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Postdoc Written Assessment

CLIMATE HAZARDS AND CROP PRODUCTION IN INDIA: A SUB-NATIONAL ANALYSIS (1947-2014)

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I. Introduction

Climate change poses a major challenge to global food security, particularly in agriculture, where shifting temperatures, changing precipitation patterns, and extreme weather events directly impact productivity. Understanding the relationship between climate hazards and crop production at a sub-national level is crucial for developing effective adaptation strategies.
This analysis evaluates the impact of climate hazards on crop production in India from 1947 to 2014, using detailed sub-national production data alongside climate datasets. By examining extreme heat events, droughts, and rainfall anomalies, the study aims to uncover spatial and temporal patterns in climate-crop interactions. India's diverse agro-climatic zones and historical crop records provide a unique opportunity for such an investigation.

To achieve this, a systematic approach was followed:

1. **Data Acquisition and Preprocessing** – Cleaning, standardizing, and aligning crop production data (1956–2008) and country-level data (1947–2014).
2. **Climate Hazard Indicator Development** – Selecting relevant climate indicators and processing spatially and temporally consistent climate datasets.
3. **Statistical Modeling and Analysis** – Identifying trends and quantifying the impact of climate hazards on crop production.
4. **Visualization and Interpretation** – Creating clear maps, time-series plots, and regression analyses to highlight key insights.
5. **Reporting** – Synthesizing findings into actionable insights to inform climate-resilient agricultural planning.

This study's findings contribute to a better understanding of how climate variability affects agricultural output at a fine spatial scale, offering valuable insights for policymakers, researchers, and stakeholders in climate adaptation and food security planning.

II. Data Preparation and Quality Assessment

Data Loading and Cleaning
The sub-national crop production dataset (1956–2008) was loaded and assessed for completeness. Since district boundaries have evolved over time, 1966 administrative divisions (~305 unique districts) were used to maintain spatial consistency. A filtering process removed crops with >30% missing data, retaining 313,177 observations across 19 major crops. Only crops with at least ten valid yearly records were included, ensuring a reliable dataset for analysis.

Data Quality Assessment
A comprehensive **quality assessment** was conducted, focusing on **temporal continuity, spatial consistency, value ranges, and missing data patterns**. The analysis confirmed **improved data reliability post-1970**, leading to a focus on this period. A visual inspection of missing values over time revealed that gaps were concentrated in the early years, particularly for area and production metrics. Additionally, **yield distributions varied significantly across crops**, with Sugarcane exhibiting the highest yield efficiency.
The figure below summarizes key patterns in the dataset:

- **Production trends** show a steady increase in Rice and Wheat output.
- **Area vs. production relationships** confirm expected correlations across major crops.
- **Yield distributions** highlight crop-specific differences, with Sugarcane standing out.
- **Missing values analysis** indicates a significant reduction in gaps after 1970, reinforcing the decision to focus on this period.

Figure 1 Data overview

Implications for Analysis
The cleaned dataset provides a robust foundation for assessing climate impacts, ensuring spatial and temporal consistency. With a focus on the post-1970 period and five major crops (Rice, Wheat, Sugarcane, Sorghum, and Maize), the next step is to define and compute climate hazard indicators, aligning them with the crop production dataset to evaluate climate-crop interactions at the district level.

III. Climate Hazard Indicator Development

Climate Data Selection and Acquisition
To assess climate impacts on crop production, we selected **ERA5 reanalysis data**, which provides high-resolution climate variables from **1970 to 2008**—fully overlapping with our crop production dataset. Alternative datasets like CHIRPS were considered but lacked sufficient temporal coverage. ERA5 offers daily climate data at **0.25° spatial resolution**, covering critical variables:

- **Precipitation** (moisture availability)
- **Temperature extremes** (heat stress)
- **Solar radiation** (energy balance)
- **Dewpoint temperature** (humidity estimation)

A Python-based **download manager** was implemented to acquire and organize ERA5 data efficiently. The system retrieved **daily records for each month** at two time steps (00:00 and 12:00 UTC), ensuring diurnal variations were captured. Data was stored in a structured directory format, facilitating preprocessing and indicator calculations.

