ENVIRONMENTAL RESEARCH
FOOD SYSTEMS

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To cite this article before publication: Iman Haqiqi 2024 *Environ. Res.: Food Syst.* in press https://doi.org/10.1088/2976-601X/ad7d12

Trade Can Buffer Climate-Induced Risks and Volatilities in Crop Supply

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Keywords: Crop production; climate change; international trade; adaptation; irrigation; climate risk.

Abstract

Climate change is intensifying the frequency and severity of extreme events, posing challenges to food security. Corn, a staple crop for billions, is particularly vulnerable to heat stress, a primary driver of yield variability. While many studies have examined the climate impact on average corn yields, little attention has been given to the climate impact on production volatility. This study investigates the future volatility and risks associated with global corn supply under climate change, evaluating the potential benefits of two key adaptation strategies: irrigation and market integration. A statistical model is employed to estimate corn yield response to heat stress and utilize NEX-GDDP-CMIP6 climate data to project future production volatility and risks of substantial yield losses. Three metrics are introduced to quantify these risks: Sigma (σ), the standard deviation of year-on-year yield change, which reflects overall yield volatility; Rho (ρ), the risk of substantial loss, defined as the probability of yield falling below a critical threshold; and Beta (β), a relative risk coefficient that captures the volatility of a region's corn production compared to the globally integrated market. The analysis reveals a concerning trend of increasing year-on-year yield volatility (σ) across most regions and climate models. This volatility increase is significant for key corn-producing regions like Brazil and the United States. While irrigated corn production exhibits a smaller rise in volatility, suggesting irrigation as a potential buffer against climate change impacts, it is not a sustainable option as it can cause groundwater depletion. On the other hand, global market integration reduces overall volatility and market risks significantly with less sustainability concerns. These findings highlight the importance of a multidimensional approach to adaptation in the food sector. While irrigation can benefit individual farmers, promoting global market integration offers a broader solution for fostering resilience and sustainability across the entire food system.

Introduction

Corn, a staple food source and key component of animal feed and biofuels, is vital to global food security. In corn production, sufficient heat is necessary for plant survival in all growth stages. Extreme temperatures can hinder plant growth significantly by affecting photosynthesis, biochemical efficiency, and nutrient transfer. Studies have shown that temperatures exceeding 29°C thresholds can result in substantial yield losses (Luo, 2011; Schlenker and Roberts, 2006).

Extreme weather events drive volatility in regional corn production, which, in turn, is a major factor influencing the volatility of prices (Diffenbaugh et al., 2012; Zhao et al., 2021). Price volatility can create social and food security concerns (Ahmed et al., 2009; Bellemare, 2015). The severity of these extremes has increased in past decades and is expected to increase in the future, posing a growing threat to agricultural production (Brás et al., 2021; Jackson et al., 2019).

Adaptation (adjusting to the effects of climate change) and mitigation (addressing the root causes of climate change) are two approaches to climate action (Fankhauser, 2017; Ferreira, 2024; McCarl and Hertel, 2018; Orlove, 2022). In this context, various strategies are suggested for agricultural adaptation to climate change with different implications for food security and environmental sustainability (Auffhammer and Schlenker, 2014; Burke and Emerick, 2016; Frisvold and Deva, 2013; Hertel and Lobell, 2014; Lobell et al., 2013; Sesmero et al., 2017). As irrigated crops are relatively less vulnerable to extreme heat, expansion in irrigation is considered an adaptation strategy to reduce the yield damage from climate change (Luan et al., 2021; Obembe et al., 2023; Rosa, 2022; Rosa et al., 2020). However, irrigation and cropland expansion will increase the sustainability stresses on natural resources and can intensify groundwater depletion.

There has been growing interest in exploring market integration as an adaptation strategy in recent years. By enabling trade between regions with diverse climate patterns, market integration offers the potential to reduce volatility in global corn supply (Baldos and Hertel, 2015; Brenton et al., 2022; Gouel and Laborde, 2018). Trade can also potentially buffer against future water scarcity concerns (Liu et al., 2014). However, the effectiveness of trade in mitigating climate risks remains a topic of debate as recent research highlights the growing threat of concurrent climate extremes and synchronized crop failures across regions (Tigchelaar et al., 2018; Zhou et al., 2023).

This study investigates the potential role of international trade and market integration in reducing volatility in the global corn supply under climate change scenarios. This study is motivated by several recent observations. First, the increasing interconnectedness of global agricultural markets after COVID-19 and the Ukraine war, with the growing importance of corn as a global commodity, suggest that trade could play a crucial role in stabilizing supply (Ali et al., 2022; Hu et al., 2024; Hung, 2021; Zhang et al., 2024). Second, theoretical models of international trade indicate that trade can help diversify risk, smooth out supply shocks, and create welfare gains (Baldwin and Freeman, 2022; Caselli et al., 2020; Obstfeld, 1994). Given these considerations, we hypothesized that international trade could serve as a buffer against the increased volatility associated with climate change-induced yield fluctuations.

To investigate the role of trade in reducing market volatility, this study employs a statistical model to estimate corn yield response to heat stress and utilize climate data to project future production volatility and risks. Then, it explores the impact of both irrigation practices and market integration on volatility using three key metrics: Sigma (σ) for overall volatility, Rho (ρ) for the risk of substantial yield loss, and Beta (β) for relative volatility compared to the global market. This study investigates the benefits of irrigation and market integration in mitigating volatility and risks associated with future climate change.

Background

Heat and water stress are significant factors in corn production. Optimal photosynthesis occurs between 25°C and 30°C; beyond this range, efficiency declines. Low temperatures can delay plant development, increase frost risk, hinder pollination, and reduce grain production. Corn is especially sensitive to high temperatures during flowering, pollination, and grain filling, with temperatures over 30°C impairing pollination and kernel development, leading to yield losses. High temperatures also increase respiration rates and water loss through transpiration, intensifying water stress. Plant water stress can reduce nutrient uptake, photosynthesis, and biochemical efficiency, causing wilting, membrane damage, stunted growth, and reduced leaf longevity, ultimately lowering yields (Carter et al., 2016; Sánchez et al., 2014). For a visual representation of yield response to heat and water, refer to Figures S2-a, S2-b, and S2-c.

Irrigation is an effective strategy to reduce the damage from climate extremes. It offers two advantages over rainfed production. First, it cools the temperature and moderates the heat stress depending on the applied irrigation technology (Braun and Schlenker, 2023). Second, it provides sufficient soil moisture, improving nutrient uptake, and enhancing photosynthesis and biochemical efficiency (Ferin and Kucharik, 2024).

Methods

Two major approaches in evaluating climate impacts on crops are data-driven statistical models and process-based crop models. While process-based models offer a detailed representation of crop growth, they often require substantial computational resources and extensive parameterization. In contrast, statistical models, can provide robust and interpretable results with significantly lower computational demands (Lobell and Asseng, 2017). The computation burden of these studies has motivated development of emulators for processed-based crop models (Franke et al., 2020). This study opted for a statistical panel model due to its suitability for analyzing large-scale datasets and its computational efficiency (approximately 20,000 CPU hours to execute). Employing a more complex, process-based model would have substantially increased the computational burden, potentially hindering the ability to conduct a comprehensive analysis. Studies show that panel models are ideal for assessing climate impacts on agriculture because they use group fixed effects to absorb all time-invariant variation and thus rely on weather deviations from the mean that are random and exogenous (Blanc and Schlenker, 2017). Many previous studies have more simplifications and considered simple temperature metrics in their estimations (Blanc, 2017). Including the growing degree days, considering the temperature threshold, and separate estimation of the coefficients for irrigated and rainfed corn will provide sufficient complexity and will capture the most important variables necessary to address the research question.

