ICRISAT AND WFP: India Working Paper

Quantifying Climate Hazards and Its Relationship with Food Availability: A Comprehensive District Level Analysis in India

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Quantifying Climate Hazards and Its Relationship with Food Availability: A Comprehensive District Level Analysis in India

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Introduction

The escalating impact of climate change has emerged as a pivotal concern of the 21st century, transcending geographical boundaries and affecting myriad facets of human existence. Among the various sectors grappling with its consequences, the domain of food production stands at the forefront, intricately interwoven with the well-being of societies and the stability of global economies. Climate change, driven predominantly by anthropogenic activities, has triggered alterations in temperature patterns, precipitation regimes, and the frequency of extreme weather events (Li *et. al*, 2023). These transformations have cascading effects on the agricultural landscape, compelling a comprehensive examination of the intricate nexus between climate variability and food production (Haq *et al*, 2015).

In the context of India, a nation where agriculture forms the bedrock of its economy and sustenance, the impact of climate change on food production assumes paramount significance. With a population projected to reach over 1.6 billion by 2050 (James, 2011), ensuring food security in the face of changing climatic conditions becomes a complex challenge with far-reaching implications. India's geographical diversity, encompassing everything from arid deserts to fertile plains and coastal regions, renders it particularly susceptible to the vicissitudes of climate change. The escalating concentration of greenhouse gases in the atmosphere has propelled shifts in temperature, precipitation patterns, and the frequency of extreme weather events. These alterations, superimposed upon the intricate tapestry of India's agricultural landscape, have the potential to disrupt crop cycles, affect water availability, and induce perturbations across the entire food supply chain.

Rice, wheat, and other staple crops that serve as the cornerstone of the Indian diet are vulnerable to the vagaries of changing climate (Khan *et al*, 2009). Elevated temperatures during critical growth stages can stunt growth and diminish yields, while erratic monsoon patterns can lead to water scarcity or inundation, both of which undermine agricultural productivity. Furthermore, variations in pest and disease dynamics driven by warmer conditions pose additional challenges to crop management (Hodson, 2011; Skendžić, *et al*, 2021). In the context of a rapidly growing population, where a significant portion of the populace still depends on agriculture for their livelihoods, the consequences of climate change on food production reverberate beyond immediate agricultural concerns. Impediments to food security can engender socio-economic instability, impacting rural communities and exacerbating existing inequalities.

Rainfall and temperature are the two main attributes of climate change that affects agriculture. While individual climate variables like temperature and rainfall undoubtedly hold intrinsic importance, the multifaceted nature of climatic impacts on agriculture demands a more comprehensive approach. Therefore, we need to create a composite climate hazard index, rather than simply using individual climatic hazards such as temperature and rainfall. The rationale behind the composite hazard index is as follows.

Firstly, agricultural productivity is influenced by a confluence of climatic elements, each exerting varying degrees of influence depending on the agroclimatic context. Ignoring the intricate interactions between these factors might lead to an oversimplified understanding of the challenges faced by agricultural systems. A composite index, crafted by amalgamating multiple indicators, affords a more nuanced assessment that accounts for the intricate balance of variables affecting agricultural production.

Secondly, climatic hazards rarely manifest in isolation. The effects of elevated temperatures, for instance, might be exacerbated by altered rainfall patterns, resulting in drought conditions that greatly affect crop growth. Conversely, excessive rainfall might lead to flooding, damaging crops and soil structure. The interactions between different hazards can either amplify or attenuate their impact, making it crucial to capture their combined effects through a composite index. Furthermore, agricultural systems operate within specific agroclimatic zones, each characterized by its own unique set of challenges and sensitivities. A composite index allows for the customization of weights assigned to different indicators, considering their significance within specific zones. This tailor-made approach ensures a more accurate representation of the challenges faced by different regions, as compared to a one-size-fits-all consideration of individual hazards.

The primary aims of this paper encompassed two distinct yet interconnected objectives. **The first objective was centered around the formulation of a comprehensive climate hazard index**. This index was designed to encapsulate a spectrum of 26 indicators that hold paramount significance in the realm of agricultural production. These indicators, carefully selected to encompass a holistic understanding of the challenges posed by climatic conditions, were assigned distinct weights based on their relative importance within specific agroclimatic zones. This weighting approach acknowledges the dynamic interplay between different factors across varying geographic contexts, enabling a nuanced assessment of climatic risks. **The second objective of this study involved a detailed exploration of the intricate relationship between crop production and the climate hazard index**. By harnessing empirical data and analytical methodologies, this objective aimed to unveil the extent to which food crop production correlates with the climate hazard index across diverse agro-climatic zones. This multifaceted analysis endeavored to unravel the complex interactions between climatic vulnerability encapsulated by the index and their repercussions on crop production in distinct agricultural settings.

By pursuing these two-fold objectives, this paper aspires to contribute valuable insights into the intricate dynamics of climate impacts on agriculture. The climate hazard index developed under this study not only serves as a quantitative tool for assessing the agro-climatic zones-specific vulnerability of crop production but also provides a platform for informed decision-making regarding adaptive strategies, resource allocation and investment planning. Additionally, the correlations elucidated between the climate hazard index and crop production offer a deeper understanding of the intricate interplay between climatic factors and agricultural outcomes. In a world increasingly grappling with the uncertainties of a changing climate, such insights are useful for formulating effective policies and practices that can bolster agricultural resilience and ensure sustainable food production in the face of evolving climatic challenges.

After providing a brief introduction and contextual backdrop, the subsequent section of this paper provides an in-depth account of the formulation process behind the climate hazard index. Subsequently, the results and discussion section looks into the comprehensive analysis of the outcomes. These outcomes encompass the dynamics of the climate hazard index, analyzing its trend over time and within diverse agro-climatic zones. Furthermore, the section explores the nexus between crop production and the climate hazard index, unravelling the underlying correlations that elucidate the vulnerability of agriculture to climatic nuances. Finally, the paper culminates in the conclusive section, where synthesized findings lead to the presentation of conclusions and a roadmap for future endeavors.

Development of Climate Hazard Index for Agriculture

The development of the climate hazard index for Agriculture comprises a structured procedure encompassing the following three fundamental steps:

- Indicators Selection
- Climate Hazard Index Computation
- Weights Assignment

Indicators Selection

The temperature and rainfall are the pivotal climatic attributes with substantial implications for agriculture. In the context of constructing the historical climate hazard index, a comprehensive approach was adopted, encompassing various dimensions of temperature and rainfall, alongside the incorporation of disastrous weather events. This multifaceted examination encompasses an array of factors to holistically evaluate the climatic impact on agricultural systems. Specifically, the analysis includes the 8 distinct facets of temperature, 15 diverse facets of rainfall patterns, and an evaluation of 3 facets associated with disastrous weather events. The intricate details of these various aspects are meticulously presented in Table 1, providing a comprehensive overview of the elements considered within the framework of the study.

***Table 1**: List of climate hazard indicators in the computation of climate hazard index*

S. No.	Attribute	Indicator and Measurement (unit)	Rationale	Relationship with hazard	Source of data
1	Temperature	Monsoon maximum temperature (˚C) from 1990 to 2018	An increase in monsoon maximum temperature implies adverse effects on crop yields	Direct	Derived from maximum temperature data for 1990 to 2018 of IMD
2		Monsoon minimum temperature(˚C)during1990 to 2018	An increase in monsoon minimum temperature implies adverse effects on yields	Direct	Derived from minimum temperature data for 1990 to 2018 of IMD
3		Heat wave occurrences (days) during 1990 to 2018	An increase in heat wave occurrences will imply adverse yield effects	Direct	Derived from temperature data for 1990 to 2018 of IMD
4		Cold wave occurrences (days) during 1990 to 2018	An increase in cold wave occurrences will imply adverse yield effects	Direct	Derived from temperature data for 1990 to 2018 of IMD
5		Severe heat wave occurrences (days) during 1990 to 2018	An increase in severe heat wave occurrences will imply adverse yield effects	Direct	Derived from temperature data for 1990 to 2018 of IMD
6		Severecoldwaveoccurrences (days) during 1990 to 2018	An increase in severe cold wave occurrences will imply adverse yield effects	Direct	Derived from temperature data for 1990 to 2018 of IMD

S. No.	Attribute	Indicator and Measurement (unit)	Rationale	Relationship with hazard	Source of data
7		Number of times more than 3 days of temperature >=35 during monsoon during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from temperature data for 1990 to 2018 of IMD
8		Terminal heat stress Temperature rise in February and March during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from temperature data for 1990 to 2018 of IMD
9	Rainfall	Coefficient of variation (CV) of annual rainfall (%) during 1990 to 2018	Higher the CV, more the rainfall, which is favorable to agricultural productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
10		Coefficient of variation (CV) of monsoon rainfall (%) during 1990 to 2018	Higher the CV, more the rainfall, which enables sowing of crops in right time, better establishment of crop stand, better crop growth and productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
11		Coefficient of variation (CV) of June rainfall (%) during 1990 to 2018	Higher the CV, more the rainfall, which enables sowing of crops in right time	Direct	Derived from rainfall data for 1990 to 2018 of IMD
12		Coefficient of variation (CV) of July rainfall (%) during 1990 to 2018	Higher the CV, more the rainfall, which enables sowing of crops in right time and better establishment of crop stand	Direct	Derived from rainfall data for 1990 to 2018 of IMD
13		Number of annual rainy days during 1990 to 2018	Increase in number of rainy days implies a better distribution of rainfall	Inverse	Derived from rainfall data for 1990 to 2018 of IMD
14		Number of monsoon rainy days during 1990 to 2018	Increase in number of rainy days implies a better distribution of rainfall	Inverse	Derived from rainfall data for 1990 to 2018 of IMD
15		Heavy rainfall (days) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
16		Very heavy rainfall (days) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
17		Number of times more than 14 days of dry spell in monsoon (number/time slice) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
18		Number of times more than 14 days of wet spell in monsoon (number/time slice) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
19		Number of times more than 10 days of dry spell in monsoon (number/time slice) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD

S. No.	Attribute	Indicator and Measurement (unit)	Rationale	Relationship with hazard	Source of data
20		Number of times more than 10 days of wet spell in monsoon (number/time slice) during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from rainfall data for 1990 to 2018 of IMD
21		Drought proneness during 1990-2018	Increase in drought proneness means higher yield risk	Direct	Derived from rainfall data for 1990 to 2018 of IMD
22		Flood proneness during 1990 to 2018	Increase in flood proneness means higher yield risk	Direct	Derived from rainfall data for 1990 to 2018 of IMD
23		Average highest rainfall in a single day as % to annual normal during 1990 to 2018	An increase indicates the possibility of crop productivity getting affected. Increase in the intensity of such extreme rainfall event also means higher probability of floods with all the attendant problems. It is also an indicator of uneven distribution of rainfall	Direct	Derived from rainfall data for 1990 to 2018 of IMD
24	Disastrous weather events	Number of Floods, Flash floods, Cloud burst, and Landslides during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from disastrous weather events data for 1990 to 2018 of IMD
25		Number of Cyclonic storms during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from disastrous weather events data for 1990 to 2018 of IMD
26		Number of Hailstorms during 1990 to 2018	These events will adversely affect crop stand and crop productivity	Direct	Derived from disastrous weather events data for 1990 to 2018 of IMD

COMPUTATION OF CLIMATE HAZARD INDEX

To calculate the climate hazard index for agriculture (CHIA), each climate indicator (CI) underwent a normalization process. This normalization was conducted to standardize all the indicators onto a common scale and eliminate their unit dimensions. The method employed for this normalization is detailed as follows:

$$CI_{dt} = \frac{(X_{dt} - \mu_{zt})}{\sigma_{zt}}$$

$CI_{idt} = (X_{dt} - \mu_{zt})/\sigma_{zt}$ when the climate indicator is positively related to the CHIA

$CI_{idt} = -(X_{dt} - \mu_{zt})/\sigma_{zt}$ when the climate indicator is inversely related to the CHIA

Where CI_{dt}, X_{dt}, μ_{zt} and σ_{zt} are the normalized climate indicator, actual climate indicator, mean and standard deviation with corresponding indicator (i), district(d), time (t) and zone (z). To derive the CHIA, the normalized indicators were aggregated. This aggregation process involved the multiplication of the zone weight[1] (w_z) with climate indicator (CI_{dt}) (to ensure the incorporation of the relevant regional context. Now the CHIA is:

$$CHIA_{dt} = \sum_{i=1}^{26} w_z CI_{idt}$$

Numerical value of the $CHIA_{dt}$ in between $-\infty$ to ∞. Higher the value of $CHIA_{dt}$ higher is the historical climate hazard problem.

[1] Detail of the zone weight are discussed in the following next section.

Weights assignment

The rationale behind assigning distinct weights to various agro-climatic zones and corresponding indicators when developing the climate hazard index lies in the acknowledgment of the inherent diversity and varying sensitivities of indicators within different geographic regions. Agro-climatic zones are characterized by unique combinations of climatic conditions, soil types, topography, and ecological factors, which collectively influence their susceptibility to different climate-related hazards. By applying uniform weights across all zones for a particular indicator, the index might oversimplify the intricate interplay between climatic variables and their impacts on agriculture. Tailoring weights according to specific agro-climatic zones for a particular indicator allows for a more accurate representation of the relative importance of different indicators within each distinct context. This approach recognizes that certain hazards might be more pronounced or have different implications in particular zones, necessitating a nuanced consideration that standard weights cannot provide. Thus, varying the weights based on the indicator and agroclimatic zones ensures that the index captures the specific vulnerabilities and challenges faced by different regions. This nuanced approach enables a more precise evaluation of climate-related risks, facilitating targeted adaptation strategies and fostering resilience in agriculture across diverse geographical contexts.

The comprehensive procedure of assigning weights to various indicators based on distinct agroclimatic zones underwent a meticulous and collaborative approach with the objective to foster a nuanced understanding of the intricate relationships between indicators and their real-world implications. This collaborative approach involved a series of five focus group consultation meetings (Figure 1), where experts and representatives hailing from diverse stakeholder organizations like various research programs of ICRISAT, World Food Programme (WFP), Agriculture and allied departments of various state governments including Telangana, Odisha and Maharashtra convened to deliberate upon the intricacies of weight allocation. These sessions served as pivotal platforms for knowledge exchange, constructive discourse, and informed decision-making, ensuring that the process was enriched with multifaceted insights.

Along with these participatory consultations, several individual-level discussions with scientists from various Indian Council of Agricultural Research (ICAR) institutes were conducted to delve deeper into the critical aspect of weight assignment. These one-on-one interactions provided an avenue for in-depth exploration of the relative significance of different indicators within specific agroclimatic contexts.

In essence, the collaborative consolidation of focus group consultation meetings, individual-level discussions, and expert consultations formed the cornerstone of the

***Figure 1**: Different stakeholder meetings during weight calculation process*

weight assignment process. This inclusive methodology not only heightened the credibility and robustness of the outcome but also imbued the developed climate hazard index with a pragmatic applicability, rendering it a valuable tool for understanding and addressing the intricate challenges posed by climate change within agricultural systems. Table 2 provides intricate details regarding the weights employed in the formulation of the CHIA.

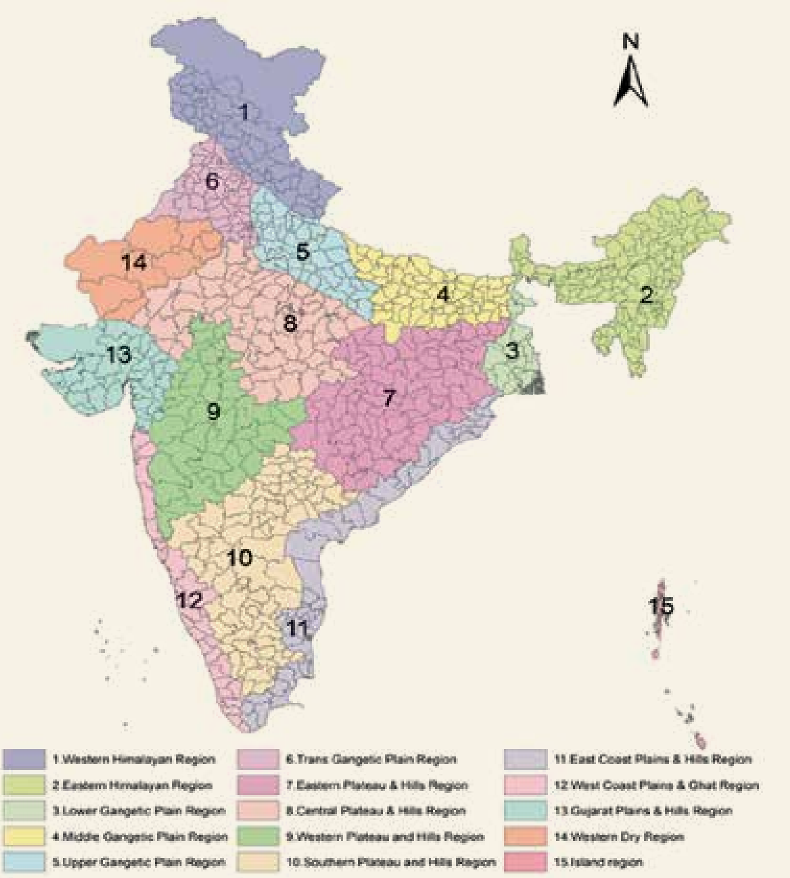
***Table 2:** Weights given to different indicators of climate hazard index across various agro-climatic zones*

Indicators	India	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11 & 12	Z13 & 14
Monsoon Maximum Temperature	0.04	0.04	0.05	0.06	0.04	0.05	0.05	0.06	0.05	0.06	0.06	0.00	0.10
Monsoon Minimum Temperature	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.03
Heat wave occurrences (days)	0.04	0.04	0.04	0.02	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.03
Cold wave occurrences (days)	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.03
Severe Heat wave occurrences (days)	0.02	0.02	0.02	0.00	0.02	0.02	0.02	0.02	0.03	0.02	0.00	0.00	0.02
Severe Cold wave occurrences (days)	0.03	0.05	0.00	0.00	0.03	0.03	0.03	0.00	0.03	0.04	0.03	0.00	0.03
CV of Annual rainfall (%)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.03
CV of Monsoon rainfall (%)	0.03	0.03	0.06	0.06	0.03	0.04	0.03	0.03	0.04	0.06	0.07	0.05	0.05
CV of June rainfall (%)	0.02	0.02	0.02	0.02	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00
CV of July rainfall (%)	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.05
Number of annual rainy days	0.02	0.02	0.05	0.03	0.04	0.04	0.04	0.02	0.02	0.03	0.03	0.00	0.03
Number of monsoon rainy days	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.05	0.04	0.06	0.06	0.00	0.05
Heavy rainfall days	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.03
Very heavy rainfall days	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.05	0.05
No of times more than 14 days of dry spell in monsoon (no/time slice)	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.00	0.06
No of times more than 14 days of wet spell in monsoon (no/time slice)	0.04	0.04	0.04	0.03	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.00
No of times more than 10 days of dry spell in monsoon (no/time slice)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.02
No of times more than 10 days of wet spell in monsoon (no/time slice)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.00
Drought proneness	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.10	0.10
Flood proneness	0.05	0.05	0.05	0.05	0.10	0.05	0.05	0.05	0.05	0.04	0.04	0.20	0.04
Average highest rainfall in a single day as % to annual normal	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.05	0.03	0.03	0.05	0.03	0.03
Number of times more than 3 days of temperature >=35 during monsoon	0.06	0.06	0.06	0.02	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.04	0.08
Floods_Flash floods_Cloud burst_ Landslide	0.06	0.08	0.06	0.10	0.09	0.03	0.03	0.07	0.06	0.04	0.04	0.15	0.05
Cyclonic storms	0.05	0.00	0.05	0.13	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.30	0.07
Hailstorms	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.03	0.05	0.05	0.05	0.02	0.02
Terminal heat stress-Temperature rise in Feb and Mar	0.04	0.05	0.00	0.00	0.00	0.07	0.09	0.00	0.05	0.00	0.00	0.00	0.00
Total weight	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Box 1: Agro-climatic zones

There are 15 Agro-climatic zones in India namely Western Himalayan Region, Eastern Himalayan Region, Lower Gangetic Plains Region, Middle Gangetic Plains Region, Upper Gangetic Plains Region, Trans-Gangetic Plains Region, Eastern Plateau and Hills Region, Central Plateau and Hills Region, Western Plateau and Hills Region, Southern Plateau and Hills Region, East Coast Plains and Hills Region, West Coast Plains and Ghat Region, Gujarat Plains and Hills Region, Western Dry Region and Island Region. However, for our analysis, East Coast Plains and Hills Region and West Coast Plains and Ghat Region were merged considering the similar type of climate stress like cyclones experienced in both the regions. Since a major part of the Gujarat Plains and Hills Region constitute dry arid areas, it was merged with the Western Dry Region of Rajasthan to reduce the number of recommendation domains.