Data Processing and Indicator Development
The raw ERA5 data required significant preprocessing, including:

- **Unit conversion** (e.g., temperature to °C, precipitation to mm/day)
- **Relative humidity estimation** (derived from temperature and dewpoint temperature)
- **Aggregation of sub-daily values** into daily and monthly statistics
- **Spatial masking** to align with India's district boundaries

From the processed climate data, five **climate hazard indicators** were computed at the **district level**:

1. **Monthly Precipitation** – Total monthly rainfall (mm), capturing water availability.
2. **Growing Degree Days (GDD)** – Accumulated temperature above 10°C, reflecting crop development potential.
3. **Extreme Temperature Days** – Monthly count of days exceeding **35°C**, indicating heat stress.
4. **Heat-Humidity Index (HHI)** – A combined measure of **temperature and humidity**, capturing compound stress effects.
5. **Hot-Dry Days** – The number of days with **>35°C temperature and <1mm precipitation**, identifying extreme drought-heat interactions.

Each indicator was stored in **NetCDF format**, ensuring consistency in spatial resolution (0.25° grid) and temporal aggregation (monthly values).

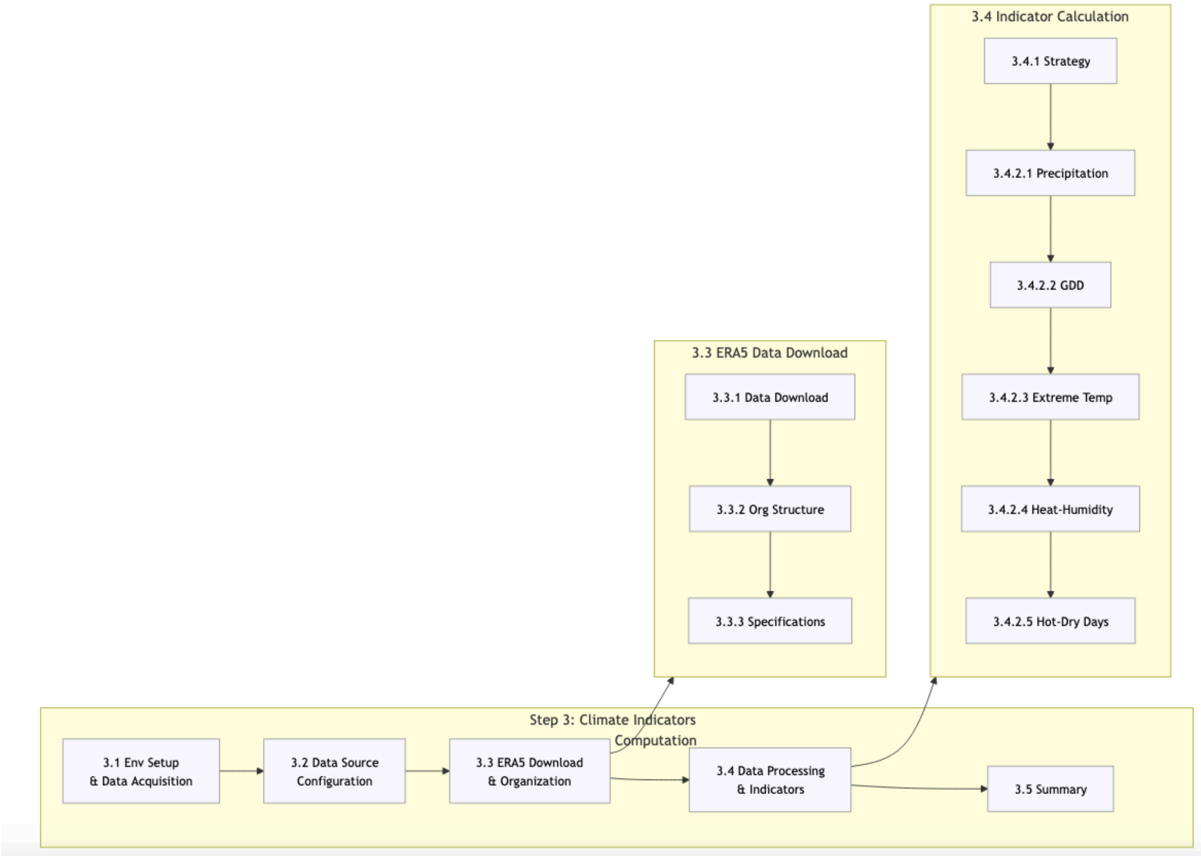

Figure 2 Workflow for Climate Hazard Indicator Development, outlining the steps for setting up the environment, acquiring ERA5 climate data, processing raw data, and computing key climate hazard indicators.

IV. Statistical Analysis of Climate-Crop Relationships

Climate-Crop Data Integration

To analyze the impact of climate on crop production, we integrated **climate hazard indicators** with the cleaned crop production dataset. The study focused on **five major crops (Rice, Wheat, Sugarcane, Sorghum, and Maize)** across **308 common districts** from **1970 to 2008**. A unified pipeline was developed to filter, merge, and align both datasets at the district level, ensuring full temporal and spatial consistency.

Crop-Level Sensitivity and Impact Analyses

This section evaluates how crop yields respond to climate variability by analyzing the effects of precipitation, extreme temperatures, and compound climate stressors. Using fixed-effects panel regressions and state-level analyses, we assess both crop-specific and regional sensitivities, identifying key climate drivers influencing productivity. Additionally, we investigate extreme climate events to determine their impact on agricultural yields and highlight vulnerable crop-region combinations. A structured summary of these analyses is presented in Table 1, which outlines key findings and their implications. The results emphasize the critical role of climate stressors, the spatial heterogeneity in climate-crop relationships, and the need for targeted adaptation strategies to mitigate climate risks in agriculture.

