Factors Affecting Crop Yields and Production:

Climate Vulnerability, Country Resilience, and Yield Trends

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ABSTRACT

This study explores trends in agricultural production globally over the period of 2015-2023, with a predominant focus on the interaction between climate and crop yields both across crops and countries. Using open-source agricultural and climatic data, we develop key weather metrics to assess the vulnerability and resilience of agriculture over our 9-year time period. Our findings suggest that out of the four major cereals, soybeans are the most vulnerable to negative climatic factors, such as heat stress and abnormal precipitation levels. At the country level, we identify agricultural systems that maintain stable yields despite large swings in climate variability. Canada is a prime example where year-to-year yields remain relatively stable despite large climatic fluctuations. Our trend analysis indicates that several regions are already experiencing yield stagnation or decline, and that a continuation of current trends implies an elevated risk of future production shortfalls in the absence of adaptive responses. Taken together, these findings provide actionable insights for policymakers seeking to strengthen climate-resilient agricultural systems and safeguard long-term food security and economic prosperity.

Keywords: *crop yields, trend analysis, climate resilience, vulnerability*

I. INTRODUCTION

Agricultural production is a foundational aspect of many countries' economic prosperity and peoples' everyday food security. Yet, the increase of abnormal climatic patterns such as frequency of extreme temperatures and extended periods of reduced rainfall threatens the delicate systems upon which agriculture relies. (IPCC 2023). This study seeks to quantify the relationships present between agricultural production and weather variation to provide actionable results for policy makers to build more resilient food systems across the globe. The study takes a three-pronged approach: 1) We begin by investigating which crops globally are most susceptible to climatic variations to identify where attention may be most needed in crop adaptation. 2) We shift our focus to see which countries are currently most resilient to climatic variation within their agricultural systems. 3) Finally, we zoom out to explore overall food production trends to identify areas which may be at risk of significant climate-related production disruptions in the near future.

The rest of the report is structured as follows: Section 2 provides an oversight of the data used in our analysis and the methodologies employed. Section 3 dives into the key results from our three main research topics. Finally, Section 4 closes the report with a discussion on limitations within our study and policy implications of our analysis. For all additional figures and tables, please refer to Section 5 Appendix, as well as Section 6 Data Dictionary for the full description of the data set used in our analysis.

II.DATA AND METHODOLOGY

A. Data Sources

This study utilizes two datasets for the time period of 2015-2023. We gather historical crop production data as well as country metadata from the Food and Agriculture Organization of the United Nations. Key variables in this data set include region, income group, annual crop yield and total crop production across our four major cereal crops (soybean, maize, wheat, and rice). Our second data set comes from the open-source website Open-Meteo and provides daily weather data for countries across our time period. This dataset captures important weather metrics such as temperature extremes, precipitation, and evapotranspiration.

B. *Data Preprocessing and Derived Metrics*

In order to conduct meaningful analyses, we preprocessed our raw data in a few key ways. To identify yield response to climate, we derived three climate metrics to measure variability across time. Using thresholds of less than 0°C or more than 30°C, we tagged daily extreme heat events. We also derived growing degree days (GDD) from daily temperature minima and maxima with a crop-independent baseline temperature of 10°C to establish a secondary measure of heat stress. Finally, we calculated the standard deviation of daily precipitation from the yearly mean as a way to capture sensitivity to precipitation variation. Once all of these metrics were calculated, we aggregated them on a yearly basis to provide us with climate variability metrics which match the temporal resolution of our crop data. Finally, we merged our data sets into one analysis-ready aggregated crop and weather set.

C. *Methodology*

Analysis of the integrated data set was conducted in Python using the following packages: pandas, numpy, statsmodels, matplotlib, and seaborn. For the analysis of crop-specific yield sensitivity to climate variation, we leverage the panel nature of the data to run crop-specific OLS regressions with two-way fixed effects (TWFE: country and year) and country-clustered standard errors, along with key controls and robustness checks. Significance levels demarcated with * p< 0.10, ** p< 0.05, *** p, 0.001

The analysis of country-level agricultural resilience is based on measures of climate variability and yield stability over the period 2015-2023. Climate variability is proxied using the standard deviation of the annual temperature range for each country. Which captures fluctuations in temperature extremes over time. Yield resilience is measured using the coefficient of variation for crop yields.

Countries are then classified into resilience and climate variability categories using the interquartile ranges, where the lowest quartile represents high resilience or low climate variability, the highest quartile represents low resilience or high climate variability, and the remaining two quartiles are grouped as others. This classification framework allows us to map and compare countries based on their exposure to climate variability and their ability to maintain stable agricultural yields.

