SERENA: System for Evaluating Risks and Extreme Natural activities on Agriculture and Application to World Economies

A Forward-Looking Analysis using Global Circulation Models Data

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Abstract

This paper examines the spillover effects of weather events on inflation via commodity prices, utilizing a bottom-up approach enhanced by forward-looking Monte Carlo simulations. The SERENA methodology, developed for this study, facilitates the integration of geospatial climate models into economic analysis. By leveraging Representative Concentration Pathways (RCP) scenarios and data from the Atmosphere-Ocean General Circulation Models (AOGCMs), we assess how climate-induced fluctuations in commodity prices affect inflation. The inclusion of Monte Carlo simulations captures the dynamic and uncertain nature of weather patterns, enabling robust forecasts under varying climate scenarios. Our findings indicate significant spillover effects, with extreme weather driving commodity price shocks of up to 100% by 2040. These price shocks, in turn, exert upward pressure on inflation, with a 1% rise in commodity prices leading to an average 2% increase in US CPI inflation. These results provide valuable insights for policymakers and investors aiming to understand the economic and financial impacts of climate change.

Keywords: Climate change, credit risk, equity valuation, inflation

JEL classification: G11, G12, Q02, Q11, Q54

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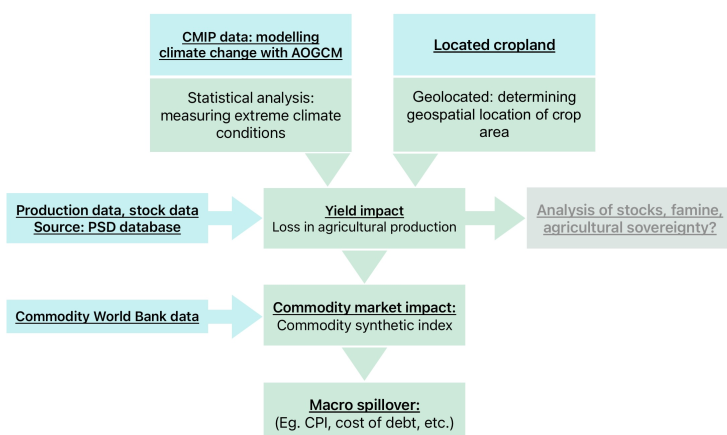
1 Introduction

Anthropogenic climate change and its influence on extreme weather events have been evident for several decades, in particular in the slowing down of production and agriculture (Ortiz-Bobea *et al.*, 2021). In France, for instance, climate change has manifested in rising temperatures, more frequent heatwaves, intense rainfall, floods, rising sea levels, and severe storms (World Bank, 2021). Notably, extreme heatwaves have exacerbated the occurrence of wildfires, causing widespread destruction of infrastructure. According to Abatzoglou *et al.* (2019), the frequency of fire-favorable weather is projected to increase globally due to climate change, a trend also confirmed for France (Barbero *et al.*, 2020; Fargeon *et al.*, 2020). Furthermore, the risk of fire weather doubles when global temperatures exceed 3°C compared to 2°C above pre-industrial levels. Among various sectors, including industry and tourism, agriculture is particularly vulnerable to the impacts of climate change.

This paper examines the transmission of climate-related shocks to inflation and fixed income markets, with significant implications for financial decision-making by portfolio and asset managers. The modeling framework, inspired by Le Guenedal *et al.* (2022), follows a multi-step process that maps the transmission channels of climate variables from CMIP models[1] to financial asset prices. Initially, representative variables of abnormal (and extreme) climate conditions are constructed. As illustrated in Figure 1, the first step involves extracting signals from climate models that capture extreme events. The second step assesses the impact of these events on agricultural production. Production shocks subsequently lead to price shocks in commodity markets, influencing inflation and emerging market bond spreads. The study integrates both historical data calibration and future simulations using climate models.

Figure 1: Propagation of climate to bond spreads



[1] The Coupled Model Intercomparison Project (CMIP) facilitates comparison and harmonization of outputs from climate models, such as atmosphere and ocean general circulation models (AOGCMs), and helps estimate future climate conditions under various Representative Concentration Pathways (RCPs).

Climate data Previous studies have demonstrated the utility of these geospatial datasets for economic and financial research, supporting the integration of climate data into broader economic analyses. Specifically, ERA5 global daily dataset is used by Hogan and Schlenker (2024), where the authors explain non-linear relationships between daily temperature extremes and US agricultural yields. The results indicate that the non-linear temperature relationship with yields is correctly predicted with ERA5 daily data, and more so when transforming the data into daily temperature extremes than when using average temperatures. Moreover, the authors suggest that correctly capturing the effects of daily extremes is more important for a good model than the choice of weather data.

