032	0.549	0.520	0.033	0.304	0.649	0.032	0.468	0.641
Manipur	0.402	0.030	0.548	0.030	0.031	0.418	0.420	0.032	0.301	0.032	0.032	0.432	0.593	0.678	0.489
Meghalaya	0.250	0.027	0.027	0.028	0.028	0.705	0.520	0.487	0.744	0.436	0.734	0.688	0.338	0.384	0.327
Mizoram	0.027	0.027	0.027	0.028	0.260	0.412	0.416	0.379	0.028	0.028	0.028	0.431	0.571	0.544	0.242
Madhya Pradesh	0.515	0.542	0.028	0.263	0.029	0.273	0.593	0.389	0.470	0.441	0.277	0.266	0.027	0.402	0.025
Nagaland	0.408	0.416	0.031	0.033	0.032	0.615	0.447	0.321	0.585	0.034	0.034	0.634	0.681	0.677	0.518
Odissa	0.530	0.658	0.291	0.290	0.031	0.031	0.031	0.031	0.628	0.535	0.031	0.357	0.030	0.029	0.420
Punjab	0.566	0.689	0.028	0.633	0.028	0.028	0.028	0.268	0.029	0.564	0.029	0.029	0.029	0.592	0.028
Rajasthan	0.543	0.724	0.287	0.523	0.031	0.031	0.031	0.375	0.595	0.482	0.032	0.464	0.031	0.030	0.029
Sikkim	0.473	0.028	0.028	0.638	0.509	0.345	0.029	0.029	0.029	0.029	0.627	0.353	0.030	0.356	0.393
Tamil Nadu	0.474	0.755	0.783	0.614	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.027	0.028	0.331	0.027
Tripura	0.026	0.028	0.271	0.030	0.031	0.518	0.413	0.645	0.030	0.030	0.271	0.515	0.602	0.527	0.367
Uttar Pradesh	0.446	0.597	0.033	0.033	0.032	0.549	0.381	0.480	0.706	0.385	0.032	0.300	0.031	0.643	0.628
Uttrakhand	0.023	0.025	0.026	0.300	0.026	0.244	0.247	0.245	0.696	0.355	0.026	0.511	0.025	0.025	0.377
West Bengal	0.313	0.027	0.028	0.029	0.275	0.440	0.030	0.283	0.659	0.406	0.409	0.787	0.433	0.457	0.369

The Climate Risk Index (CRI) data for the Indian states from 2001 to 2015 shows varying levels of climate risk over time. In the first glance the index shows similar patterns to drought hazard index. However, we can see the effects of vulnerability and exposure indices too. The analysis shows that the state consisting of Assam, Arunachal Pradesh and Himachal Pradesh which correspond to the eastern Himalayan agro-climatic zones are prone to a high climate risk whereas plateau and hill regions such as Haryana, Rajasthan, Madhya Pradesh, and Maharashtra face relatively moderate climate risk associated with droughts in India. On the other hand, states such as Kerela, and Andhra Pradesh which correspond to agro-climates zones such as western and eastern coastal plains and Ghats show the least vulnerability to climate risks. States such as Uttrakhand and Bihar also show low probabilities of being affected by climate risk during the study period. A few years such as 2002, 2009 and 2012 show how climate risk throughout all states indicating an increase in risks faced by the agricultural period over those years. Overall, the CRI data highlights the variability and trends in climate risk across different Indian states, emphasizing the need for targeted climate adaptation and risk management strategies.

Fig 5: The map of India showing climate risk for the years 2001 and 2015, respectively



The analysis aids in identifying areas that require targeted intervention and measures against the impact of the drought hazard. This could include the adoption of drought-resistant crop, water conservation practices, and/or promotion of alternate livelihoods that are less dependent on agriculture in areas where high climate risk is observed over the years.

3.5. Results for the impact of Climate risk on Rice yield

Results for first stage regression are given in table 6 and 7:

Table 6: The F statistics for the first stage regression:

Model	**Prob>F**	**F(4,25)**
Rice Yield	0.000	275.17

Table 7: Results of first stage regression:

Variable	Coefficient
Climate risk index	1.2 (4.08)
Fertilizer Lag (IV)	**0.71***** **(0.36)**
Diff Mechanisation	39.4 (28.3)
Average size of landholdings	-5.3 (4.03)
Constant	36.95 (8.69)
R-squared: Within Between Overall	0.58 0.97 0.93
Observations	338

Robust standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

From the above results we can see that lag of fertilizer consumption per hectare is an efficient instrumental variable as it is significant at 1% level of significance. To test for weak instruments, we can also see the joint significance of the instruments' coefficients via an F-test. The rule of thumb is that an F-statistic of more than 10 means the instrument is valid, it is 275.17 in our analysis (Stock and Yogo, 2002).