For the trend analysis, we analyze long-run agricultural production dynamics by estimating region- and crop-specific yield trends over the full sample period using linear time-trend regressions. These estimated slopes are used to classify regions as experiencing yield growth, stagnation, or decline. To assess future risk, we extrapolate observed yield trends forward under a continuation-of-trends assumption and compare projected yields against recent production baselines. This approach allows us to identify regions where persistent negative or near-zero yield trends imply an elevated risk of future production shortfalls, particularly in the presence of ongoing climatic stress.

III.KEY RESULTS

A. *Impact of Climate Variability on Crop Yield*

To understand which crops are more susceptible to climatic variation, we will statistically analyze the relationship between crop yields, heat stress, and precipitation variability. Our yield data is measured in kilograms per hectare, with heat stress being measured as number of extreme heat days in a year, and finally precipitation variability being the annualized average of daily precipitation volume (mm) deviation. To account for the heterogeneity and time-series nature of our data, we use a TWFE model, the general from of which is shown below:

$$Crop_{c,t} = \beta_0 + \beta_1 PrecipitationSD_{c,t} + \beta_2 ExtremeHotDays_{c,t} + \beta_3 FertilizerUse_{c,t} + \beta_4 IrrigationPct_{c,t} + \alpha_c + \tau_t + \epsilon_c,$$

Full regression results are included in the appendix. Based on the results, Table 1 and Table 2 provide a ranked assessment of crop yield sensitivity to climatic variation. We see that across both weather metrics soybean yields have the highest sensitivity to weather variability. For a one unit change in aggregated daily precipitation SD (either more or less precipitation than the yearly mean), soybean yield is estimated to fall by ~85 kg per ha. Additionally, for each additional day in a year the temperature reaches above 30°C, we can estimate soybean yields to decrease by ~12 kg per ha. Following soybeans, we see that maize and wheat are the two next most sensitive crops, and surprisingly rice seems to have positive impacts from precipitation variation and heat stress.

It is important to note here that aside from soybeans, none of the coefficients were found to be significant, and so we cannot make causal inferences regarding the specific estimated impacts of weather variation on crop yields. Our limitation section covers potential reasons for this in more detail. Despite our lack of statistical significance, we can still see that the ranking of our crop yield sensitivity is consistent across both sensitivity measures. Our robustness checks, which substitute different cutoff measures for extreme heat temperatures and the precipitation coefficient of variation for standard deviation, also show the same rankings.

Table 1+2: Crop Yield Sensitivity to Precipitation SD and Heat Stress from 2015-2023

Rank	**Crop**	**Daily Precip SD**
1	Soybeans	-84.798 (48.493)*
2	Maize	-44.423 (57.167)
3	Wheat	-8.939 (38.092)
4	Rice	44.438 (38.917)

Rank	**Crop**	**Extreme Hot Days**
1	Soybeans	-11.979 (4.340)***
2	Maize	-0.447 (6.719)
3	Wheat	3.004 (2.759)
4	Rice	4.497 (3.379)

B. Understanding Agricultural Resilience

To assess the extent to which countries are able to maintain resilient yields despite climatic variation, we analyze the relationship between climate variability and yield stability across countries. Climate variability is measured using year-to-year variation in minimum and maximum temperatures, capturing the range of climatic conditions that crops experience. Yield resilience is measured using yield variability and is defined as the stability of crop yields over time. This approach allows us to identify countries that maintain stable yields despite experiencing substantial climate fluctuations.

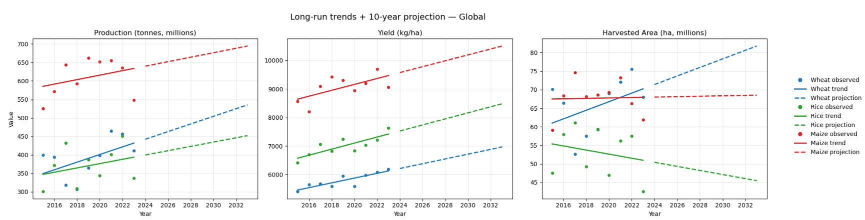
Our findings show that countries such as Canada, the United States, and Turkey experience large variations in temperature. When examining yield variability, we find that countries including Malawi, Canada, and South Africa maintain stable yields over time. Combining these two dimensions, we find that Canada is the only country that exhibits high yield resilience in the presence of high temperature variability.