Summary of Findings

The statistical analysis revealed **distinct climate-crop relationships** across crops, regions, and extreme events:

1. **Crop-Specific Sensitivity** – Climate impacts varied by crop, with Sorghum and Wheat showing the highest sensitivity.
2. **Regional Differences** – Climate effects were **state-dependent**, with water availability driving productivity in arid zones and heat stress limiting growth in northern states.
3. **Extreme Climate Events** – High-temperature and low-precipitation extremes had significant but uneven impacts, affecting some crops and regions more than others.

Table 1 Crop-Level Sensitivity and Impact Analyses Summary

Analysis Aspect	Key Findings	Implications
Crop-Specific Climate Sensitivity	Precipitation and extreme temperatures significantly impact crop yields, with Sorghum and Wheat being most sensitive. Compound stressors had stronger effects than individual variables. Climate impacts intensified post-1990.	Moderate-to-low R^2 values suggest additional agronomic and socioeconomic factors influence yield variability. Highlights the importance of compound stress analysis.
Regional Variation Analysis	State-level analysis showed precipitation had the greatest impact in arid states (e.g., Gujarat, Rajasthan) for Sorghum, while temperature extremes affected Wheat in northern states (e.g., Haryana, Punjab, Uttar Pradesh).	Regional differences indicate the need for localized climate adaptation strategies, particularly for water-scarce and heat-prone regions.
Extreme Event Analysis	Identified 11 significant extreme climate events and 3 compound events (high temperatures + low precipitation) causing amplified yield losses. Certain crop-region pairs (e.g., Gujarat-Sorghum) were highly vulnerable.	Findings emphasize the necessity of integrating extreme event risks into climate resilience planning to protect vulnerable crops and regions.

V. Visualization and Interpretation

Building on the statistical findings in Section 4, we now visualize where, how, and to what extent climate factors influence crop yields. These visualizations highlight regional vulnerabilities, long-term trends, and extreme event impacts, offering valuable insights for adaptation planning.