This study employs a three-step approach to investigate the future volatility and risks associated with global corn supply under climate change. First, based on observed yields and high-resolution weather data, a statistical model is developed to estimate how corn yields respond to heat stress. Then, the estimated yield response function is applied to climate data from NEX-GDDP-CMIP6 to project future corn yield fluctuations across various regions and construct regional probability density functions (PDFs). Finally, the potential benefits of two key adaptation strategies are analyzed: irrigation expansion and market integration. This includes quantifying the risks using three key metrics: Sigma (σ) to capture volatility, Rho (ρ) for the risk, and Beta (β) to measure relative volatility.

Yield Response Function

The empirical model assumes that plants generate biomass daily using available resources like heat, water, and soil nutrients. It follows Schlenker and Roberts (2009) and use the beneficial heat index, harmful heat index, and cumulative rainfall. The assumption is that the effects of heat are cumulative over the growing season. In other words, the end-of-season yield (y) is the integral of daily heat impacts over the season. This relationship can be demonstrated via the following equation:

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \qquad \text{(eq. 1)}$$

where $\varphi_{it}(h)$ is the time distribution of heat (h) over the growing season in county i and year t, while the heat ranges between the lower bound $\underline{h}$ and the upper bound $\overline{h}$; precipitation and other factors are denoted as z_{it}, and c_i is a time-invariant county fixed effect. Assuming a piece-wise linear form for $g(h)$, and considering the exposure to each temperature interval, the integral can be approximated with the following equation:

$$y_{it} = \sum_j \gamma_j [\emptyset_{it}(h+1) - \emptyset_{it}(h)] + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \qquad \text{(eq. 2)}$$

where j indexes the pre-determined temperature intervals and $\emptyset_{it}$ is the heat cumulative distribution function for county i at year t. Following D'Agostino and Schlenker (2016), the daily distribution of temperatures is approximated, assuming a cosine function between the daily minimum and maximum temperature. Let $\bar{t} = \text{acos}\left(\frac{2b - T_{max} - T_{min}}{T_{max} - T_{min}}\right)$, then degree days (DD) at each day is defined using

$$DD(b) = \begin{cases} \frac{(T_{max}+T_{min})}{2} - b & if\ b \le T_{min} \\ \frac{\bar{t}}{\pi}\left[\frac{(T_{max}+T_{min})}{2} - b\right] + \frac{(T_{max}-T_{min})}{2\pi} sin(\bar{t}) & if\ T_{min} < b \le T_{max} \\ 0 & if\ T_{max} < b \end{cases} \qquad \text{(eq. 3)}$$

where b is the base for calculating degree days and can take the base and critical values. The major assumption is that plant growth is approximately linear between two bounds. For example, regarding corn growth, degree days between 10°C and 29°C can be considered linearly beneficial, and degree days above 29°C are considered linearly harmful. Thus, the yield response function is estimated for irrigated and non-irrigated corn using the following equation:

$$y_{it} = \alpha DD_{it}^{10-29} + \beta DD_{it}^{29} + \delta_1 P_{it} + \delta_2' P_{it}^2 + \lambda_s t + \lambda_s' t^2 + c_i + \varepsilon_{it} \qquad \text{(eq. 4)}$$

where i is an index for location, t is the index of time, s is the index for states, y_{it} is the log corn yields, D_{it} represents growing degree day variables, P shows cumulative precipitation over the growing season, t shows the time trend variable (t = year – 1950), c_i is a time-invariant county fixed effect, ε is the residual, and *α, β, δ, λ* are the regression parameters showing the marginal impacts. The model is estimated using a panel fixed-effect approach.

Then, corn yield ratios are calculated for global corn-growing areas following Diffenbaugh et al. (2012) employing the estimated yield response functions. By taking the difference between the two consecutive years. This response function can be employed to project the year-on-year yield change as the yield ratio:

$$YR_{i,t} = \frac{y_{i,t}}{y_{i,t-1}} = exp\left(\alpha\left[\emptyset_{i,t}^- - \emptyset_{i,t-1}^-\right] + \beta\left[\emptyset_{i,t}^+ - \emptyset_{i,t-1}^+\right] + \delta_1\left[P_{i,t} - P_{i,t-1}\right] + \delta_2\left[P_{i,t}^2 - P_{i,t-1}^2\right]\right) \qquad \text{(eq. 5)}$$

$$YR'_{i,t} = \frac{y'_{i,t}}{y'_{i,t-1}} = exp\left(\alpha'\left[\emptyset_{i,t}^- - \emptyset_{i,t-1}^-\right] + \beta'\left[\emptyset_{i,t}^+ - \emptyset_{i,t-1}^+\right] + \delta'_1\left[P_{i,t} - P_{i,t-1}\right] + \delta'_2\left[P_{i,t}^2 - P_{i,t-1}^2\right]\right) \qquad \text{(eq. 5')}$$

where $y_{i,t}$ is the log of non-irrigated corn yield, $y'_{i,t}$ is the log of non-irrigated corn yields, $\emptyset^{-}_{i,t}$ is the growing-season DDs between the base of 10 °C and 29 °C, $\emptyset^{+}_{i,t}$ is the growing-season DDs above 29 °C. Using regional production share, gridded variables are aggregated to the regional level (r).

$$R_{r,t} = \sum_i \omega_i YR_{i,t} \quad \text{(eq. 6)}$$

$$R'_{r,t} = \sum_i \omega_i YR'_{i,t} \quad \text{(eq. 6')}$$

Sigma: Volatility Index

To quantify volatility in crop yields across different regions and climate scenarios, the standard deviation (SD) of the year-on-year yield ratio is employed as the volatility metric. This approach captures the year-to-year fluctuations in regional production of corn. Knowing the yield ratio from equation 6, the Sigma coefficient is:

$$\sigma_i = \sqrt{\frac{\sum\left(R_{i,t} - \bar{R}_i\right)}{N_i}} \quad \text{(eq. 7)}$$

By calculating the SD for each region and climate scenario, a measure is obtained that shows how much a region's crop production fluctuates with varying climate conditions. A comparison of the volatility levels between regions and scenarios is conducted to identify areas most prone to significant year-on-year yield fluctuations.

Rho: Risk of Substantial Loss

To quantify the associated risk of substantial loss across diverse climate scenarios, 1,224 empirical probability distribution functions (PDFs) are constructed. Each PDF represents a unique combination of the CMIP6 climate model (24), scenario (3), and regions (17). This approach captures the underlying stochastic behavior of yield fluctuations. By establishing the PDFs, a metric for climate risk is constructed, specifically the risk of substantial crop production loss, which is identified as occurring when the magnitude of a negative shock exceeded a threshold (*a*).

$$\rho = P(x < a) = \int_{-\infty}^{a} f(x)dx \quad \text{(eq. 8)}$$

where, ρ is the risk of substantial loss, *P* is probability, and *f(x)* is the estimated probability density function. This study considers a = 10%. Through the integration of the empirical PDF's tail beyond this point, the likelihood of such an extreme event is quantified. The 10% threshold was carefully selected based on a combination of criteria. With the price elasticity of demand ranging between 0.1 to 0.2 (Muhammad et al., 2011), a 10% decline in supply may lead to a 50% to 100% increase in prices, which is considered a substantial shock. Further, the 10% threshold is consistent with observed shocks in major corn-producing countries. In the past 30 years, only two years had a yield shock larger than 10% in the US (1995 and 2012). Thus, a threshold of 10% would be roughly equivalent to the 5% likelihood of loss, a standard threshold for statistical risk analysis.

It is important to note that while this definition can be tailored to reflect country-specific and scenario-specific nuances, this study adopts a uniform threshold to streamline the analysis. This simplification facilitates the interpretation of risk across diverse regions, ensuring that the findings are applicable on a broader scale.

Beta: Coefficient of Relative Volatility

This study has incorporated the beta coefficient to evaluate the relative volatility of regional crop production vis-à-vis the global markets. The beta coefficient, denoted as β, is calculated using the formula:

$$\beta = \frac{Cov(\sigma_i, \sigma_m)}{Var(\sigma_m)} \qquad \text{(eq. 9)}$$

where σ_i represents regional crop volatility and σ_m denotes the volatility rate of the global market. The covariance between the regional and global returns, $Cov(\sigma_i, \sigma_m)$, is divided by the variance of the global market returns, $Var(\sigma_m)$, to determine the beta coefficient. A beta coefficient above one suggests that the region's crop production is more volatile than the global market, indicating higher risk and sensitivity to global economic dynamics. Conversely, a beta coefficient below one implies that the region's crop production is less volatile, potentially serving as a buffer against global market shocks. By leveraging this metric, we can discern the nuanced risk profiles of different regions and gain insights into the influence of global market forces on local agricultural outputs.