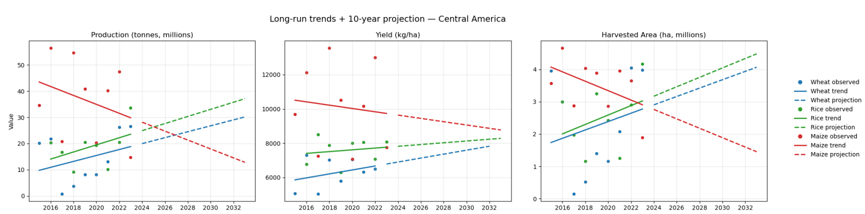
To further explore yield resilience, we examine input use and economic characteristics across countries. We find that fertilizer use is positively associated with yield resilience, and that high income countries exhibit higher fertilizer use compared to other income groups. This suggests that a given country’s income level plays an important role in enabling yield stability. In addition, we find that maize is the most common crop among highly resilient countries.

Focusing on Canada as a case study, we find that it has the second-highest level of fertilizer use and the highest level of irrigation coverage in the sample, indicating a high level of input intensity. These factors likely help crop production remain stable over time despite large temperature fluctuations. Canada’s classification as a high-income country further supports its ability to invest in resilience promoting inputs. Overall, these results suggest that higher levels of fertilizer use and irrigation are associated with greater agricultural resilience, even in the presence of substantial climate variability.

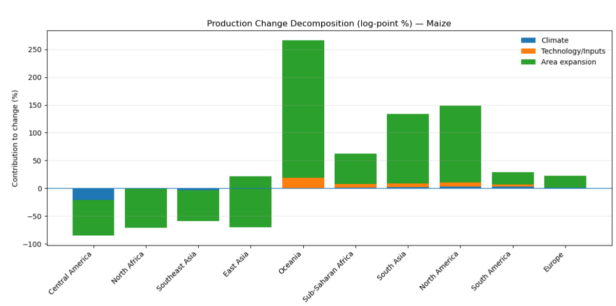
C. *Production Trends and Future Outlook*

To evaluate whether current production trajectories are sustainable under increasing heat exposure, we first estimate long-run yield, production, and harvested area trends and project them forward ten years. At the global level, wheat and rice demonstrate steady upward yield trends, while maize shows continued growth but at a more moderate pace. In contrast, Central America stands out as a clear divergence for maize; yields trend downward over the 2015-2023 window, and projected production declines despite global maize production continuing to rise. This contrast indicates that regional production risk is not clearly captured by global aggregates.





Decomposing total production change into climate, time trend (technology/inputs, non-climate related drivers), and area components highlights the source of this divergence. For Central America, the yield slope is negative, (–96.6 kg/ha per year), and the climate component contributes –59.9 log-points to production change over the sample window of 2015-2023. Although the time trend component is positive (+38.4 log-points), it is insufficient to offset both climate pressure and declining harvested area (-63.2 log-points). As a result, maize production in Central America contracts over the period. This is contrasted by global maize production, which remains supported by a positive time trend component and relatively stable harvested area, offsetting negative climate contributions in some regions.



Across crops, maize shows the most negative climate contributions in multiple regions, while wheat and rice show smaller climate effects relative to their time trend components. For wheat, several regions rely heavily on area expansion to sustain production growth, whereas rice production growth is often driven by technological improvements rather than land expansion. These results suggest that maize is the most climate-sensitive crop within the sample, especially in regions where technological gains are insufficient to counteract rising extreme heat exposure.

Extending the analysis by income group reveals that global production growth conceals important regional disparities. High-income regions show sustained upward yield trends for all three crops, particularly maize and rice, even where harvested area declines. In contrast, lower and lower-middle income regions demonstrate flatter yield growth and contracting area trends, with maize production declining in some instances. These patterns suggest that while global aggregates remain positive, climate pressures and limited technological offsets may place lower-income regions at greater risk of climate-related production shortfalls.

IV. DISCUSSION

A. Limitations

Our project has a few key limitations. With the weather data gathered, we are looking at a relatively small time-series of nine years. This provides less variation in the data and limits our ability to establish causal inference about climate's impact on agricultural production. For future studies, it would be prudent to gather more weather data to match the time scale of the FAO crop data. Additionally, our weather metrics are pulled for country centroids, meaning we may not be capturing true weather metrics for crop-specific growing regions in a country. In a future study, we would want to pull weather data specific to each crop's primary growing area for each country.

Specifically for the crop-climate sensitivity analysis, our TWFE analysis removes a significant amount of variation from the data, suggesting that country or time specific factors play a more integral role in crop yield outcomes as opposed to weather. While we balanced our panel and ensured there were no highly collinear variables in our model, the relatively small sample size may impact our estimations. Moving forward, we should collect more data and test more model specifications to ensure the robustness of our results.