Climate Sensitivity Map of India

The Figure 3 presents state-level climate sensitivities for Rice, Wheat, Sugarcane, and Sorghum, using regression slopes from regional analyses. Rainfall sensitivity maps (Rice, Sorghum) show positive (orange) and negative (blue) responses to precipitation changes, with Gujarat displaying negative rainfall sensitivity for Sorghum. Extreme temperature maps (Wheat) highlight heat-vulnerable northern states (blue), while hot-dry day maps (Sugarcane) identify areas where extreme heat-drought conditions significantly reduce yields. These maps reveal regional climate vulnerabilities, guiding adaptive agricultural strategies.

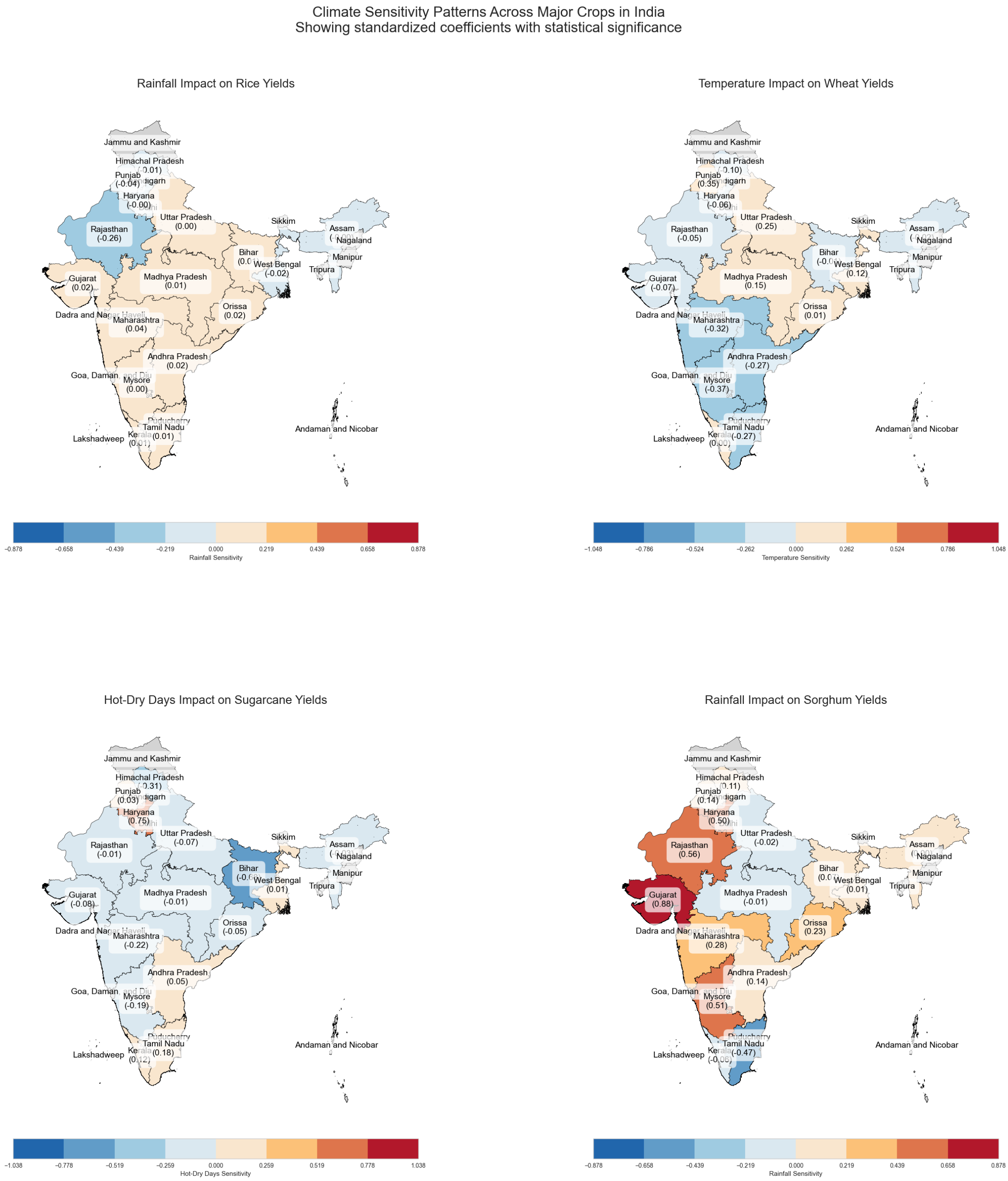

Figure 3 Climate Sensitivity Patterns Across Major Crops in India

Time-Series of Yield Anomalies by Crop

Figure 4 tracks standardized yield anomalies from 1970 to 2008, providing insights into long-term trends and inter-annual variability. Yield anomalies represent deviations from a crop's expected yield in a given year, standardized to allow comparisons across time and crops. A positive anomaly indicates that yields were higher than the historical average, while a negative anomaly signals below-average yields.