Zone Number	Zone Name	States covered
Zone 1	Western Himalayan Region	Jammu and Kashmir, Uttarakhand
Zone 2	Eastern Himalayan Region	Assam, Sikkim, West Bengal, and all North-Eastern states
Zone 3	Lower Gangetic Plains Region	West Bengal
Zone 4	Middle Gangetic Plains Region	Uttar Pradesh, Bihar
Zone 5	Upper Gangetic Plains Region	Uttar Pradesh
Zone 6	Trans-Gangetic Plains Region	Punjab, Haryana, Delhi, and Rajasthan
Zone 7	Eastern Plateau and Hills Region	Maharashtra, Uttar Pradesh, Odisha, and West Bengal
Zone 8	Central Plateau and Hills Region	Madhya Pradesh, Rajasthan, Uttar Pradesh
Zone 9	Western Plateau and Hills Region	Maharashtra, Madhya Pradesh, and Rajasthan
Zone 10	Southern Plateau and Hills Region	Andhra Pradesh, Karnataka, Tamil Nadu
Zone 11	East Coast Plains and Hills Region	Odisha, Andhra Pradesh, Tamil Nadu, and Puducherry
Zone 12	West Coast Plains and Ghat Region	Tamil Nadu, Kerala, Goa, Karnataka, Maharashtra
Zone 13	Gujarat Plains and Hills Region	Gujarat
Zone 14	Western Dry Region	Rajasthan
Zone 15	The Islands Region	Andaman and Nicobar Islands, Lakshadweep



Categorization of climate hazard index

It's worth emphasizing that the index values are relative in nature, mainly intended for the prioritization of districts. These values are centered around the mean, where values closer to this average indicate a situation considered 'average.' Conversely, values that deviate from the mean signify either an enhanced or diminished scenario, due to the normalization technique utilized. To facilitate the classification of districts, the creation of a range for the CHIA becomes essential. This range establishes a framework for categorizing districts based on their respective CHIA values. The subsequent Table 3 delineates the specific ranges for CHIA values, offering a structured mechanism for the systematic evaluation and classification of districts according to their susceptibility to climatic hazards and associated agricultural implications. Here we have followed the category developed by (Ramarao *et al.,* 2019). However, the distribution of districts into different categories changes with the number of categories or with the threshold values of each category, the choice of which is subjective.

***Table 3**: Categorization of climate hazard index*

If the value of $CHIA_{dt}$ is	Category
> $1.5 * SD_{zt}$	Very High
Between $0.5 * SD_{zt}$ to $1.5 * SD_{zt}$	High
Between $-0.5 * SD_{zt}$ to $0.5 * SD_{zt}$	Medium
Between $-1.5 * SD_{zt}$ to $-0.5 * SD_{zt}$	Low
< $-1.5 * SD_{zt}$	Very Low
Where SD_{zt} is Standard deviation over districts of a particular zone and time.	

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Data Source

CLIMATE DATA

As explained in the indicator selection section, rainfall and temperature were identified as pivotal climatic attributes. To elucidate the data collection process, we collected rainfall and temperature data from the India Meteorological Department (IMD) database, spanning the temporal interval of 1990 to 2018. The collected Rainfall data (https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_Bin.html) used was new high spatial resolution (0.25X0.25 degree) long period daily gridded rainfall dataset over India. Likewise, the temperature data (https://www.imdpune.gov.in/cmpg/Griddata/Max_1_Bin.html) used in this study was high resolution 1By1 degree gridded daily temperature data. These initial datasets were subsequently subjected to further processing to transform it into district-level data, ensuring a more granular level of analysis.

The disastrous weather events data (https://imdpune.gov.in/library/publication.html) from 1990 to 2018 used in this study was downloaded from IMD disastrous weather events database. Hailstorms, Floods and heavy rains and Cyclonic storms were selected for this study. The year-wise and state/district-wise data was compiled and processed. **All the datasets were meticulously gathered for a total of 576 districts across the geographical expanse of India**.

Upon the transformation of grid-level data into district-level data, a subsequent stage involved in the conversion of this information into distinct indicators for temperature and rainfall as elucidated in the indicator selection section. These indicators provide a refined representation of the climate attributes, facilitating a more comprehensive assessment of their impact on agricultural systems.

Crop data

For analyzing the correlation between crop production and climate hazard, we considered both kharif food crops including Rice, Maize, Kharif Sorghum, Pearl Millet, Finger Millet, Pigeon pea, Soyabean, Groundnut and Sesamum and the Rabi food crops including Wheat, Rabi Sorghum, Chickpea and Rapeseed & Mustard. To ensure a robust analysis, the production data for the above-mentioned crops, spanning the period from 1998 to 2017, was collated from the database of ICRISAT district level data (http://data.icrisat.org/dld/src/crops.html). This comprehensive dataset encompasses all 576 districts, providing a rich repository of information that spans varying geographical and climatic contexts.

To facilitate the comprehensive analysis of the correlation between crop production and climate hazards, our study encompassed a diverse spectrum of food crops from both kharif and rabi seasons, and through the meticulous collection of production data, our study aimed to establish a nuanced understanding of the intricate correlation between agricultural output and climate hazards across a wide range of regions and cultivation practices.

To determine the districts considered within our study, a detailed criterion was employed involving the formation of a minimum cropped area for each specific crop over the period spanning 1998 to 2017. The determination of this minimum area was the result of a collaborative approach that entailed a series of five focus group consultation meetings. These sessions brought together a panel of experts and representatives from an array of stakeholder organizations, including those from domains such as agriculture and allied, research institutions, and government bodies (discussed in the weight assignment section). Table 4 provides a threshold (minimum) magnitude of cropped area of a particular crop to get a district included in the analysis, accompanied by the corresponding count of districts that were included in the analysis for each crop.

__Table 4__: Criteria for the inclusion of districts in the analysis for various crops

Crop type	Crop name	Minimum cropped area considered (ha) for inclusion of the district	Number of districts included in the analysis (1998-2017)
Main Crops	Rice	5000	340
	Wheat	5000	268
	Maize	2500	187
Coarse Crops	Sorghum Kharif	1000	62
	Sorghum Rabi	500	40
	Pearl millet	1000	121
	Finger millet	1000	39
Pulses	Chickpea	2000	137
	Pigeonpea	2000	121
	Soyabean	1000	63
Oil seeds	Groundnut	2000	126
	Sesamum	1000	91
	Rapeseed & Mustard	1500	160

Photo courtesy: Freepik.– JComp

Results and Discussion

STATUS AND TREND OF CHIA

An increase in the value of the Climate Hazard Index for Agriculture (CHIA) indicated the severity of climate-related hazards in a particular district. As elaborated in the methodology section, we **classified CHIA into four distinct categories: very high, high, medium, low, and very low extent of climate variability (hazards)**. Our analysis revealed that the overall mean CHIA value was 0.1627, accompanied by a standard deviation of 0.3122. However, the average CHIA values within the very high and high climate variability categories were 0.4109 (with a standard deviation of 0.2475), while the average values within the low and very low categories were -0.3013 (with a standard deviation of 0.1243).

Across the examined dataset, the highest CHIA value, 2.8027, occurred in the Thoothukkudi district of Tamil Nadu in the year 2000. This is followed by the Nellore district of Andhra Pradesh in 2001 with a CHIA value of 2.7453, and the Kancheepuram district of Tamil Nadu in 2016 with a CHIA value of 2.6326. Conversely, the lowest CHIA score of -0.8721 was observed in the Yamunanagar district of Haryana in 2014, trailed by the Araria district of Bihar in 2010 and the Panchkula district of Haryana in 1993, with CHIA values of -0.8417 and -0.8168, respectively.

Taking a 29-year average, the Ariyalur district of Tamil Nadu recorded the highest CHIA score of 0.7964 among all 574 districts. It was followed by the Karur district of Tamil Nadu and the Jaisalmer district of Rajasthan, with scores of 0.8009 and 0.7613, respectively. On the other hand, over the same 29-year span, the Rupnagar district of Punjab exhibits the lowest CHIA score of -0.4958 among the 574 districts, signifying a lower impact of climate on agriculture. This is trailed by the Nawanshahr district of Punjab and the Kolhapur district of Maharashtra, with scores of -0.4688 and -0.4578, respectively.

The districts Ariyalur, Karur, and Perambalur of Tamil Nadu, along with Bikaner of Rajasthan, face the most significant impact. These districts fall into the "very high" category of the CHIA index for 27 out of 29 years, indicating their consistent vulnerability. The Tiruchirappalli district of Tamil Nadu and the Jaisalmer district of Rajasthan experience high-category CHIA levels for 26 and 23 years, respectively. This suggests that these districts encountered substantial climate-related challenges every year under consideration. The CHIA score under high climate variability categories for districts such as Una of Himachal Pradesh, Marigaon of Assam, and Karauli of Rajasthan, with 23 out of 29 years falling into the high climate hazards category. Similarly, the Srinagar district of Jammu & Kashmir, along with Dhubri and Nalbari districts of Assam and the Balrampur district of Uttar Pradesh, experienced high CHIA levels for 22 years.