Table 8: Results for second stage regression:

Variable	Rice yield
Climate risk index	-315.5** (117.2)
Fertilizer	5.42*** (1.24)
Diff Mechanisation	-799.4** (302.0)
Average size of landholdings	-249.4** (114.7)
Constant	2021.0*** (250.0)
R-squared: Within Between	0.14 **0.20**

Overall	0.19
Observations	364

Robust standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

We can see from the results that all the variables have a significant impact on crop yields. The level of significance differs from 1% to 10%. The coefficients also show expected signs which implies that the results are in line with the literature. We can then infer from the results that a change in the climate risk index by one unit is associated with a decrease in rice yield by 315.6 kgs per hectare. For fertilizer, a change in fertilizer use by one unit is associated with an increase in rice yield by 5.40 kgs per hectare (taking into account its lagged value). With instrumentation by its lagged value, the coefficient for fertilizer consumption per hectare represents the estimated effect of changes in the fertilizer from one period to another on rice yield, while controlling for the influence of its past values. Similarly, a unit change in farm mechanisation (the change in farm mechanisation from one period to another) is associated with a decrease in rice yield by 799.4 kgs per hectare during that period. This implies that an acceleration or intensification in mechanisation, relative to its past level, has a negative impact on yield. Then, a unit change in the average size of landholdings is associated with a decrease in rice yield by 249.4 kgs per hectare during the current period.

The findings underscore the vulnerability and exposure of crop yield to adverse climate conditions such as droughts, in the present study. The importance of climate-resilient farming practices and adaptation strategies to mitigate the adverse impacts of climate risk on foodgrain productivity. The study also focuses on the importance of nutrient management and soil fertility enhancement through appropriate fertilizer application. Optimal use of fertilizers to maximize yield while minimizing environmental impacts, considering factors like nutrient balance, soil health, and cost-effectiveness. The results suggest the need for careful implementation and gradual adoption of farm mechanisation technologies. The study indicates that an increase in mechanization from one period to the next leads to a fall in yield possibly due to an excessive use of power tillers and tractors, which may not be an appropriate measure of mechanization. Other possible reasons for the decrease in the yield due to an increase in gradual farm mechanisation could be disruptions in farming practices, labor displacement, or inadequate adaptation to new technologies. Highlight the importance of balanced farm mechanisation strategies that prioritize efficiency without compromising yield stability. A fall in yield due to an increase in average farm size may reflect challenges related to farm management efficiency or resource allocation. The results have implications for smallholder farmers versus large-scale agricultural operations, considering factors like economies of scale, resource access, and land productivity management.

4. Conclusion

This study is an attempt to explore the climate risk and its impact on rice productivity in Indian states, aligning with the broader objectives of the Sustainable Development Goals (SDGs). Climate risk assessment risk plays a pivotal role in advancing the sustainability of agri-food systems by providing a comprehensive understanding of the potential challenges and vulnerabilities posed by climate change. From the results, we can see that states such as Nagaland, and Arunachal Pradesh with high exposure; states such as Uttar Pradesh, Assam, and Arunachal Pradesh with high vulnerability and high climate risk values require more attention. This includes selecting climate-resilient crop varieties, adjusting planting schedules, and adopting sustainable water management practices. Along with additional aid in the allocation of resources, investments in infrastructure, and the implementation of technological innovations that can mitigate the adverse effects of climate change on crop production are required. Managing climate risk will eventually help with the productivity of rice yield and therefore contribute to maintaining food stability in

India. Moving forward sustainability can be achieved in our agri-food systems by informed decision-making, backed by robust risk assessments prioritizing these high-exposure states.

References

1. Adger, W. N., Brown, I., & Surminski, S. (2018). Advances in risk assessment for climate change adaptation policy. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2121), 20180106.
2. Amarnath, G., Alahacoon, N., Smakhtin, V., & Aggarwal, P. (2017). Mapping Multiple climate-related Hazards in South Asia. Colombo, Srilanka: International water management institute.
3. Antwi-Agyei, P., Fraser, E. D., Dougill, A. J., Stringer, L. C., & Simelton, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socio-economic data. Applied Geography, 324-334.
4. Aufhammer, M., Ramanathan, V., & Jefrey, R. (2012). Climate change, the mansoon and rice yield in India. Climate Change, 111(2),411–424.
5. Baig, I. A., Chandio, A. A., Ozturk, I., Kumar, P., Khan, Z. A., & Salam, M. (2021). Assessing the long and short-run asymmetrical effects of climate change on rice production: empirical evidence from India. Environmental Science and Pollution Research, 1-22.
6. Brundtland, G. H. (1987). Our Common Future World Commission On Environment And Development, https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf, Accessed on 11 January 2024.
7. Dasgupta, S., Barua, A., Vyas, S., & Ravindranath, N. (2019). Climate vulnerability assessment for adaptation planning in India using a common framework. Department of science and technology.
8. Drought mitigation center. (2018). Retrieved from https://drought.unl.edu/Monitoring/SPI/SPIProgram.aspx.
9. Eckstien, D., Kunzel, V., & Schafer, L. (2021). Global Climate Risk Index. Germanwatch.
10. EDO, C. E. (2020), "Standardised Precipitation Index (SPI) ", European commission. Retrieved from https://edo.jrc.ec.europa.eu/documents/factsheets/factsheet_spi.pdf.
11. Greiving, S., Lindner, C., Luckernkotter, J., Peltonen, L., Juhola, S., & Vehmas, J. (2013). Climate Change and Territorial Effects on regions and local economies. Europe: ESPON Programme
12. Guntukula, R. (2019). Assessing the impact of climate change on Indian agriculture: Evidence from major crop yields. Journal of Public Affairs, 20(1), e2040.
13. Haque, S., Ahmed, S., Azad, A. K., Alam, S., Hossain, Z., & Rahman, M. (2021). Bangladesh climate and disaster risk atlas. Hazard- Volume 1.
14. Helbeing, D. (2013). Globally networked risk and how to respond. Nature 497, 51-59.
15. IPCC (2012), Glossary of terms. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley

(eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 555-564.

16. IPCC (2014) Summary for policymakers in: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1-32.
17. IPCC (2022), Technical Summary: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 37–118.
18. King, D., Schrag, D., Dadi, Z., Ye, Q., & Ghosh, A. (2017). Climate change: A risk assessment.
19. Krishniah, K., & Shobha Rani, N. (2000). New avenues for augmenting and sustaining rice exports from India. International Rice Commission Newsletter, Vol. 49, FAO.
20. Kumar, S., & Sidana, B. K. (2019). Impact of Climate Change on the Productivity of Rice and Wheat Crops in Punjab. Economic & Political Weekly, 54(46), 38-44.
21. Lavell, A., Oppenheimer, M., Diop, C., Hess, J., Lempert, R., Li, J., . . . Myeong, S. (2012). Climate change: new dimensions in disaster risk, exposure, vulnerability, and resilience. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. UK, and New York, NY, USA: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge.
22. Li, X., Fang, S., Zhu, Y., & Wu, D. (2021). Risk Analysis of Wheat Yield losses at the county level in mainland china. Frontiers in environment science.
23. McKee, T. B., Doesken, N. J., and Kleist, J. (1993), The relationship of drought frequency and duration to time scales, In Proceedings of the 8th Conference on Applied Climatology, Vol. 17, No. 22, pp. 179-183.
24. Mohanty, A., & Wadhawan, S. (2021). Mapping India’s Climate Vulnerability A district level assessment. India: Council on Energy, Environment and Water.

25. Mysiak, J., Torresan, S., Bosello, F., Mistry, M., Amadio, M., Marzi, S., . . . Sperotto, A. (2018). Climate Risk Index for Italy. Phil. Trans. R. Soc. A, 376: 20170305. doi:https://doi.org/10.1098/rsta.2017.0305.
26. Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffmann, A., & Giovannini, E. (2008). Handbook on constructing composite indicators: Methodology and user guide. European Commission in Ispra, Italy: OECD.
27. Pretty, J. (2008). Agricultural sustainability: concepts, principles and evidence. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1491), 447-465.
28. Raghuvanshi, R., Ansari, M., Amardeep, & Verma, A. (2018). Adaptation to Climate Change by Farmers in Himalayan Region of Uttrakhand. Research Journal of Agricultural Sciences 9 (2), 399-403.
29. Sarker, M. A., Alam, K., & Gow, J. (2012). Exploring the relationship between climate change and rice yield in Bangladesh: An analysis of time series data. Agricultural Systems, 112, 11-16.
30. Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., . . . Rober, D. (2021). A framework for complex climate change risk assessment. One Earth, 4, (4), 489-501.
31. Singh, A. K., & Sharma, P. (2018). Measuring the productivity of food-grain crops in different climate change scenarios in India: Evidence from time series investigation. Climate Change, 4(16), 661-673.
32. Shahid, S., Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh. Nat Hazards 46, 391–413. https://doi.org/10.1007/s11069-007-9191-5.
33. Stock, James H., Jonathan H. Wright, and Motohiro Yogo. "A survey of weak instruments and weak identification in generalized method of moments." Journal of Business & Economic Statistics 20.4 (2002): 518-529.
34. Tan, B.T.; Fam, P.S.; Firdaus, R.B.R.; Tan, M.L.; Gunaratne, M.S. (2021) Impact of Climate Change on Rice Yield in Malaysia: A Panel Data Analysis. Agriculture, 11, 569. https://doi.org/10.3390/agriculture11060569.
35. Tripathi, A., & Mishra, A. K. (2017). Knowledge and passive adaptation to climate change: An example from Indian Farmers. Climate Risk Management, 195–207.
36. United, Nations, The UN Sustainable Development Goals. United Nations, New York, 2015. Available at http://www.un.org/sustainabledevelopment/summit/., accessed 10 January 2024.
37. World Meteorological Organization (2012), Standardized Precipitation Index User Guide (WMO-No. 1090), Geneva.