The results show Wheat, Sorghum, and Maize exhibiting a gradual upward trend, reflecting overall productivity gains, likely due to technological advancements, improved management practices, and policy interventions. In contrast, Rice remains stable, with limited year-to-year fluctuations, suggesting a more consistent production system. Sugarcane, however, shows moderate fluctuations, with pronounced deviations in the mid-1980s and early 2000s, potentially linked to climate anomalies, market shifts, or agronomic factors.

This visualization helps identify long-term patterns, showing how different crops have responded to climate variability and broader agricultural transformations over nearly four decades.

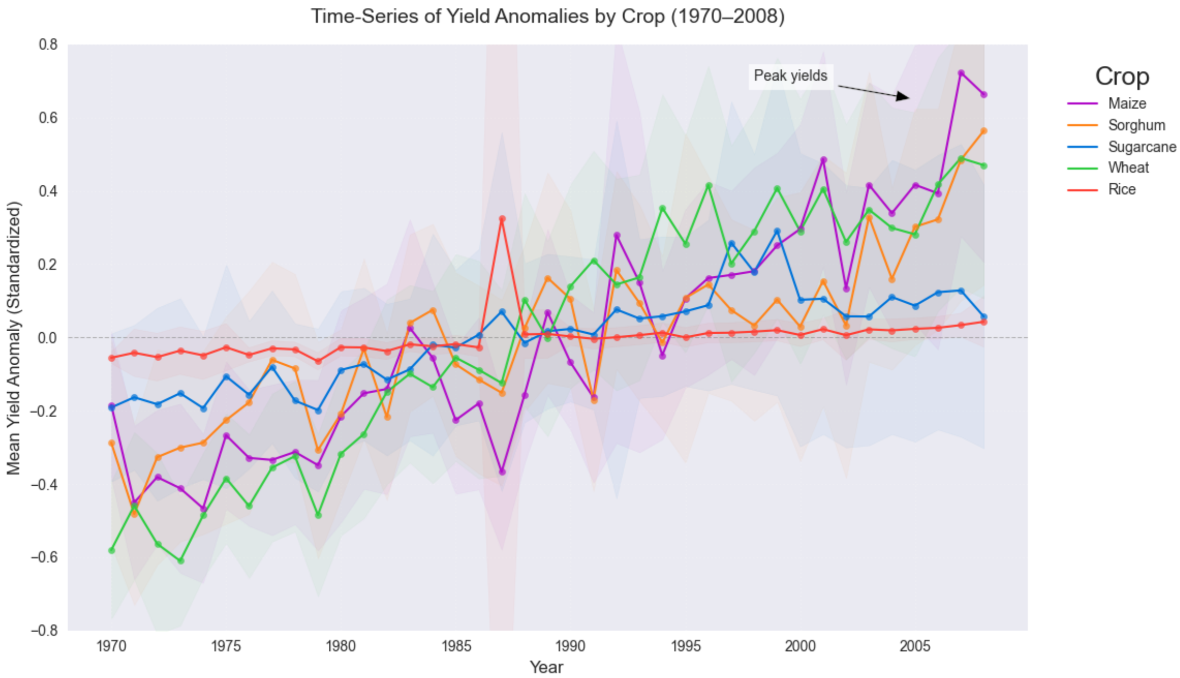

Figure 4 Time-Series of Yield Anomalies by Crop (1970–2008)

Compound Event Impact Chart

This bar chart at Figure 5 compares single-variable vs. compound climate extremes, showing how multi-hazard stressors amplify yield losses. Gujarat–Sorghum experiences sharp yield declines under compound events, emphasizing extreme vulnerability, while Haryana–Sugarcane shows resilience, maintaining neutral or positive anomalies. These findings highlight the greater risks posed by overlapping climate stressors and the need for integrated adaptation planning.