On the contrary, the Narmada district of Gujarat registers low CHIA values for 27 instances, while the Surat district of Gujarat and the Mysore district of Karnataka record 25 and 24 instances, respectively, falling into the low hazards category. The Rupnagar district of Punjab demonstrated a frequency of 19 occurrences in the "very low" CHIA category, indicating lesser vulnerability. Similarly, the Yamuna Nagar district of Haryana and the Kolhapur district of Maharashtra experienced 15 and 14 instances, respectively, in the "very low" CHIA category. Following Figure 2 (A-E) shows the trend of CHIA over time across districts in India.

Photo courtesy:the bing

Figure 2A: Climate hazard index for Agriculture (CHIA) over time (1990-1995)

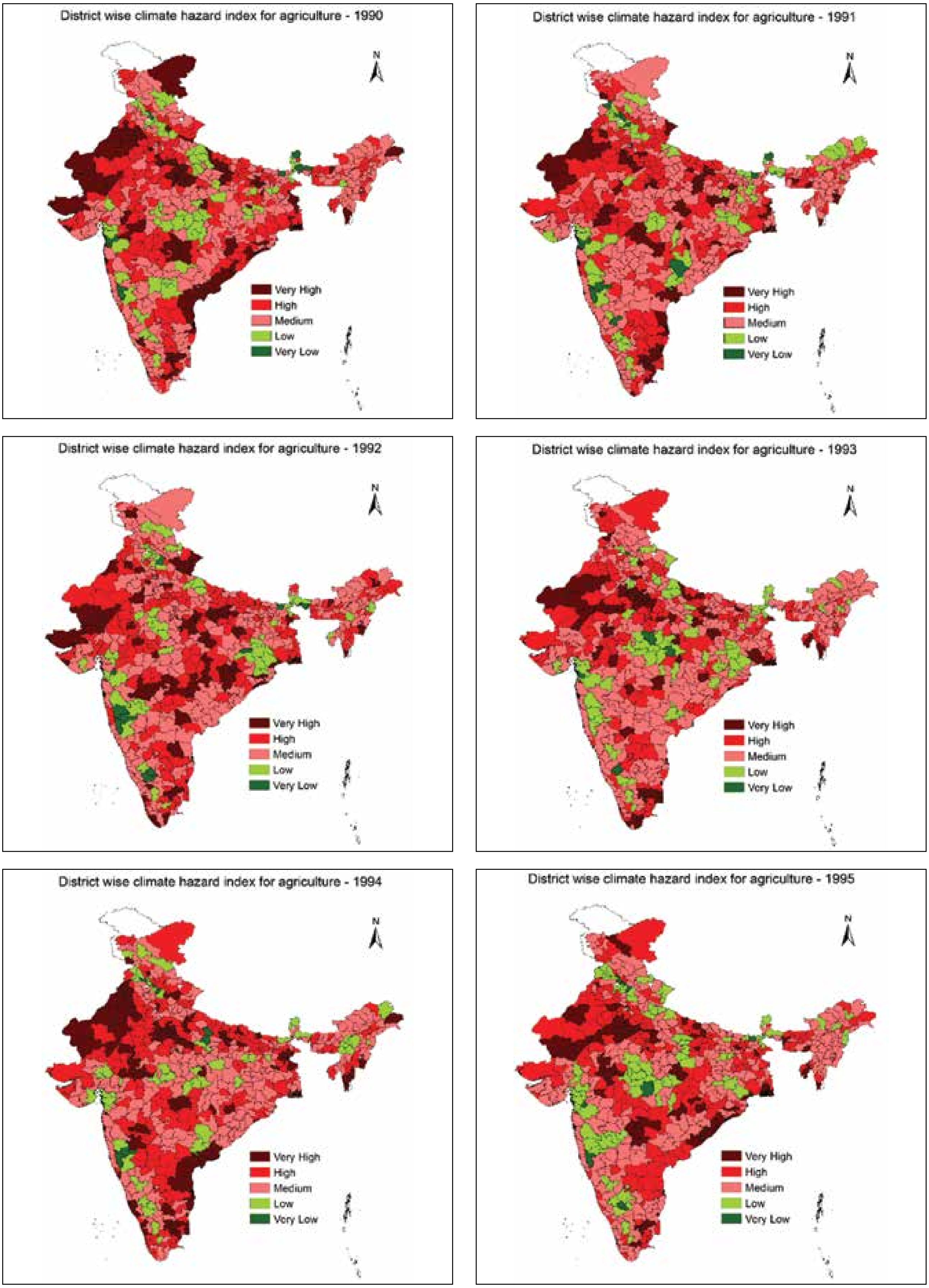


***Figure 2B**: CHIA over time (1996-2001)*

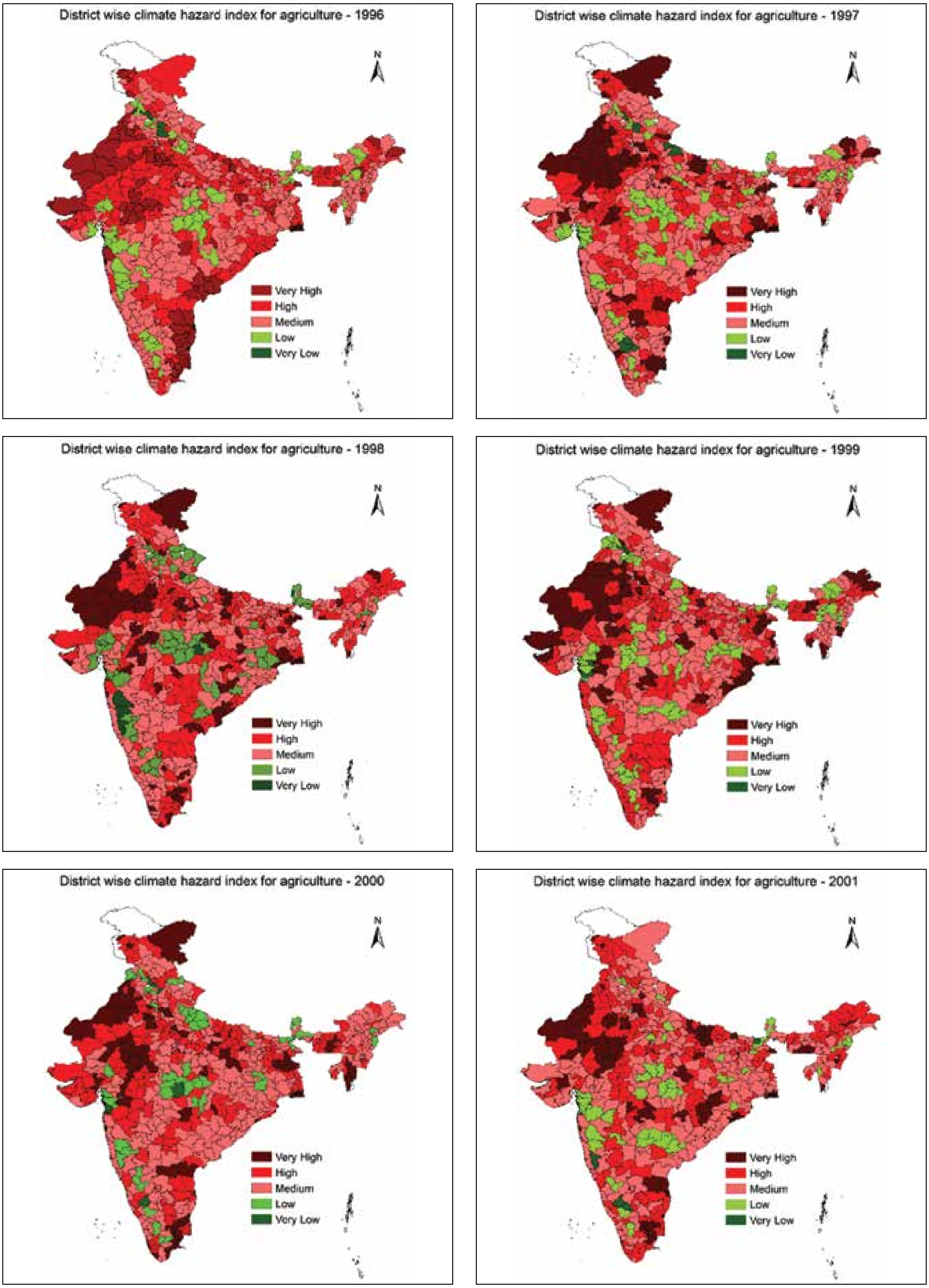


***Figure 2C**: CHIA over time (2002-2007)*

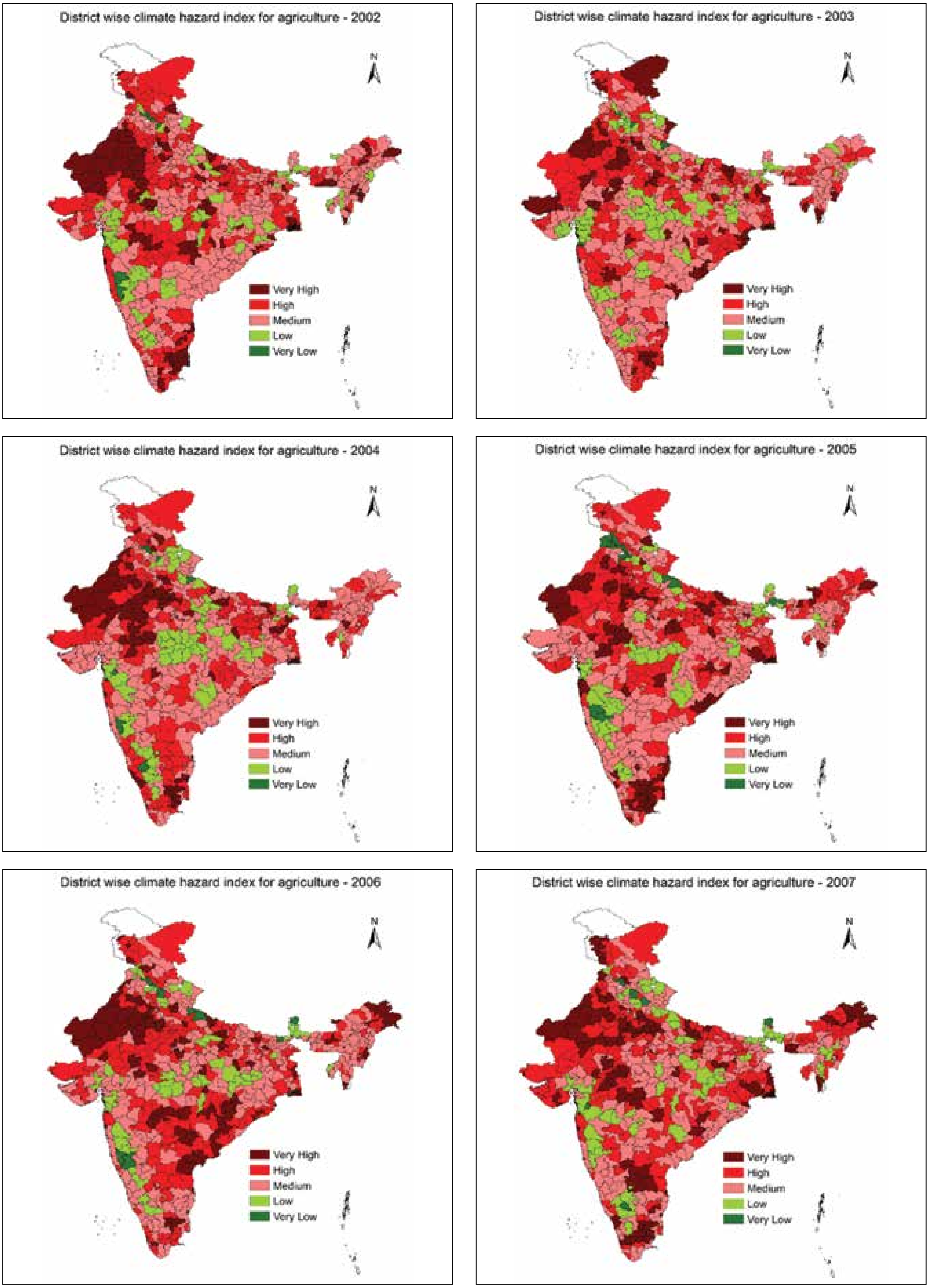


***Figure 2D**: CHIA over time (2008-2013)*

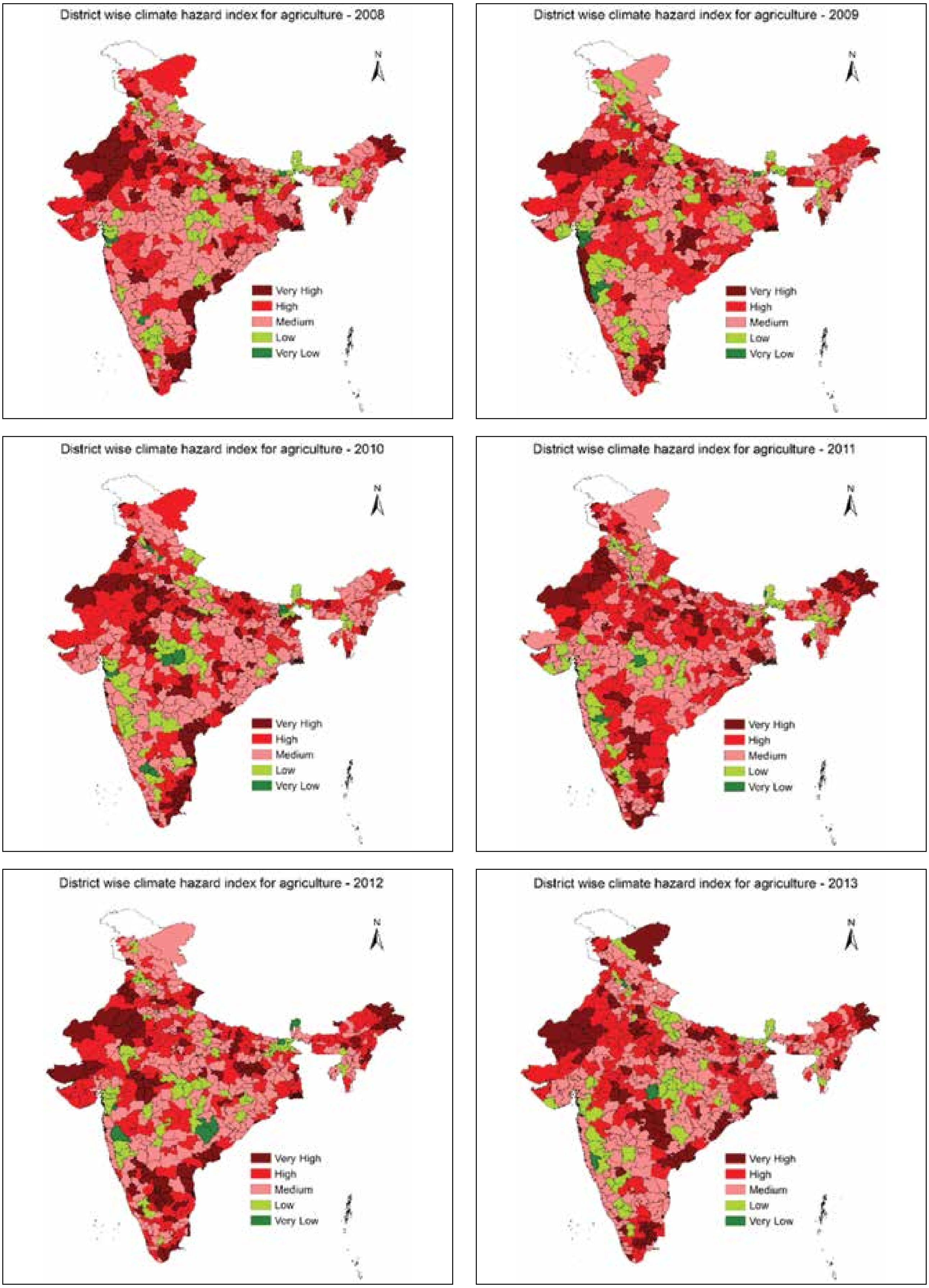
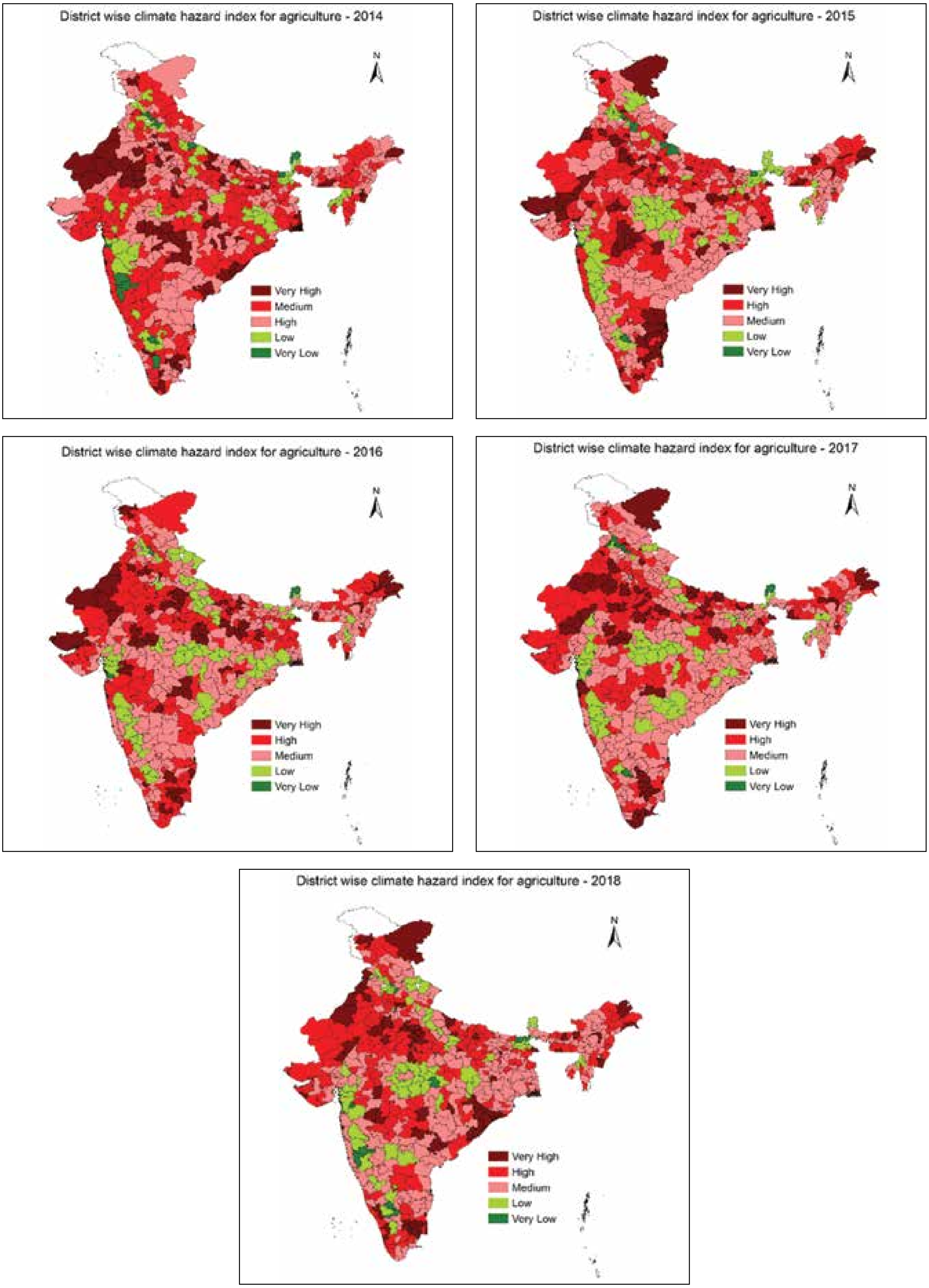


Figure 2E: CHIA over time (2014-2018)



Relationship between CHIA and the Crop Production

The aim of this study was to examine whether there is a negative correlation between climate hazards and food (crop) production. As a result, we focused our discussion solely on the negative correlations, both significant and non-significant. For a comprehensive breakdown of all the detailed findings, please refer to Table A in the Appendix.