Experiment design

This study designed five experimental scenarios to investigate the influence of irrigation adaptation on total crop yield volatility and risk. These scenarios represent a range of irrigation extents, from minimal irrigation (1% share of cropland) to a scenario where nearly all cropland is irrigated (99% share). This spectrum captures conditions across a variety of likely irrigation regimes. Subsequently volatility and risk metrics are calculated for each scenario to assess the potential consequences of varying irrigation levels on crop production stability.

To explore the potential effects of trade on production stability, five market integration scenarios are simulated: US-Mexico, US-Brazil, US-China, US-Mexico-China, and US-Brazil-China. These scenarios examine how expanded trade partnerships among these major economies might influence production volatility. By calculating production volatility for each scenario, the potential benefits of trade integration is measured for mitigating production fluctuations and risks.

Computation

Stata software was employed to estimate the crop yield response function to heat stress. To process the NetCDF files containing NEX-GDDP data, the R statistical environment and the "terra" package are utilized. The ACCESS-Anvil platform, sponsored by the National Science Foundation (NSF), was leveraged for computational tasks involving yield projection, variability analysis, and risk assessment.

Results

Climate Change Increases Year-on-Year Volatility in Heat Stress

The heterogeneity is higher at the grid cell level. Globally, climate change causes an increase in the average crop heat stress index (DD 29°C). By the mid-century, average degree days above 29°C are expected to increase significantly in many corn fields in the US, India, South Africa, and South America. In addition, the standard deviation and pattern of mean DD 29°C is expected to change (Figure 1).

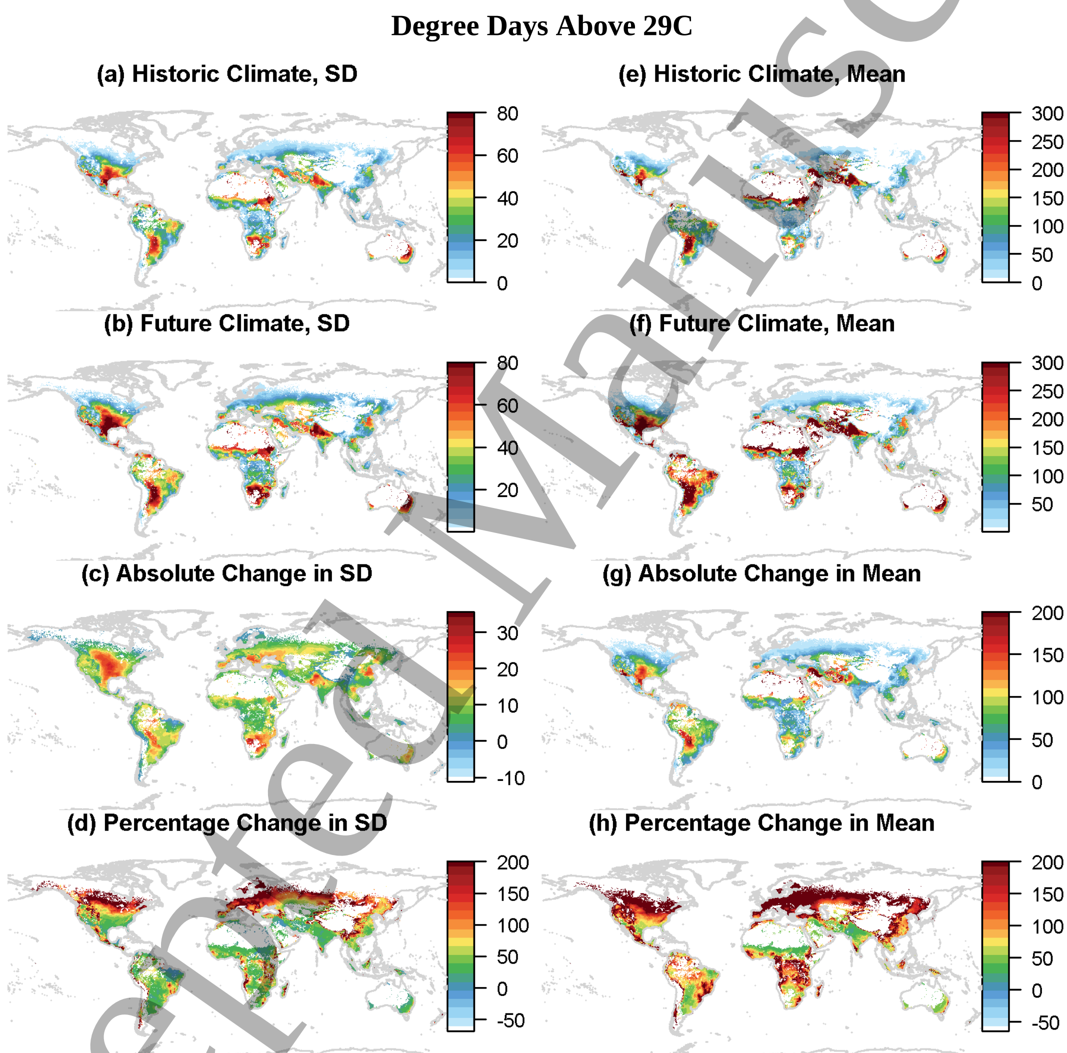

Figure 1. Crop heat stress index (degree days above 29C) for past (1985-2014) and future (SSP2-4.5, 2035-2064) climate. The maps illustrate historic SD (a), future SD (b), absolute change in SD (c), % change in SD (d), historic mean (e), future mean (f), absolute change in mean (g), % change in mean (h) of the heat stress index. Comparing the historical to future scenarios shows that climate change increases the mean of the heat stress index for all regions, with the most significant increases projected in the United States, South America, South Asia, and Western Asia. The calculation is based on NEX-GDDP-CMIP6 data. The white coloring shows non-cropland areas.

The results at the regional level reveal substantial variation in the volatility of weighted average beneficial and harmful heat (DD10°C-29°C and DD 29°C, respectively) across regions under current and future climate scenarios. The Southern part of the US is expected to experience a considerable increase in the volatility of harmful heat. The increase in SD of extreme heat is more widespread across the globe. On average, China exhibits lower levels of beneficial and harmful heat than the US and Brazil, which experience significantly higher levels of both. Notably, the United States displays an upward trend in harmful heat stress under future climate projections in this case.