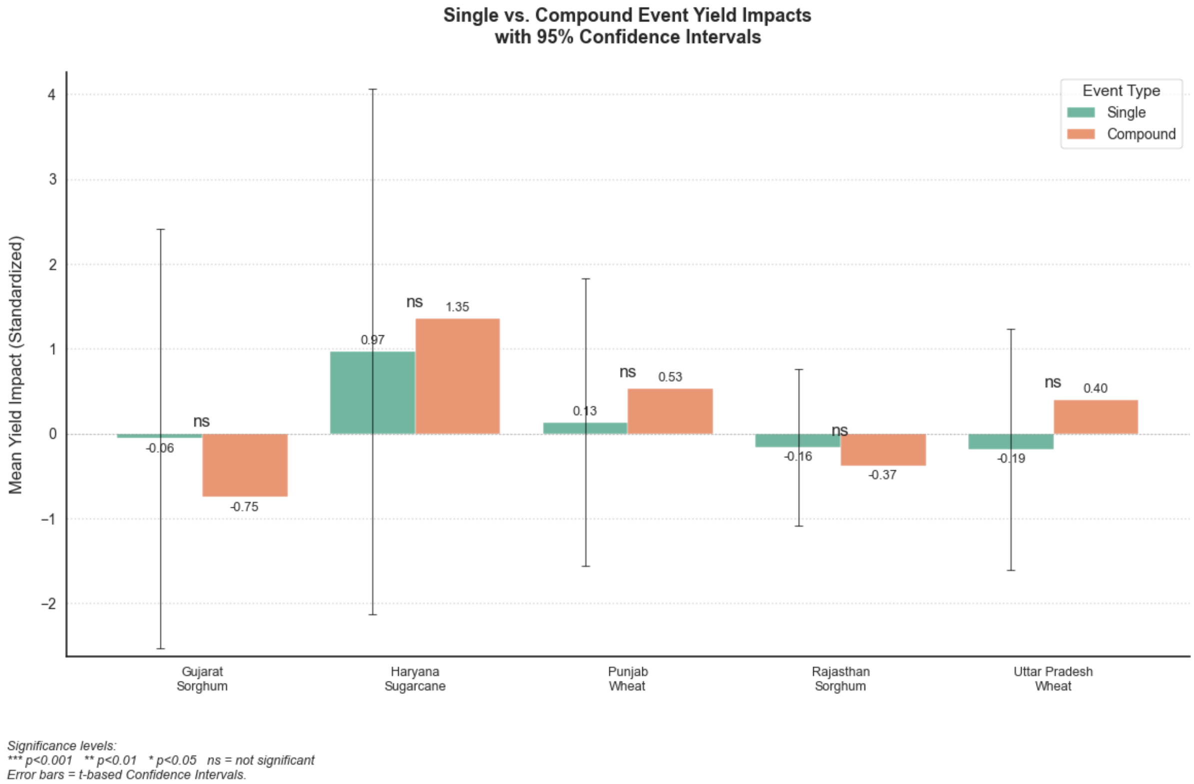

Figure 5 Single vs Compound Event Yield Impacts with 95% Confidence Intervals

Crop-Specific Climate Sensitivity Bar Chart

The bar chart at Figure 6 summarizes regression coefficients, illustrating how key climate variables (e.g., precipitation, extreme temperatures) influence each crop. Rice and Maize respond positively to temperature but negatively to hot-dry days. Wheat is highly sensitive to heat stress, while Sorghum is strongly influenced by precipitation variability. Interaction effects reveal complex multi-stressor responses, underscoring the need for crop-specific adaptation strategies.