As outlined in the crop data section, our study encompasses four distinct food crop types: major cereals, coarse cereals, pulses, and oilseeds. In the subsequent sections, we delve into the correlation between production of these crops and the CHIA.

Major cereals

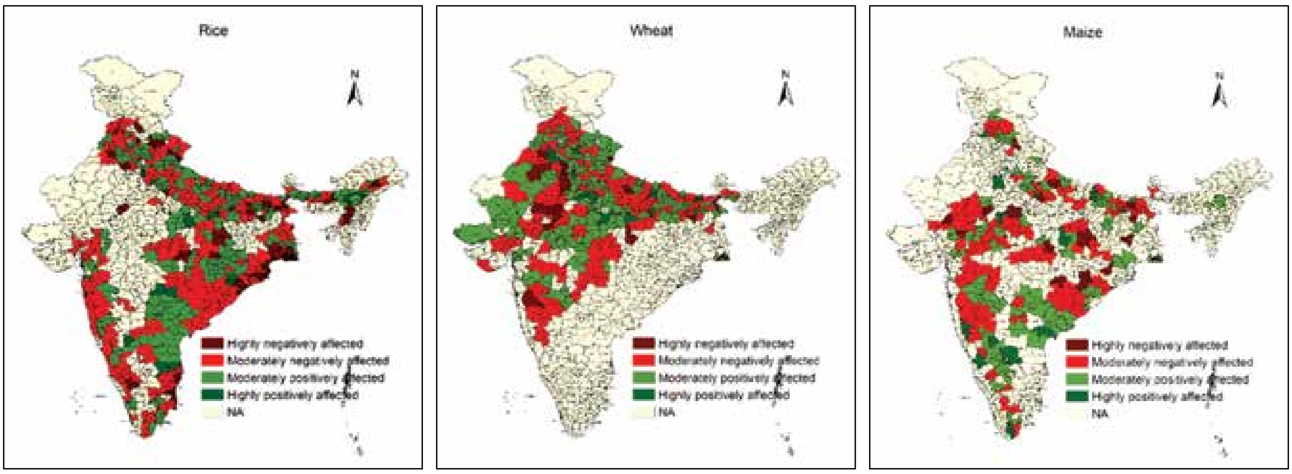
Rice

Rice, also known as paddy, is a crucial staple food in India, playing a vital role in ensuring food security. However, the cultivation of rice is highly vulnerable to the impacts of changing climate and weather patterns. Our analysis has revealed a connection between rice production and the CHIA in 208 districts across India, showing a negative correlation. Map 1 in Figure 3 provides a clear visual representation of this relationship between rice production and CHIA. The analysis sheds light on the fact that the effects of climate hazard were particularly pronounced in certain regions. Among these, 43 districts falling within agro-climatic zone 11 & 12, which includes coastal regions in the eastern and western parts of India, experienced significant challenges in rice production due to climate hazard. Similarly, 20 districts within each of the agro-climate zones, including Zone 4, Zone 6, Zone 7, and Zone 5, also faced adverse impacts on rice cultivation and production due to climate variability. Notably affected specific districts within these zones were Jagatsinghapur and Ganjam in Zone 11 & 12, Nalanda, and Madhepura in Zone 4, Sirsa and Bhiwani in Zone 6, Surguja and Balaghat in Zone 7, and Etawah and Bareilly in Zone 5. These districts stand out as regions disproportionately affected due to climate hazards, significantly affecting rice production. More details on zone-wise distribution are presented in Table A1 in the Appendix.

Wheat

Wheat holds the position of being the second most crucial staple crop in India. The production of wheat in 136 districts was notably influenced by a range of distinct climate hazards, leading to the emergence of a discernible negative correlation between the Climate Hazard Index for Agriculture (CHIA) and wheat production. Among these districts, 34 are situated in zone 4, the upper Gangetic Plain, exhibiting a noteworthy negative correlation with CHIA. This trend was further echoed in zones 8 and 6 with 24 and 18 districts. Map 2 of Figure 3 shows a detailed presentation of the correlation between wheat production and CHIA. Within zone 4, districts like Shrawasti in Uttar Pradesh and Madhepura in Bihar demonstrate notably higher negative correlation between the CHIA and wheat production. A similar pattern holds true for districts within zone 8, namely Bundi and Alwar in Rajasthan. Meanwhile, in zone 6, Rohtak in Haryana also showcased a significant negative correlation. Climatic hazards have a direct and impactful relationship with the production of wheat, further highlighting the complex interplay between climate and agricultural outcomes. Details of the distribution across states are presented in Table A1 in the Appendix.

***Figure 3**: Distribution of correlation between CHIA and production of major cereal crops*



Maize

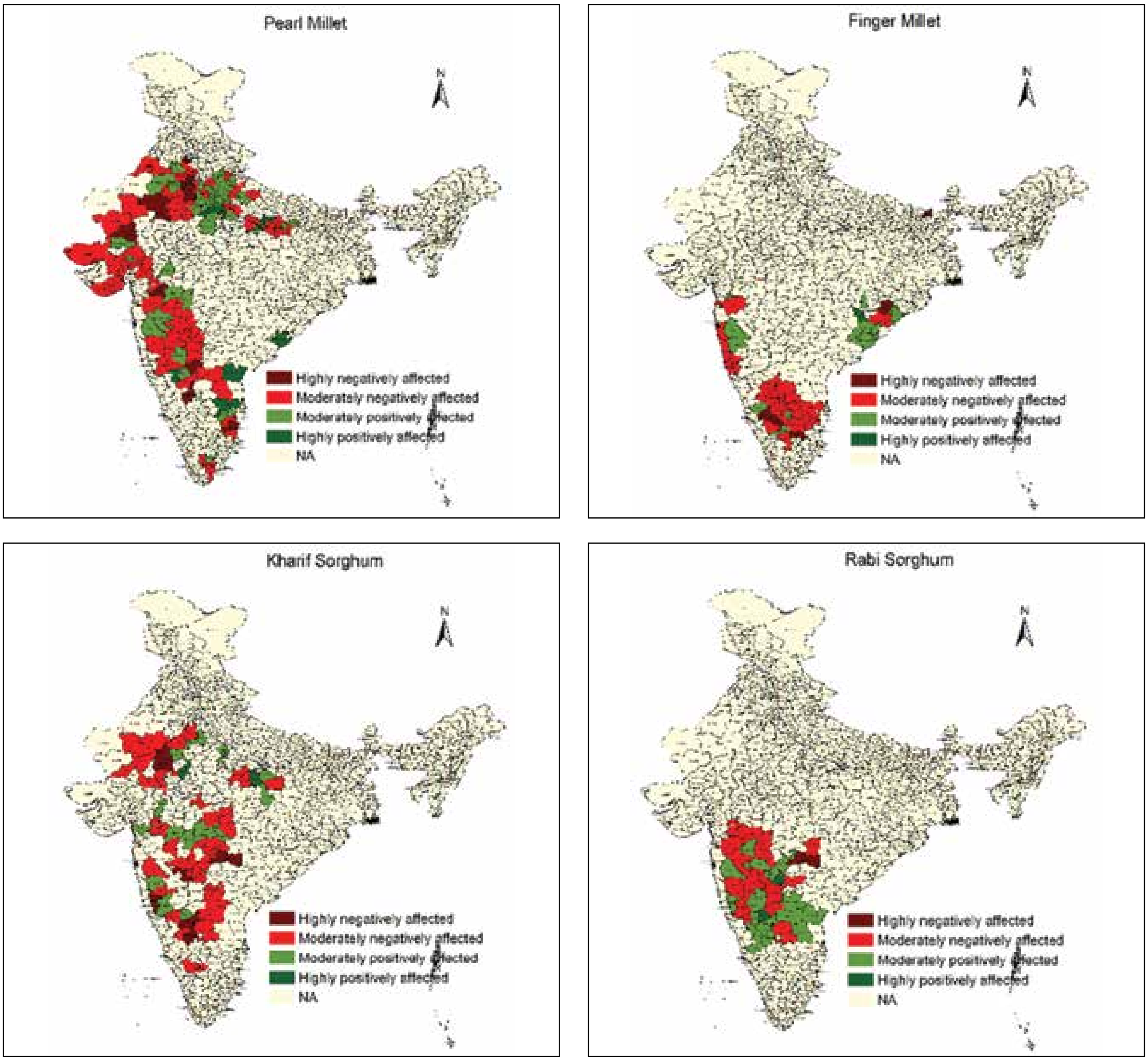
Maize holds the distinction of being the third most vital staple crop in India. The production of maize in specific regions displays a notable correlation with the CHIA, thereby influencing its production. Among these regions, 20 districts within zone 8, 18 districts within zone 4, and 12 districts within zone 7 exhibit a significant negative correlation with the CHIA.

Map 3 of Figure 3 offers an elaborate depiction of the correlation between maize production and CHIA, furnishing a visual representation of this intricate relationship. Among the districts, Bundi and Mandla, situated in Rajasthan and Madhya Pradesh respectively, within zone 8 showcased the most pronounced negative correlation between maize production and the CHIA. In zone 4, the districts of Banka and Saharsa in Bihar also manifested a negative correlation between CHIA and maize production. Further afield, Kalahandi in Odisha and Kanker in Chhattisgarh emerged as two significant districts within zone 7, where a negative correlation between CHIA and maize production was apparent. Climatic hazards interact intricately, playing a pivotal role in shaping the production of maize and underscoring the interplay between climate and agricultural output. Details concerning the geographical distribution across states can be found in Table A1, located within the Appendix.

Coarse cereals

Our analysis also encompassed the examination of three distinct coarse cereal (nutri-cereals) crops: kharif sorghum, rabi sorghum, pearl millet, and finger millet.

Figure 4: Distribution of correlation between CHIA and production of different coarse cereals



Within this context, we observed noteworthy trends in the correlation between these crops and the CHIA. Specifically, we found that 43 districts cultivating kharif sorghum, 20 districts cultivating Rabi sorghum, 77 districts cultivating pearl millet, and 26 districts cultivating finger millet exhibit a negative correlation with the CHIA. Though the millets and sorghum are relatively more climate resilient, however these crops mostly being grown in rainfed, and marginal lands are also affected due to climate change.