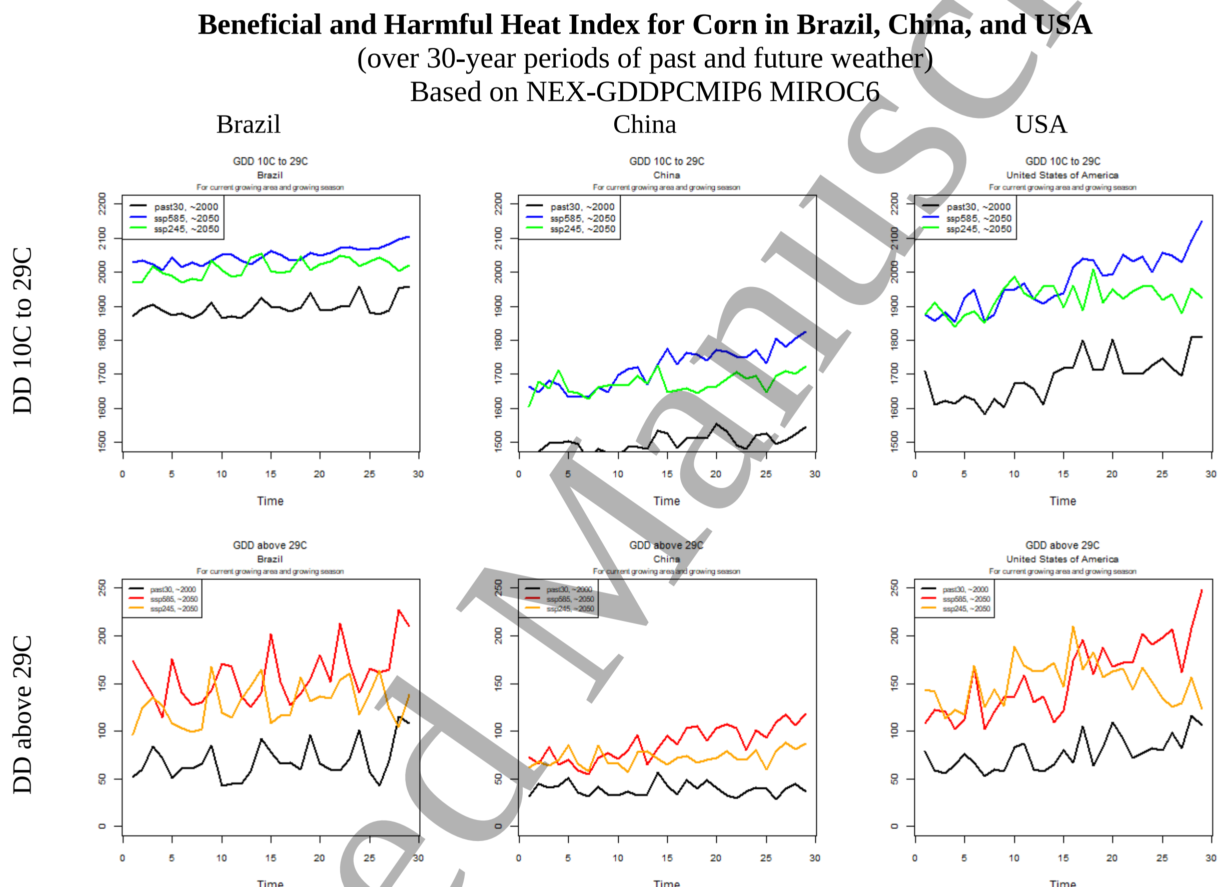

Figure 2. Historical and future degree days for corn for three major corn-producing regions. Panels (a-c) depict the beneficial heat index, while panels (d-f) show the harmful heat index. Black lines represent historical indexes (1985-2014), and colored lines represent future indexes under SSP5-8.5 and SSP2-4.5 scenarios (2035-2064). The level of heat stress and its volatility differs across regions. China exhibits the lowest harmful heat index mean and volatility in all scenarios. The figures allow for a comparison of historical trends with future projections under different emission scenarios for each country. Look at the SI for other regions and climate models.

Climate Change Increases the Volatility in Corn Supply for All Regions

Without considering market adjustments and adaptations, climate change will cause a loss in global irrigated and rainfed maize production (Figure 3). These changes are the results of changes in global average temperature and the increase in the likelihood of extreme heat events. Notably, the climate impact on non-irrigated corn yield is significantly negative at the grid cell level. The results show that as irrigated corn production is less vulnerable to extreme heat, the climate-induced production loss can be almost half of the rainfed corn. The regional variation is considerable, with changes ranging from -90% to +20%. The climate impact on corn yield can be positive for locations with relatively cold climates, such as Canada, Russia, and Europe. This implies that the positive impact of the increase in beneficial heat is dominant at these locations.

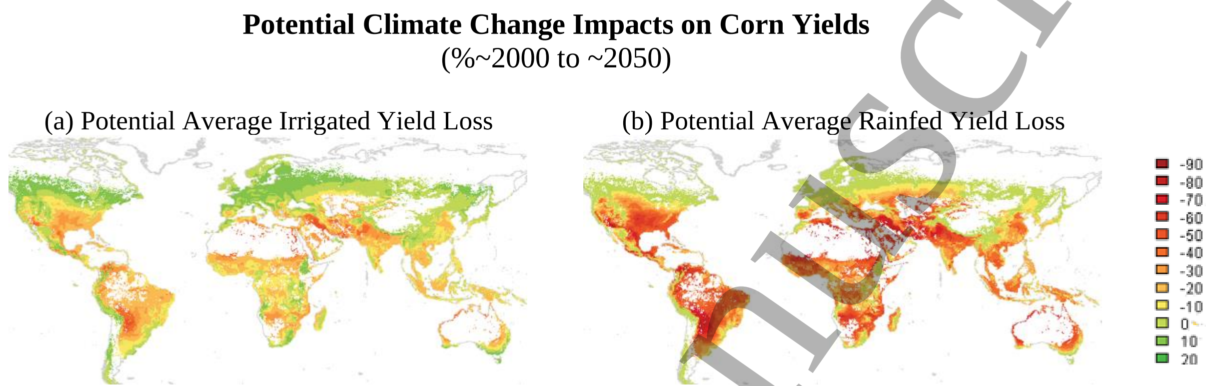

Figure 3. Potential yield loss due to future heat stress.

The regional sigma coefficient, the standard deviation of year-on-year corn yield ratios, highlights significant spatial disparities in climate-induced risks and volatilities. In the current climate, countries like Pakistan (31.6), India (19.4), Argentina (16.7), and the United States (7.4) exhibit the highest SD for rainfed corn yields, indicating greater year-to-year fluctuations (Table 1). This suggests that these regions are particularly susceptible to climate-driven disruptions in corn production.

Shifting climate patterns under SSP2-4.5 projections reveal a trend. While all regions experience increased SD for rainfed corn yields, irrigated yields show a smaller and sometimes even negative change in SD (e.g., Canada, France, Germany). This implies that in these regions, the irrigated corn is gaining yield from the beneficial heat associated with climate change, potentially benefiting these regions. Note that This approach assumes no change in cropland distribution, which might not reflect future changes in land-use patterns. The scenarios of change in irrigated areas are introduced in the adaptation scenarios.

The analysis reveals a concerning trend of increasing year-on-year yield volatility across most regions and climate models (Figure 4 and SI). This increase is particularly pronounced for key corn-producing countries like Brazil and the United States. However, irrigated corn production shows promise as an adaptation strategy. Compared to rainfed agriculture, irrigated systems exhibit significantly lower increases in yield volatility across regions.

Table 1: Sigma coefficient of corn yield volatility due to heat stress (standard deviation on year-on-year yield ratio in %).

	Irrigated				Rainfed			
	Historic Climate	Future Climate	Absolute Change	% Change	Historic Climate	Future Climate	Absolute Change	% Change
China	2.3	3.8	1.4	61%	6.5	10.5	4.0	61%
Indonesia	2.0	2.8	0.8	38%	5.5	7.1	1.6	28%
India	7.2	8.4	1.3	18%	19.4	23.2	3.8	20%
Pakistan	11.8	15.5	3.6	31%	31.6	43.6	12.0	38%
Canada	3.4	3.3	-0.1	-3%	2.5	6.9	4.4	179%
USA	5.1	7.5	2.4	47%	16.7	22.6	6.0	36%
Mexico	4.7	6.2	1.5	32%	14.3	17.9	3.6	25%
Argentina	5.8	9.1	3.3	58%	17.4	23.8	6.4	37%
Brazil	3.5	6.4	2.9	82%	10.1	15.4	5.3	52%
France	5.1	4.9	-0.2	-4%	4.3	8.8	4.5	104%
Germany	5.7	5.4	-0.3	-6%	3.4	5.0	1.6	46%
Russia	2.9	2.9	0.0	0%	4.6	7.9	3.4	74%
Ukraine	4.6	4.6	0.0	0%	5.7	11.8	6.1	107%
Kazakhstan	2.7	3.3	0.6	21%	5.6	10.2	4.6	81%
Turkey	3.4	5.4	1.9	56%	11.6	17.2	5.6	48%
Ethiopia	2.2	2.3	0.1	3%	4.0	6.0	2.0	49%
South Africa	4.5	6.5	2.0	46%	15.2	20.5	5.3	35%

Note: The standard deviation (SD) values in this table represent the average across 20 Global Climate Models (GCMs) included in the NEX-GDDP-CMIP6 climate products. These products utilize daily weather information at a high resolution of 15 arc-minutes. The heat stress index for each grid cell within each country's growing season for each individual climate model was calculated. The standard deviation (sigma) of year-on-year corn yield ratios was then calculated for each model for both the current climate and future scenario (SSP2-4.5). Finally, the SD values presented in this table represent the average across all 20 climate models after the sigma calculation at both the model and grid-cell level.