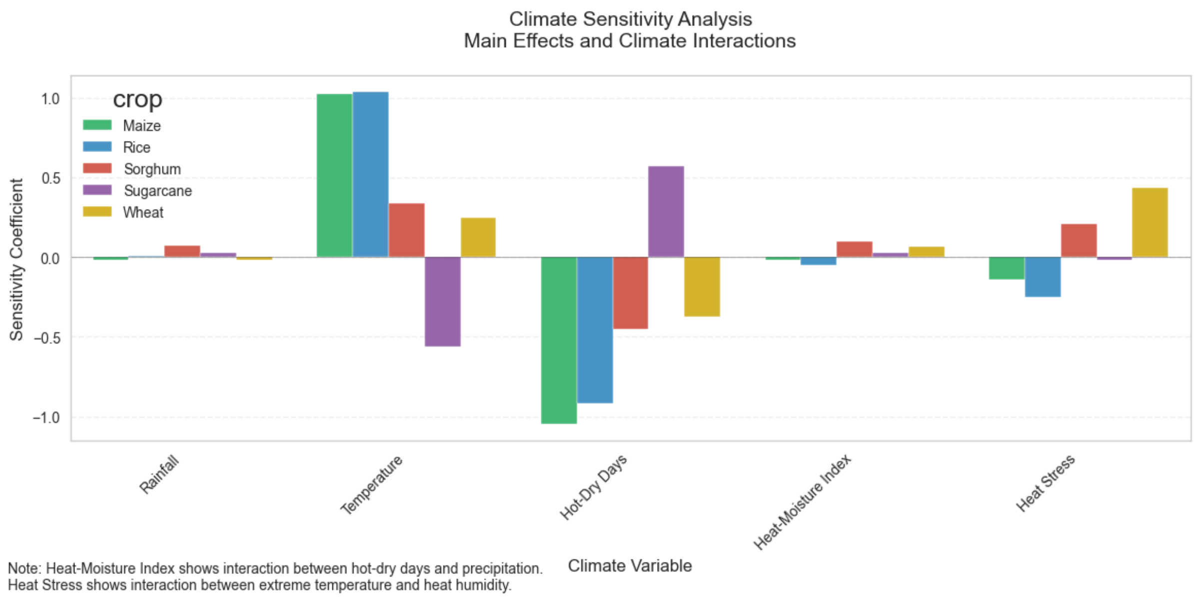

Figure 6 Climate Sensitivity Analysis: Main Effects and Climate Interactions

Distribution of Yield Anomalies Over Time (Box Plots)

The box plots in Figure 7 illustrate decadal trends in standardized yield anomalies, revealing long-term shifts in productivity, stability, and extreme deviations. Each box represents the interquartile range (IQR) of yield anomalies for a given decade, while whiskers highlight variability beyond this range. Outliers indicate years with significant deviations from expected yields, often linked to climate extremes or policy interventions.

Over time, all crops exhibit net yield increases, with Sorghum showing the largest gains, suggesting substantial productivity improvements. Wheat and Maize displayed greater inter-annual variability in early decades, likely reflecting sensitivity to weather variability and technological transitions. However, their yield distributions stabilized post-2000, possibly due to enhanced climate adaptation measures and improved input use.

The dashed decadal mean lines highlight shifting productivity baselines, emphasizing how climate trends, policy reforms, and agricultural innovations have influenced long-term crop performance. Variability trends further underscore that while yields have improved, sensitivity to climate extremes remains a critical factor, reinforcing the need for region- and crop-specific adaptation strategies.