The regions encompassing in zones 9, 10, and 8 emerged as the highest degree of negative correlation between the production of kharif sorghum and the CHIA. Delving into the specifics, districts like Adilabad in Telangana, Bhilwara in Rajasthan, and Bellary in Karnataka stand out as prime examples of districts showcasing pronounced negative correlation with kharif sorghum production.

Moving on to rabi sorghum, we observed a similar pattern where districts within zone 9 exhibit negative correlation between CHIA and rabi sorghum production. Adilabad in Telangana, Osmanabad in Maharashtra, and Medak in Telangana **emerged as the top** three districts displaying the most negative correlation between CHIA and the production of rabi sorghum.

In pearl millet, we found that 16 districts from zones 13&14, along with 12 districts from zone 9, manifest the highest count of districts displaying a negative correlation between CHIA and pearl millet production. These trends were then followed by zones 10 and 9. Zooming in, we identified the Dhule district in Maharashtra as the most highly negatively correlated district in terms of pearl millet production, closely trailed by Mahendragarh and Kaithal in Haryana.

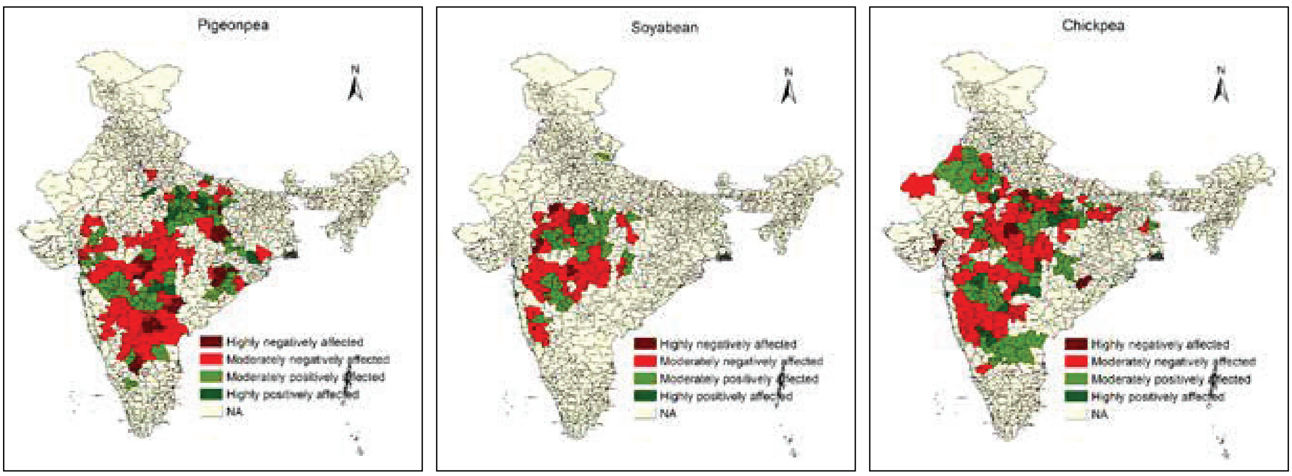
Turning to finger millet, 11 districts within zone 10 and 8 districts within zones 11&12 illustrate a negative correlation between finger millet production and the CHIA. Among these, the production of finger millet in the Salem district of Tamil Nadu surfaces as the district with the most pronounced negative correlation. This is followed by districts like Hassan and Mandya in Karnataka. Following Figure 4 with maps shows an elaborate depiction of the correlation between different coarse cereals production and CHIA.

In addition to climate hazards, the lack of demand and unattractive market price of coarse grains has also been one of the reasons of decline in their production. The interplay between climatic hazard and non-climatic factors forms a complex landscape that has shaped coarse grain production. This in turn has affected the economic incentives for farmers to cultivate these crops, resulting in lower overall production levels. The negative correlation with CHIA underscores the multifaceted nature of challenges faced by the agricultural sector, highlighting the need for a comprehensive approach to address both climatic and non-climatic factors.

Pulses Crops

In our comprehensive analysis, we focused on the examination of three major pulse crops: pigeon pea, soyabean, and chickpea. The production of these pulses in various districts revealed intriguing correlation with the CHIA. Specifically, we observed that the production of pigeon pea was negatively correlated with CHIA in 69 districts, soyabean in 36 districts, and chickpea in 76 districts. Following the maps in the Figure 5 shows an elaborate depiction of the correlation between production of different pulse crops and CHIA.

Figure 5: Distribution of correlation between CHIA and different pulses



The impact of climate hazards on these pulse crops varies across different geographic regions. Among the districts cultivating pigeonpea, those within zone 9, followed by 15 districts within zone 10 and 12 districts within zone 8, exhibit the most pronounced negative correlation with the Climate Hazard Index for Agriculture (CHIA). Within these regions, the district of Washim in Maharashtra emerges as the most adversely affected, displaying the highest negative correlation with CHIA. Tumkur in Karnataka and Surguja in Chhattisgarh follow closely as districts with significant negative correlations.

Similarly, the production of Soyabean is also significantly impacted by climatic hazard across different zones. Within zone 9, 21 districts showcase the highest negative correlation with CHIA, while 11 districts within zone 8 also experience notable impacts. Among the districts, Bundi in Rajasthan exhibits the most adverse correlation, with Jhabua in Madhya Pradesh and Akola in Maharashtra are closely behind.

Turning to chickpea production, we find that 31 districts within zone 8, followed by 18 districts within zone 8, present the most significant negative correlation with CHIA. Bhind in Rajasthan emerges as the most adversely affected district, displaying the highest negative correlation with the Climate Hazard Index for Agriculture. Vidisha in Madhya Pradesh and Ahmedabad in Gujarat also stand out as districts with substantial negative correlations.

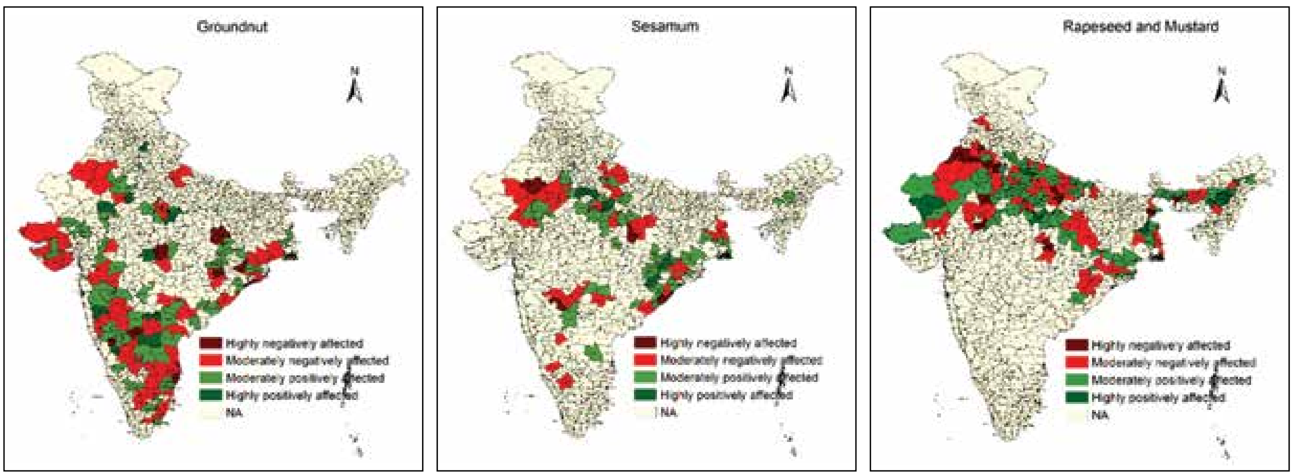
Oil seeds

Within our comprehensive analysis, we have delved into the dynamics of three distinct major oilseed crops: groundnut, sesamum, and rapeseed & mustard. These crops play a crucial role in the agricultural landscape, and we've explored their production patterns in relation to the CHIA. Notably, we've found that the production of groundnut was negatively correlated with CHIA in 67 districts, sesamum in 42 districts, and rapeseed & mustard in 81 districts. The correlation between the production of various oilseed crops and the CHIA has been mapped and presented in Figure 6. The influence of climatic hazards on these oilseed crops varied across different geographical zones. Among the districts cultivating groundnut, those within zone 10 exhibited the highest negative correlation with CHIA, followed by 14 districts within zones 11 & 12, and 9 districts within zone 9. Within these regions, the Surguja district in Chhattisgarh showcased the most significant negative correlation with CHIA in terms of groundnut production. Bolangir in Odisha and Kancheepuram in Tamil Nadu closely followed as districts with substantial negative correlations.

Similarly, for sesamum, we found that production was notably affected by climatic hazards within specific zones. Within zone 8, 12 districts exhibited the highest negative correlation with CHIA, followed by 7 districts within zone 5. In terms of districts, Nagaur in Rajasthan displayed the highest negative correlation with the Climate Hazard Index for Agriculture in sesamum production. Osmanabad in Maharashtra and Shahdol in Madhya Pradesh also stand out as districts with notable negative correlations.

Moving on to rapeseed & mustard, we observed a similar pattern with notable impacts arising from climatic hazard in certain zones. Among the districts, 16 within zone 5 exhibited the highest negative correlation with CHIA, followed by 14 districts within zone 6, and 13 districts within zone 8. Hanumangarh in Rajasthan emerged as the district most significantly affected, displaying the highest negative correlation with the Climate Hazard Index for Agriculture in rapeseed & mustard production. Rewari in Haryana and Ganganagar in Rajasthan also showcased substantial negative correlations.

Figure 6: Distribution of correlation between CHIA and different oil seeds



Conclusions

Our comprehensive analysis has unveiled a significant relationship between climate hazards and diverse crop productions across various regions. Our study has revealed significant negative correlations between climate hazards and the production of major crops such as rice and wheat, as well as coarse crops, pulses, and oilseeds. These findings underscore the far-reaching impact of climate change on the agricultural landscape and food security, with specific regions and crops exhibiting varying degrees of susceptibility.