There are two key advantages of irrigation in the face of climate change. It reduces average yield losses as irrigated crops experience smaller average production declines due to climate change compared to rainfed crops. In addition, it can dampen production volatility as irrigation can buffer against the negative impacts of climate change by stabilizing crop supply to markets and mitigating the year-to-year fluctuations. This makes irrigation an option to buffer against the negative impacts of climate change on corn yield stability.

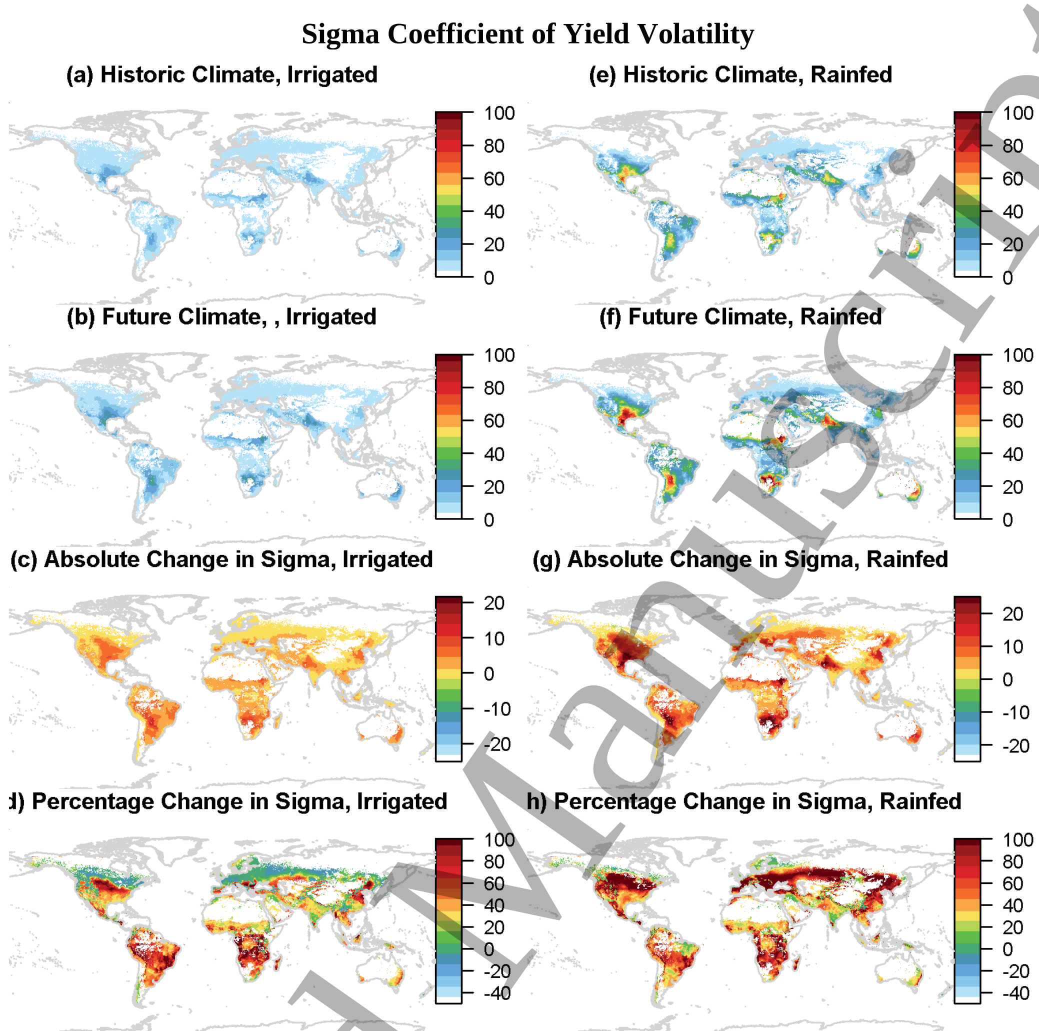

Figure 4. Future climate impact on the volatility of irrigated and non-irrigated corn yields. Global impact of climate change on mean corn yields for (a) irrigated, (b) rainfed corn, and (c) regional production volatility. While the magnitude of impacts varies regionally for both irrigated and rainfed corn, most regions are projected to experience an increase in volatility due to climate change. However, some regions may see a reduction in volatility. The calculation is based on NEX-GDDP-CMIP6 projections and assumes a non-linear relationship between heat and yields. Changes are calculated by comparing average historical weather (1985-2014) with future projections (2035-2064) averaged over 24 climate models for the SSP2-4.5 scenario.

Climate Change Will Increase the Risk of Substantial Production Loss

With increased volatility (Sigma), the risk of large reductions (Rho) will also increase. Substantial loss is any year experiencing a yield reduction exceeding 10% for a particular country. This is analyzed through the integration of area below the estimated probability distribution functions, based on projected year-on-year changes (Figure 5).