For the trend and projection analysis, an important limitation is the reliance on linear extrapolation of historical yield trends. This approach assumes that past dynamics persist into the future and does not account for structural reeks arising from technological change, policy interventions, rapid adaptation responses, or intensifying climate change. Additionally, trend estimates may be sensitive to the chosen time window, particularly given the relatively short sample period analyzed, which may overstate or understate long-run risks in all regions. Thus, projected production shortfalls must be interpreted as indicative risk signals rather than precise forecasts.

A key limitation of the resilience classification is the absence of commodity price data. Agricultural production decisions respond not only to climate conditions but also to price signals. This limitation may be particularly relevant for large exporting countries, where farmers may reduce output in response to low prices even when stable yields are technically feasible. As a result, observed fluctuations in yields may reflect economic responses rather than climatic factors, making it appear that climate variability is driving changes that are primarily driven by market conditions.

B. *Policy Implications & Recommendations*

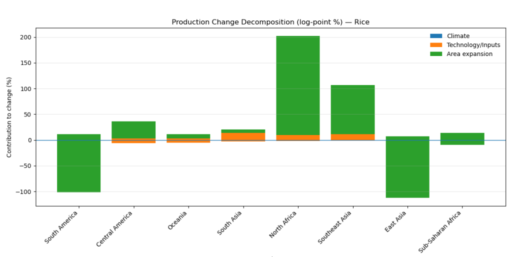
From the findings of our report, we recommend a few key strategic priorities for policy makers to follow regarding agricultural production and climate resilience. (1) Explore the development of heat-tolerant soybean varieties to mitigate the impacts of increasingly frequent extreme heat stress. (2) Implement trend-based early warning frameworks that flag regions with sustained yield declines, enabling targeted investments in climate adaptation and robust infrastructure prior to the emergence of production shortfalls. (3) The pattern obtained in the reliance analysis highlights the importance of input utilization strategies in improving resilience.

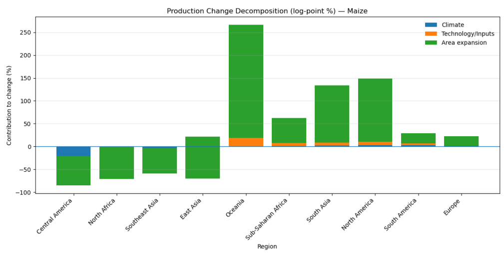
V. APPENDIX

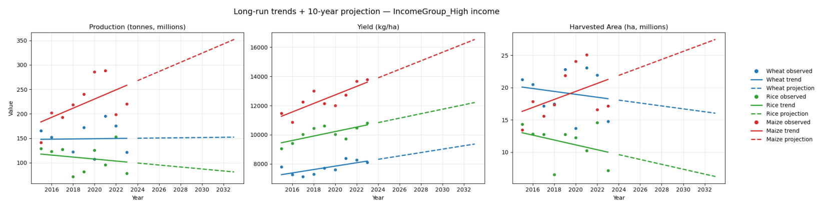
Climate Variation by Crop Regression Results:

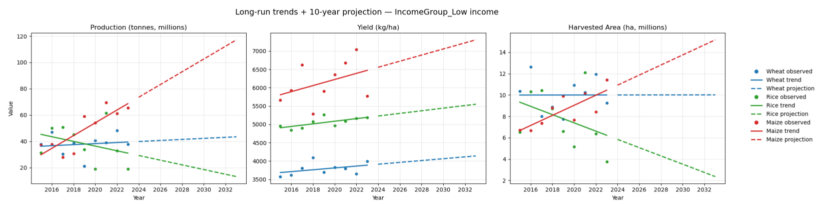
Two-way FE yield regressions

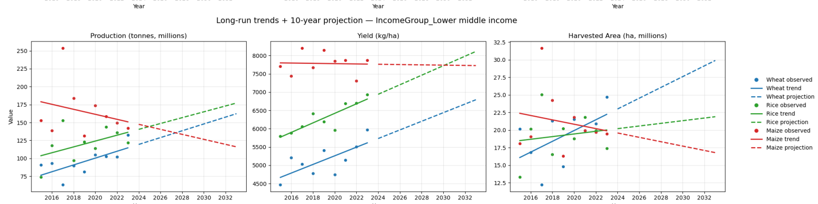
	Dependent variable: yield_kg_ha			
	Wheat	Rice	Maize	Soybeans
	(1)	(2)	(3)	(4)
daily_precip_sd	-8.939	44.438	-44.423	-84.798^{*}
	(38.092)	(38.917)	(57.167)	(48.493)
extreme_hot_days	3.004	4.497	-0.447	-11.979^{***}
	(2.759)	(3.379)	(6.719)	(4.340)
fertilizer_use_kg_ha	-3.914	-1.036	3.705	4.339
	(4.053)	(3.683)	(6.329)	(3.153)
irrigation_pct	-0.930	-3.236	-4.563	11.222
	(7.857)	(9.881)	(22.620)	(7.294)
Observations	165	117	192	124
R^2	0.765	0.905	0.701	0.724
Adjusted R^2	0.710	0.879	0.636	0.650
Residual Std. Error	936.107 (df=133)	682.417 (df=91)	1770.828 (df=157)	720.469 (df=97)
F Statistic	20.710^{***} (df=31; 133)	49.457^{***} (df=25; 91)	7.612^{***} (df=34; 157)	30.508^{***} (df=26; 97)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

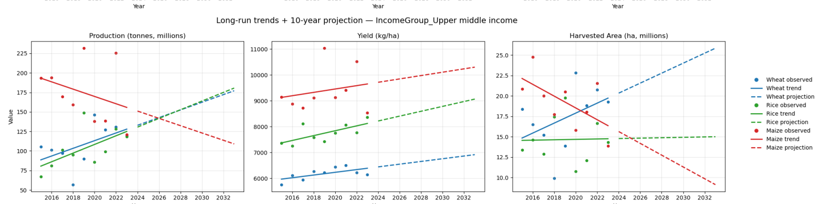



Production Change Decomposition (log-point %) — Maize
Climate
Technology/Inputs
Area expansion
Contribution to change (%)
Central America
North Africa
Southeast Asia
East Asia
Oceania
Sub-Saharan Africa
South Asia
North America
South America
Europe
Region


Long-run trends + 10-year projection — IncomeGroup_High income
Production (tonnes, millions)
Yield (kg/ha)
Harvested Area (ha, millions)
Value
Year
Wheat observed
Wheat trend
Wheat projection
Rice observed
Rice trend
Rice projection
Maize observed
Maize trend
Maize projection


Long-run trends + 10-year projection — IncomeGroup_Low income
Production (tonnes, millions)
Yield (kg/ha)
Harvested Area (ha, millions)
Value
Year
Wheat observed
Wheat trend
Wheat projection
Rice observed
Rice trend
Rice projection
Maize observed
Maize trend
Maize projection


Long-run trends + 10-year projection — IncomeGroup_Lower middle income
Production (tonnes, millions)
Yield (kg/ha)
Harvested Area (ha, millions)
Value
Year
Wheat observed
Wheat trend
Wheat projection
Rice observed
Rice trend
Rice projection
Maize observed
Maize trend
Maize projection


Long-run trends + 10-year projection — IncomeGroup_Upper middle income
Production (tonnes, millions)
Yield (kg/ha)
Harvested Area (ha, millions)
Value
Year
Wheat observed
Wheat trend
Wheat projection
Rice observed
Rice trend
Rice projection
Maize observed
Maize trend
Maize projection

VI. DATA DICTIONARY

Variable	Type	Description
country	string	Country name
iso_code	string	ISO country code (e.g., ISO 3166-1 alpha-3)
year	integer	Calendar year
region	string	Geographic region
income_group	string	World Bank income classification
crop	string	Crop type (e.g., wheat, maize, rice)
area_harvested_ha	float	Harvested area in hectares
production_tonnes	float	Crop production in metric tonnes
yield_kg_ha	float	Yield in kilograms per hectare
fertilizer_use_kg_ha	float	Fertilizer use in kilograms per hectare
irrigation_pct	float	Share of area under irrigation (percent of area)
avg_temp_weather	float	Average daily temperature (°C) over the growing year
avg_min_temp	float	Average daily minimum temperature (°C)
avg_max_temp	float	Average daily maximum temperature (°C)
avg_precipitation	float	Average daily precipitation (mm)
annual_temp_range	float	Annual temperature range
avg_transp	float	Average daily transpiration (mm)
annual_gdd	float	Annual growing degree days (base temperature as used)
annual_precip_total	float	Total annual precipitation (mm)
daily_precip_sd	float	Standard deviation of daily precipitation (mm)-aggregated
extreme_hot_days	Integer	Number of days with extreme high temperature
extreme_cold_days	Integer	Number of days with extreme low temperature
extreme_temp_days	Integer	Number of days with extreme temperatures (hot or cold)

References

Intergovernmental Panel On Climate Change (Ipcc). (2023). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781009157896