By quantifying the intricate relationship between climate hazards and food production, our study contributes to the ongoing debate on climate change adaptation and mitigation. It underscores the necessity for collaborative efforts between policymakers, researchers, and stakeholders to forge a path towards a more resilient and sustainable agricultural future in India.

The findings underscore the importance of acknowledging the intricate interplay between climatic factors and agricultural outcomes. Regions situated in agro-climate zones with higher susceptibility, particularly those along coastal areas also face more pronounced challenges in crop production due to climate hazards. This realization serves as a clarion call for tailored strategies and proactive measures to address the vulnerabilities and ensure food security.

Ultimately, this study reinforces the urgency of adopting sustainable practices and policies to mitigate the adverse effects of climate hazards on crop production. By recognizing the intricate relationship between climate and agriculture, we pave the way for a more resilient and secure food future for our nation. Building on the insights gained from this study, several key directions emerge for addressing the challenges posed by climate hazards to crop production in India. These directions can guide policy, research, and on-ground initiatives aimed at promoting agricultural resilience and ensuring food security.

- **Climate-Resilient Crop Varieties:** The importance of development and promotion of climate-resilient crop varieties that can withstand the changing climatic conditions is paramount. Investment in research and breeding programs aimed at creating crops with enhanced tolerance to heat, drought, and other climatic stressors will be crucial.
- **Adaptive and Regenerative Farming Practices:** Encouraging the adoption of adaptive and regenerative farming practices can mitigate the impact of climate hazards. Techniques such as crop diversification, intercropping, agroforestry, water-efficient irrigation, and conservation agriculture can help farmers better adapt to climatic variability.
- **Weather Forecasting and Early Warning Systems:** Strengthening weather forecasting and early warning systems and provision of context specific climate information services can empower farmers with timely information about impending climate-related challenges. This allows them to make informed decisions about planting, irrigation, and other agricultural activities.
- **Capacity Building:** Building the capacity of farmers through training and extension services can enhance their ability to respond to climate-related changes effectively. Knowledge one modern agricultural practices, risk management, and climate-smart technologies can contribute to improved crop yields.
- **Government Support:** Government policies that incentivize climate-resilient agriculture, provide insurance coverage for crop losses due to climate hazards, and offer financial support for implementing climate-smart practices can play a pivotal role in safeguarding the livelihoods of farmers and contribution to net-zero emissions.
- **Research and Innovation:** Continued research into understanding the specific impacts of different climate hazards on various crops is essential. Innovations in technology, such as precision agriculture and remote sensing, can aid in monitoring and managing climate-related risks.

- **Partnerships and Collaboration:** Collaboration between government agencies, research institutions, non-governmental organizations, and the private sector is crucial. These partnerships can facilitate the dissemination of knowledge, technology transfer, and the scaling up of successful initiatives.
- **Climate-Responsive Policies:** Integration of climate considerations into agricultural policies can ensure a holistic approach to addressing the challenges posed by climate hazards. Policies that account for both short-term adaptation and long-term sustainability are essential.
- **Awareness and Education:** Raising awareness among farmers about climate hazards and their potential impact on crop production should be a high priority. Educational campaigns and workshops can empower farmers to take proactive steps in safeguarding their crops.
- **Data Collection and Analysis:** Continued monitoring and collection of data on climate patterns, crop yields, and hazards can provide valuable insights for informed decision-making and policy formulation.

Incorporating these strategies into a comprehensive approach can help India's agricultural sector navigate the complex landscape of climate hazards. By building resilience, enhancing adaptive capacity, and promoting sustainable practices, the country can work towards ensuring a secure and productive future for its agricultural systems and food supply.

Photo courtesy: Unsplash–prasad-panchakshari

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Appendix

Table A1: Correlation between CHIA and crops' production (number of districts in different ACZs)

Crop	Type of correlation	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11 & 12	Z13 & 14
Rice	Negative Significant	5	5	3	7	1	4	3	1		1	9	
	Negative Non-significant	5	9	8	28	19	16	17	9	5	14	34	5
	Positive Non-significant	4	8	5	22	16	12	14	8	6	14	9	3
	Positive Significant		2		2	1	1	1	1		3		
Wheat	Negative Significant	1		1	1	1	4	1	5	2			1
	Negative Non-significant	9		2	33	18	14	2	19	14	2		6
	Positive Non-significant	12		3	22	19	15		23	13			12
	Positive Significant				4	1	4		4				
Maize	Negative Significant	1		1	3	2		5	5				
	Negative Non-significant	5	1	1	15	10	2	7	15	15	9	6	2
	Positive Non-significant	6	1		10	6	1	6	4	9	16	7	2
	Positive Significant				3	1	1	1	2	1	2	3	
Kharif Sorghum	Negative Significant								2	2	3		
	Negative Non-significant								11	12	10		3
	Positive Non-significant							1	6	7	2		1
	Positive Significant								2				
Rabi Sorghum	Negative Significant										1		
	Negative Non-significant							1		12	6		
	Positive Non-significant									6	10	2	
	Positive Significant										2		
Pearl Millet	Negative Significant						4		3	1	2	1	2
	Negative Non-significant				4	11	7		5	11	9	3	14
	Positive Non-significant				2	12	3		7	5	3	1	4
	Positive Significant					1			2		2	2	
Finger Millet	Negative Significant				1			1			3		
	Negative Non-significant									2	10	8	1
	Positive Non-significant							1		2	2	6	1
	Positive Significant											1	

Crop	Type of correlation	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11 & 12	Z13 & 14
Pigeonpea	Negative Significant				1			4		2	3		
	Negative Non-significant				5	3		5	12	16	12	3	3
	Positive Non-significant				7	4		5	10	7	6	3	3
	Positive Significant					3		1	2		1		
Chickpea	Negative Significant							1	3				1
	Negative Non-significant			1	7	2	3	2	28	18	7	1	2
	Positive Non-significant			1	4	4	3	5	9	13	6	1	4
	Positive Significant					2			3	2	4		
Soyabean	Negative Significant								1	2			
	Negative Non-significant							2	10	19	2		
	Positive Non-significant	1						2	12	11			
	Positive Significant								1				
Groundnut	Negative Significant							3	1		2	2	
	Negative Non-significant			1		3		4	4	9	17	12	9
	Positive Non-significant			2				7	7	7	13	9	5
	Positive Significant					1			4	1	3		
Sesamum	Negative Significant							1		1		1	1
	Negative Non-significant			3	1	7		3	12	3	4	4	1
	Positive Non-significant		1	3		4		9	15		4	5	
	Positive Significant							3	5				
Rapeseed & Mustard	Negative Significant		1	1		2	6		2	1			
	Negative Non-significant		6	4	8	14	8	10	11			1	5
	Positive Non-significant		8	6	6	15	2	7	19			4	6
	Positive Significant		3	1		1			1				1

Source: Authors' Own Calculation

***Table A**: Correlation between CHIA and crops' yield (number of districts in different ACZs)*

Crop	Type of correlation	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11 & 12	Z13 & 14
Rice	Negative Significant	1	4	4	4	2	3	5	1		1	13	
	Negative Non-significant	4	7	7	33	18	17	16	7	6	13	27	4
	Positive Non-significant	9	11	3	22	16	11	14	9	4	18	11	4
	Positive Significant		2	2		1	2		2	1		1	
Wheat	Negative Significant				2	1		6	4	3			
	Negative Non-significant	5	1	2	13	11	2	10	16	13	15	6	2
	Positive Non-significant	6	1		13	7	2	2	6	8	12	7	2
	Positive Significant	1			3			1		1		3	
Maize	Negative Significant								2	3	2		1
	Negative Non-significant							1	11	14	11		2
	Positive Non-significant								6	4	2		1
	Positive Significant								2				

Crop	Type of correlation	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11 & 12	Z13 & 14
Kharif Sorghum	Negative Significant						5		2	1			3
	Negative Non-significant				2	12	5		6	10	10	3	9
	Positive Non-significant				4	11	3		7	6	5	4	8
	Positive Significant					1	1		2		1		
Rabi Sorghum	Negative Significant										1		
	Negative Non-significant				1			2		1	10	8	1
	Positive Non-significant									3	3	6	1
	Positive Significant										1	1	
Pearl Millet	Negative Significant							2		2	1		
	Negative Non-significant				5	2		7	11	17	10	2	1
	Positive Non-significant				8	7		5	11	5	10	4	4
	Positive Significant					1		1	2	1	1		1
Finger Millet	Negative Significant								1	3			
	Negative Non-significant							4	6	19	1		
	Positive Non-significant	1							15	10	1		
	Positive Significant								2				
Pigeonpea	Negative Significant							1	1	4	4		1
	Negative Non-significant			2		2		7	9	6	15	13	5
	Positive Non-significant			1		1		6	3	6	12	10	7
	Positive Significant					1			3	1	4		1
Chickpea	Negative Significant			1				2	1			1	1
	Negative Non-significant			1	1	6		5	16	3	3	6	1
	Positive Non-significant		1	4		5		8	11	1	4	3	
	Positive Significant							1	4		1		
Soyabean	Negative Significant	1		1	1	1	4	1	5	2			1
	Negative Non-significant	9		2	33	18	14	2	19	14	2		6
	Positive Non-significant	12		3	22	19	15		23	13			12
	Positive Significant				4	1	4		4				
Groundnut	Negative Significant									1			
	Negative Non-significant							1		12	7	1	
	Positive Non-significant									5	11	1	
	Positive Significant										1		
Sesamum	Negative Significant			1			1	2	4	1	1		1
	Negative Non-significant				7	3	3	3	24	18	5	1	
	Positive Non-significant			1	4	4	2	3	12	14	10	1	5
	Positive Significant					1			3		1		1
Rapeseed & Mustard	Negative Significant		7	4	5	13	3	9	16			4	5
	Negative Non-significant		2	1	1	1	9	2		1			
	Positive Non-significant		5	6	8	16	2	6	15			1	7
	Positive Significant		4	1		2	2		2				

Source: Authors' Own Calculation

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