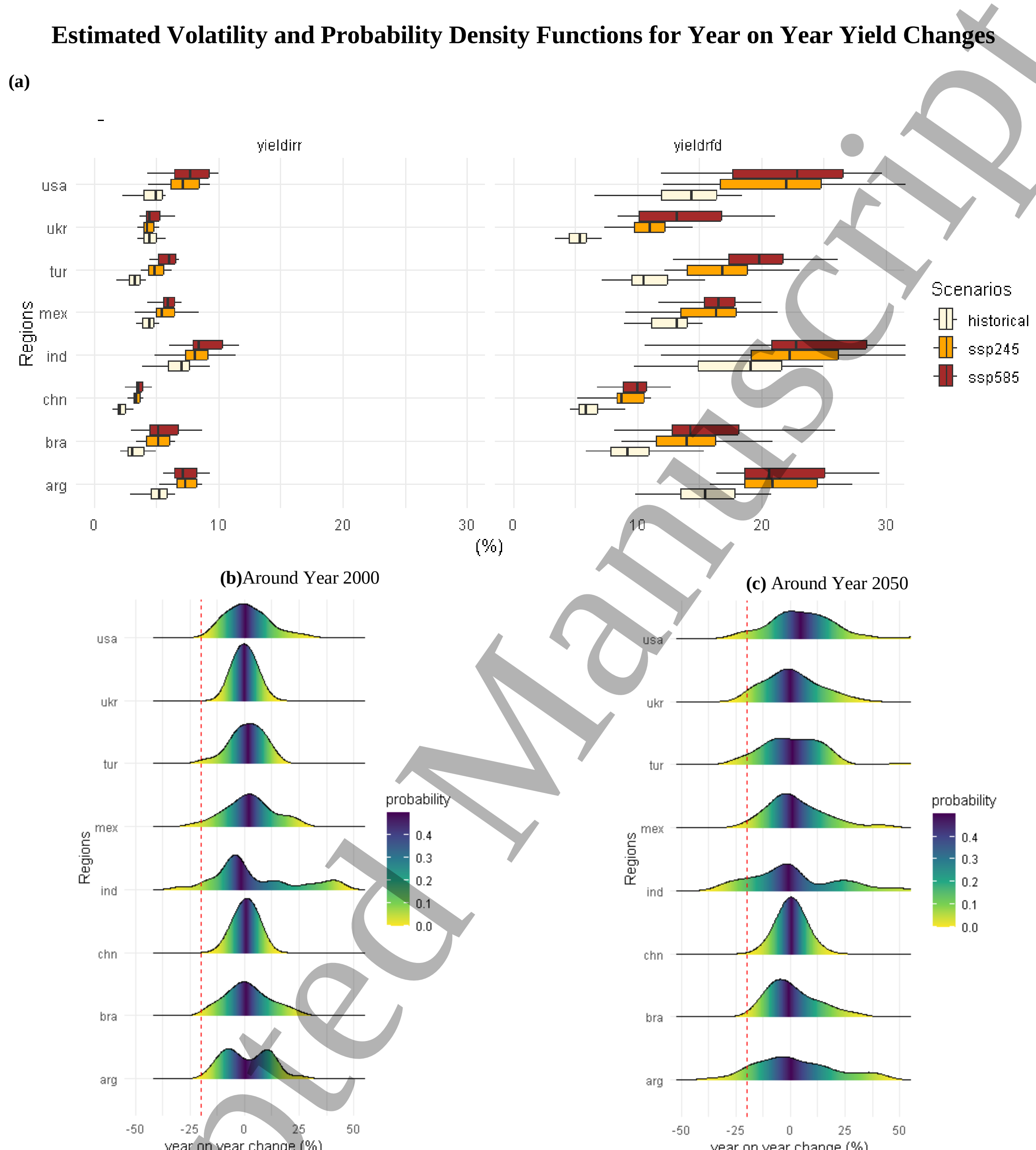

Figure 5. Estimated distributions of year-on-year non-irrigated yield change (%) for the US for the NEX-GDDP-CMIP6 MIROC6 model for 1985-2014 (left) and 2035-2064 (right).

Assuming no change in irrigated areas, the results suggest a concerning trend of increased production risks for major corn producers under climate change (Table 2). All models project a significant increase in the likelihood of substantial yield losses (SI). For example, the mean across climate models indicates an increase in the probability of substantial production loss for the United States (from 20.2% to 24.6%), Brazil (from 13.0% to 20.7%), and China (from 4.9% to 12.2%). This demonstrates the increased vulnerability of these major producers to climate-induced heat stress.

As expected, the average risk indicator value (Rho) across models is generally lower for irrigated corn compared to rainfed corn. This suggests that irrigation may offer some mitigation against climate-driven yield losses. However, the observed increase in rho for rainfed corn across most regions in the future scenario highlights the need for other adaptation scenarios. The projected rise in production risks for key corn producers, particularly India and Pakistan, which already experience high current and future risks due to heat stress, raises significant food security concerns. Considering the large populations in these regions dependent on crop production, this underscores the critical need for adaptation strategies that address both climate change mitigation and the development of climate-resilient production practices.

Table 2: Rho coefficient of substantial corn yield loss due to heat stress (probability of 10% loss).

	Irrigated				Rainfed			
	Historic Climate	Future Climate	Absolute Change	% Change	Historic Climate	Future Climate	Absolute Change	% Change
China	0.2	0.9	0.7	356%	4.9	12.2	7.2	147%
Indonesia	0.1	0.6	0.5	456%	4.0	7.2	3.2	79%
India	7.2	10.6	3.4	46%	25.3	27.9	2.5	10%
Pakistan	19.4	25.2	5.8	30%	33.4	37.0	3.6	11%
Canada	0.6	0.3	-0.3	-46%	0.3	5.3	5.0	1541%
USA	2.6	8.0	5.4	212%	20.2	24.6	4.3	21%
Mexico	1.5	4.4	2.9	195%	17.2	20.5	3.3	19%
Argentina	4.2	9.9	5.6	132%	23.8	29.5	5.7	24%
Brazil	0.8	4.0	3.3	428%	13.0	20.7	7.7	60%
France	2.8	2.2	-0.6	-22%	1.8	7.8	6.0	329%
Germany	4.0	3.4	-0.6	-14%	0.6	2.1	1.5	244%
Russia	0.3	0.5	0.2	91%	2.0	7.5	5.5	277%
Ukraine	1.8	2.1	0.2	14%	3.9	17.2	13.3	340%
Kazakhstan	0.4	1.0	0.7	172%	3.4	13.1	9.7	284%
Turkey	0.7	4.1	3.4	451%	17.9	25.5	7.6	42%
Ethiopia	0.1	0.1	0.0	45%	1.1	3.0	1.9	182%
South Africa	1.8	5.6	3.8	212%	17.8	26.9	9.1	51%

Note: The Rho values (probability of 10% regional production decline) in this table represent the average across 20 Global Climate Models (GCMs) included in the NEX-GDDP-CMIP6 climate products. These products utilize daily weather information at a high resolution of 15 arc-minutes. The heat stress index was calculated for each grid cell within each country's growing season for each individual climate model. The year-on-year yield changes were then calculated for each model, for both the current climate and future scenario (SSP2-4.5). Finally, the probability of 10% regional loss is calculated based on estimated probability density functions.

The level of risk varies across climate models for rainfed and irrigated corn production in key regions. Despite differences, the data from most climate models supports the main findings of this section (increase in risk of substantial loss). Furthermore, the results reveal a significant difference in risk between regions, with India, the United States, and Argentina likely to experience the most significant impacts on irrigated yields (Figure 6). The differences across climate models are more significant for risk in irrigated crops with more outlier data points. For irrigated corn, the uncertainty from climate models on the projected risk is higher. While the risk is lower for irrigated corn compared to rainfed production according to most of climate models, some climate models imply the risk can still be high for irrigated production. For example, in the US, four climate models suggest up to 20% likelihood of substantial irrigated reduction.

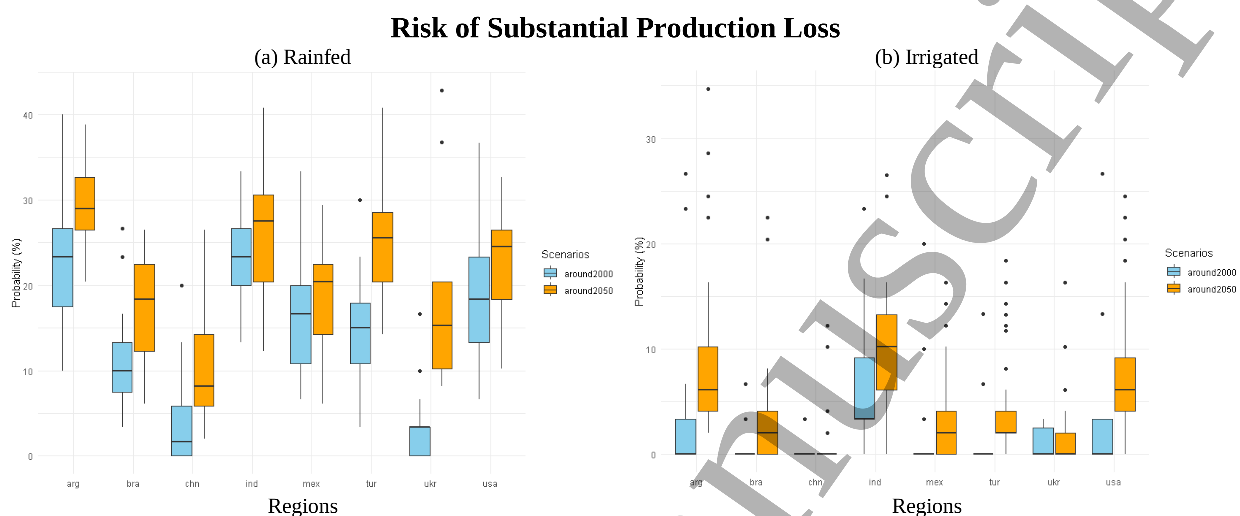

Figure 6. The risk of substantial production loss is defined as a shock greater than 10% of regional supply. The analysis utilizes NEX-GDDP-CMIP6 climate products, which incorporate daily weather information at a high resolution of 15 arc-minutes. For each individual climate model, the heat stress index was calculated for each grid cell within each country's growing season. Subsequently, the year-on-year corn yield changes were calculated for each model, considering both the current climate and the future scenario. Finally, the probability of exceeding a 10% regional loss was calculated based on the estimated probability density functions.