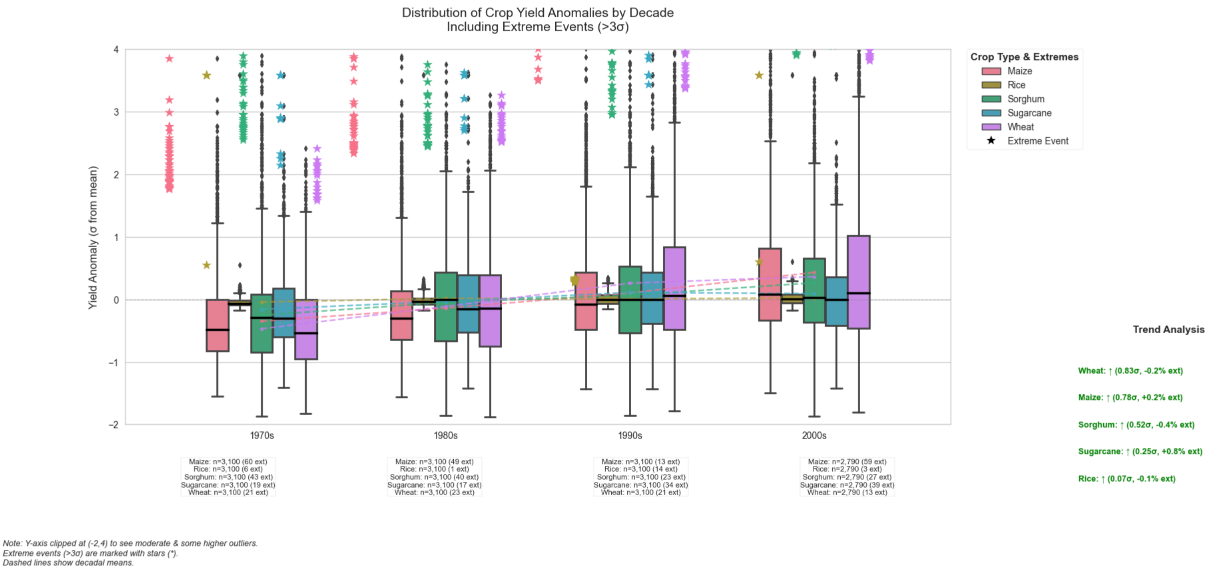

Figure 7 Distribution of Crop Yield Anomalies by Decade\nIncluding Extreme Events (>3σ)

Summary of Visualizations and Key Insights

These visualizations confirm that climate-crop relationships vary across time, space, and stressor types. Regional vulnerabilities require localized adaptation strategies. Compound events amplify climate risks, making multi-hazard resilience essential. Yield trends suggest long-term productivity improvements, likely due to technological advancements and policy interventions. Different crops exhibit unique climate sensitivities, reinforcing the need for tailored adaptation efforts. These findings provide a data-driven foundation for climate adaptation planning in Indian agriculture.

VI. Conclusion

In this study, we looked at how changing climate patterns have influenced crop production in India between 1970 and 2008. We combined detailed crop data from various regions with high-resolution climate information, allowing us to zero in on the specific climate challenges each crop faces. By designing custom climate hazard indicators and running statistical models, we pinpointed how major crops (Rice, Wheat, Sugarcane, Sorghum, and Maize) respond to different stressors across both space and time.

A few clear themes emerged. Precipitation and extreme temperatures stood out as the biggest drivers of yield fluctuations. Some regions, such as **Gujarat and Rajasthan** for Sorghum, and **Punjab and Uttar Pradesh** for Wheat, showed especially high vulnerabilities. When climate stressors overlapped, they often magnified the impact on yields, underscoring why it's so important to consider multiple threats at once.Even with these climate obstacles, we saw that overall yields have gone up in the long run, especially for Sorghum, Wheat, and Maize. Advances in technology, good policies, and better adaptation strategies likely played big roles. Still, yield variability and sensitivity to extreme events persist, pointing to the need for region-specific and crop-specific adaptation plans so farmers can stay resilient.

Looking ahead, we recommend building stronger climate-crop models that include future climate predictions, plus exploring practical responses like more efficient irrigation, growing diverse crops, and using better early-warning systems. These insights offer a solid, data-backed platform that policymakers, researchers, and farmers can use to keep our food supply secure in a changing climate.