Irrigation Expansion Reduces Risk and Volatility in Regional Crop Supply

Due to significant variations in crop responses to heat stress, strong incentives for increased irrigation will likely exist. As illustrated in Figure 7, expanding irrigation can significantly reduce the risk of substantial yield losses in the US. This analysis implies a necessary increase in the regional irrigation share to maintain historical risk levels under future climate scenarios. In the US, this requires a significant increase from the current 15% of the areas to a range of 50-75%. While there is inherent uncertainty in climate model projections regarding the exact level of required irrigation increase, all models consistently showed a reduction in risk with expanding irrigation. These results suggest that irrigation investments could be an adaptation strategy by farmers to ensure long-term crop production stability.

Integration in International Markets Reduces Supply Volatility and Risk

Increased market integration can be another effective adaptation strategy to manage climate risk. For instance, while US production volatility stands alone at a high risk of 25% for substantial yield loss in the future, integrating with different trade partners significantly reduces this risk. Partnerships with Mexico see a reduction to 20%, while Brazil brings it down to 17%. China offers the strongest individual buffering effect, lowering risk to 13%. The most significant risk reduction (7%) is achieved through comprehensive integration with all three regions (US-Brazil-China). These results highlight the potential of strategic trade partnerships to diversify production risks and enhance overall production stability.

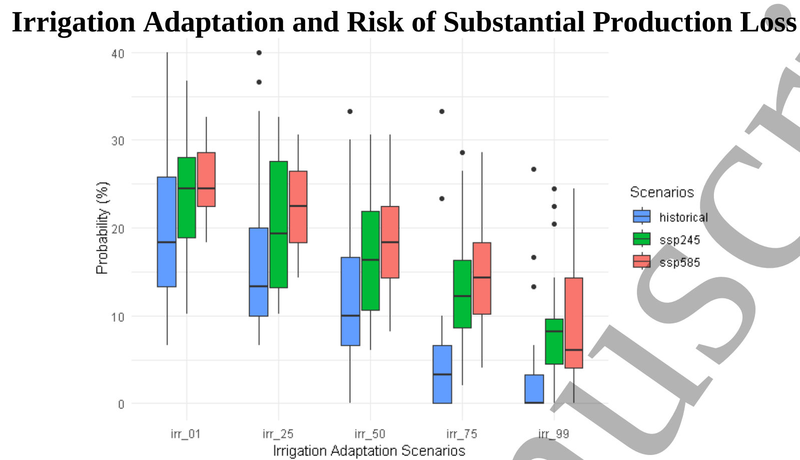

Figure 7. Irrigation expansion will reduce the risk of substantial loss in the United States under climate change (SSP2-4.5 and SSP5-8.5). The x-axis represents five hypothetical scenarios with varying irrigation shares of total cropland: 1%, 25%, 50%, 75%, and 99%. The y-axis depicts the risk of substantial production loss, defined as a shock exceeding 10% of the regional corn supply. The figure shows a significant decline in risk with increasing irrigation availability. Under the current limited irrigation scenario (assumed to be 1%), the risk of substantial loss is around 20%. However, as the irrigation share increases across the remaining scenarios, the risk progressively declines, reaching approximately 5% with near-complete irrigation coverage (99%).

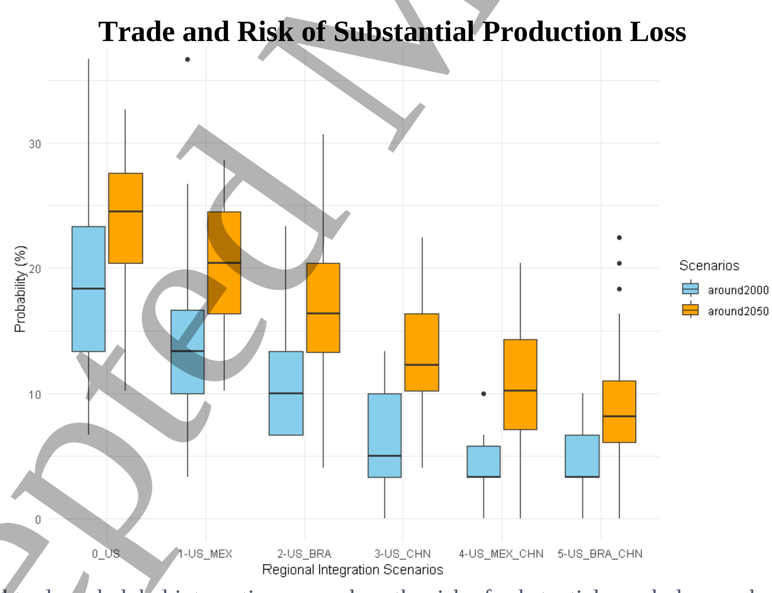

Figure 8. International trade and global integration can reduce the risk of substantial supply loss under climate change (SSP2-4.5). The x-axis shows five market integration scenarios: US-Mexico, US-Brazil, US-China, US-Mexico-China, and US-Brazil-China. The y-axis depicts the risk of substantial production loss, defined as a shock exceeding 10% of the regional corn supply.

Climate Change Will Reduce US Beta (Relative Market Risk)

To quantify how a region's corn production volatility compares to the global market, a Beta coefficient is employed that is adapted from financial market analysis. This coefficient reflects the relative volatility of a self-sufficient region's production compared to the globally integrated market. The results reveal a distinct pattern in current Beta values. Regions like the United States exhibit a relatively high Beta, indicating their corn production is more volatile than the global average. Conversely, countries like China currently have a lower Beta, suggesting their production is less susceptible to global market fluctuations. Interestingly, The future climate projections show a potential shift in this pattern. As global market volatility is expected to rise, the beta coefficient for the US might decrease, indicating that its production will become less volatile relative to the global market. On the other hand, regions like China, with currently low Betas, might experience an increase in relative volatility as their production becomes more integrated with the global market and exposed to fluctuations.

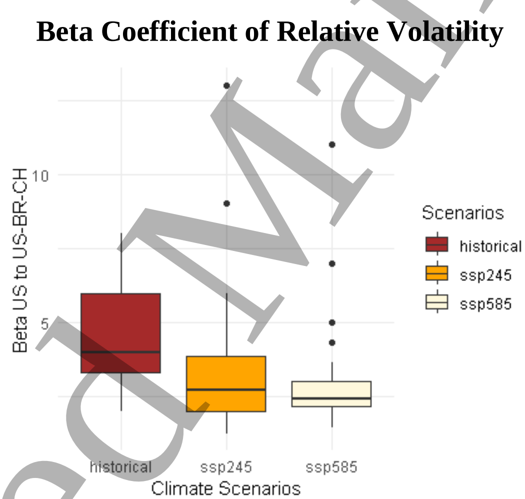

Figure 9. Beta relative volatility coefficient for the US. The key finding of this figure is the projected decrease in Beta for the US in the future scenario. This indicates that while global corn market volatility is expected to rise due to climate change, the volatility of US corn production is predicted to become relatively less pronounced compared to the global market.

Discussion

This study used a statistical model to estimate crop yield response to heat stress. This information, combined with NEX-GDDP-CMIP6 climate data, enabled us to project future production volatility and risks of substantial yield losses for corn. Additionally, the analysis assessed the impacts of irrigation and market integration on overall supply chain volatility. The findings of this study are critical for global food security as well as regional resilience. Here, the results show that corn yields exhibit higher volatility due to climate change. However, irrigation and international trade can buffer the effects of climate change in terms of mean yield damage and year-on-year variations. This paper is also an important contribution to the climate impact literature as it sheds light on the significance of irrigation and integration in reducing the negative impacts of global warming.

This study introduces a novel application of the Beta coefficient, borrowing from financial market analysis, to quantify the relative volatility of self-sufficient regions compared to globally integrated markets. The Beta coefficient sheds light on how the landscape of regional vulnerability to yield fluctuations will change under future climate scenarios. Currently, the United States exhibits a relatively high Beta, indicating its production is more volatile than the global market. However, these projections suggest this may decrease in the future due to a rise in global market volatility. Conversely, regions like China, with a currently low Beta, might experience an increase in relative volatility as their production becomes more susceptible to global market fluctuations.

The findings of this study demonstrate the potential for market integration to reduce production risks. Despite recent research on synchronized crop failures across regions (Tigchelaar et al., 2018; Zhou et al., 2023), the findings on the positive impact of global trade in reducing volatility remain robust. However, the optimal partnership patterns display higher uncertainty due to discrepancies in spatial correlation across climate models. While all models agree on the benefits of market integration, they diverge in their projections of spatial correlation of year-on-year yield shock across regions. This highlights the need for a more rigorous evaluation of climate models, particularly regarding their ability to replicate observed spatial correlations. Employing a set of climate models that accurately capture spatial dependencies would significantly enhance the reliability of future projections on optimal trade partnerships and risk reduction strategies.

Limitations

While the framework offers valuable insights, it is crucial to acknowledge its limitations. The first limitation lies in market volatility's potential overestimation and underestimation. The model does not account for market-mediated relocation of production in response to regional yield fluctuations. Furthermore, the study does not consider the complexities of economic decision-making, which are influenced by both price changes and production costs. However, the farmers' economic responses are usually studied in the long run when changes in technology and adjusting investments are possible. Including long-run farmers' responses will not affect the findings of this study regarding short-run market fluctuations but may affect the projected risk of substantial production losses.

The second limitation of this study is neglecting other potential climate extremes such as floods, frosts, and high winds. While the model does not include other potentially important variables such as floods, frosts, and high winds, empirical evidence suggests that the heat stress index can explain the majority of production volatility in recent decades, particularly at the regional scale (Haqiqi et al., 2021; Stella et al., 2021; Zhu and Burney, 2021). Thus, the study's findings will remain robust to include other extremes.

This study focused on heat stress as a key driver of yield variability. However, it is essential to acknowledge the additional influence of soil moisture and water stress on crop yields (McDonald and Girvetz, 2013; Meng et al., 2016; Urban et al., 2015). The primary difference between irrigated and non-irrigated agriculture lies in soil moisture availability. While irrigation aims to maintain optimal soil moisture levels, climate change may significantly alter temporal precipitation patterns, impacting non-irrigated production. Therefore, a comprehensive understanding of how water stress interacts with heat stress to influence yields is essential for future research. In regions projected to experience drier conditions, water stress will likely exacerbate the negative effects of heat stress. Conversely, areas anticipated to become wetter may experience a dampening effect on heat stress impacts. Unfortunately, there is a considerable uncertainty in climate projections of precipitation extremes (Lafferty et al., 2021; Lafferty and Sriver, 2023). Regardless of uncertainty from climate models, the future is expected to have more extreme precipitation events (Tabari, 2020). This means that including more accurate measures of water stress may lead to a higher measure of risk of substantial production loss. In addition, the increase in the likelihood of compound extremes may intensify the risk (AghaKouchak et al., 2020).

There is growing attention to the potential impacts of carbon dioxide (CO_2) fertilization, a factor that could offset some of the adverse effects of climate change on crop yields (McGrath and Lobell, 2013; Phillips et al., 1996; Taylor and Schlenker, 2021). However, the inclusion of CO_2 fertilization is not likely to change any of the findings of this study as its impact would be a long-run change in the trend, not the year-on-year volatility. We expect lower short-term volatility on CO2 fertilization compared to other climate extremes affecting crop yields. Sustainability Concerns

This study demonstrated that irrigation can significantly reduce climate damage to yield at the local level and can mitigate the volatility in market supply. The findings are particularly important as irrigation is considered a major adaptation strategy for climate change (Tack et al., 2017; Troy et al., 2015). With projected increases in heat stress, irrigation is likely to become more attractive to farmers. While irrigation expansion can potentially reduce market volatility, price fluctuations, and agricultural risks by mitigating heat stress damage, it presents significant sustainability challenges. Rapid depletion of groundwater resources and water scarcity pose major concerns in many regions. For the US to stay at current volatility levels, it would require irrigating around 70 million acres (~75%) of currently rainfed corn. It would require an additional 35 to 150 million acre-feet of water assuming current per acre water use (0.4 acre-feet in IN and 3.0 acre-feet in CA for corn). The energy cost for additional irrigation would be 350 to 6,000 million dollars.

There are some concerns regarding the impact of trade on sustainability stresses. This study assumes a constant cropland and irrigated area under the trade scenario, minimizing direct sustainability impacts on land and water resources within the scope of this study. In reality, trade can indirectly influence land use patterns and water resources. For instance, increased production pressures due to trade may lead to intensification, potentially exacerbating water quality issues. Moreover, trade can motivate cropland expansion in some regions and irrigation development in productive areas. It is important to emphasize that while trade can potentially contribute to environmental challenges, a growing body of literature suggests that, in the absence of trade, sustainability pressures would likely be even greater as less productive countries need more land to be self-sufficient (Graham et al., 2023). A comprehensive assessment of the trade-sustainability nexus would require a dedicated study incorporating detailed land use, water resources, and environmental impact models. This is an important area for future research and would encourage trade economists to delve deeper into these complexities.

Other applications

The framework and methodology developed in this study offer valuable insights beyond corn production and hold promise for application to other crops facing climate risks. By adapting the crop-specific yield response functions and incorporating data for different agricultural commodities, this framework could be used to assess the future volatility and risks associated with other major food crops. This would enable a more comprehensive understanding of potential vulnerabilities and inform the development of targeted adaptation strategies across the agricultural sector. Furthermore, the concept of relative volatility measured by the Beta coefficient can be applied to analyze the risk-reduction potential of market integration for other agricultural products. By investigating a broader range of crops and regions, this approach could contribute to the development of more resilient and integrated global food systems in the face of climate change.

Conclusion

This study investigated the future volatility and risks associated with corn supply under climate change, considering two key adaptation strategies: irrigation and market integration. Global warming projections suggest a dramatic rise in heat stress on agricultural systems in the coming decades. This will not only lead to direct yield losses but also exacerbate year-on-year yield volatility. Choosing the most effective adaptation strategy requires careful consideration of its potential to reduce average yield loss, buffer volatility, and minimize economic and environmental costs.

The findings of this study highlight the effectiveness of irrigation as a strategy for farmers to adapt to climate change. However, it is important to emphasize that large-scale irrigation expansion in many regions could lead to unsustainable groundwater depletion. In contrast, the analysis suggests that global market integration offers significant advantages. By enabling trade between regions with diverse climate patterns, market integration can effectively reduce volatility and risks in food markets, thereby preserving precious water resources.

This study underscores the importance of a multidimensional approach to climate change adaptation in the agricultural sector. While irrigation can be a valuable tool for individual farmers, promoting global market integration offers a broader solution that fosters resilience and sustainability across the entire food system. Future research efforts should focus on developing and evaluating additional adaptation strategies that balance economic needs with environmental sustainability, ensuring global food security in a changing climate.

Acknowledgments

This work was supported by the US Department of Energy, Office of Science, Biological and Environmental Research Program, Earth and Environmental Systems Modeling, MultiSector Dynamics under Cooperative Agreement DE-SC0022141. The data processing, computation, and storage were completed on Purdue Anvil supercomputer and cyberinfrastructure supported by the National Science Foundation HDR award # 2118329: "NSF Institute for Geospatial Understanding through an Integrative Discovery Environment (I-GUIDE).

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors. The climate products used in this study, NEX-GDDP-CMIP6, are available here: https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6. The map of cropland area is available from GFSAD: https://lpdaac.usgs.gov/products/gfsad30afcev001. The crop growing season is obtained from SAGE: https://sage.nelson.wisc.edu/data-and-models/datasets/crop-calendar-dataset/. The shapefile for country borders (to aggregate from grid cells to regions) is from the World Bank https://datacatalog.worldbank.org/search/dataset/0038272/World-Bank-Official-Boundaries.

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