Other examples include Kotz *et al.* (2023) where ERA5 reanalysis of historical observations is used to define the implications of climate change for past and future inflation. The authors find that increasing average temperatures result in non-linear upwards inflationary pressures that last for over 1 year. Also, future warming might cause a spike of 0.92-3.23 and 0.32-1.18 for food and headline inflation with respect with different climate scenarios. A similar result with the same climate data is found by Ciccarelli *et al.* (2023), precisely that increases in monthly mean temperatures have inflationary pressures in summer and autumn for a study of four EU economies, and the response was the strongest in the warmest countries. Stone *et al.* (2008) report that global reanalysis datasets are useful for climate risk management.

Pagani *et al.* (2017) forecast sugarcane yields using agroclimatic indicators in the largest sugarcane-producing country, Brazil. The study uses linear regressions where agroclimatic indicators and outputs of the sugar Canegro model are fitted with historical yields. The results indicate that agroclimatic indicators explain 38% of yield variability during the growth phase from January to April, and 73% during the the harvesting period in September–October. Tigchelaar *et al.* (2018) quantify how yield variability will change for major corn producing countries under 2 °C and 4 °C of global warming. Although the results do not take into account potential breeding innovations, the authors find that as the global mean temperature increases, coefficient of variation (CV) of corn yields increases significantly due to the increase in volatility and decrease of mean in yields, and the probability of production losses increases exponentially with temperature rise.

Pricing The consequences of weather extremes having an impact on agricultural production and its transmission to agricultural commodity prices have been explored by several branches of literature. There is much evidence that temperature anomalies create significant volatility in agricultural markets. Makkonen *et al.* (2021) show based on a quantile regression methodology that there is a decrease in futures returns of soybean, corn and cotton in low quantiles (bullish markets), and positive impact on the returns soybean, corn, wheat, cocoa, and cotton in high quantiles (bearish markets). Cai and Sakemoto (2022) show that El Niño Southern Oscillation1 has a strong relationship with agricultural, food, beverages and raw material commodity prices.

Faccia *et al.* (2021) demonstrate that extreme temperatures impact inflation, as well as consumer and producer prices, including food prices, across a panel of 48 advanced and emerging economies. However, while the inflationary pressures on food from hot summers are evident in the short term, they tend to dissipate in the medium term. Additionally, extreme climate change presents significant tail-risk spillover effects on commodity futures markets, particularly affecting agricultural commodities and energy sectors (Jia *et al.*, 2023).

Kitsios *et al.* (2022) leverage climate model forecasts of the El Niño Southern Oscillation (ENSO) to predict commodity prices. Their findings suggest that spot price returns perform better and surpass models that do not account for ENSO factors. This highlights the added value of integrating climate insights into investment decisions. Moreover, another study on the El Niño phenomenon and agricultural commodity markets reveals that, although El Niño can sometimes reduce commodity production, leading to price hikes, this is not always the case (Sun *et al.*, 2023). The study suggests that agricultural commodity markets can, at times, preemptively reflect extreme global climate conditions.

Spillover Commodity price spikes have long been recognized as contributors to inflationary pressures. De Gregorio (2012) highlights that food inflation exerts a stronger influence on core inflation than energy inflation. A similar finding is presented by Gelos and Ustyugova (2017), showing that economies with a higher weight of food in their consumption baskets experience more pronounced inflation increases from commodity price shocks. Further, an IMF study (Celasun *et al.*, 2012) suggests that oil and food prices significantly influence mid-term U.S. inflation (0-5 years), with a direct pass-through from commodity prices to headline inflation.

Commodity prices are especially important for commodity-dependent economies, serving as critical determinants of bond spreads for commodity exporters. Bastourre *et al.* (2012) examines emerging countries specializing in commodity production and confirms the hypothesis that commodity prices are negatively correlated with bond spreads. Arezki and Brückner (2012) presents an intriguing finding that commodity price booms lower sovereign bond spreads in emerging democracies, while raising spreads in autocratic regimes. This result is linked to real GDP per capita growth, which increases in democracies but decreases in autocracies when commodity prices rise.

In fact, Drechsel and Tenreyro (2018) provide a detailed explanation of how emerging economies experience more volatile economic cycles. By modeling an economy where rising commodity prices reduce interest rate spreads, they demonstrate positive effects on GDP, consumption, and investment, along with higher volatility in consumption and investment, and adverse effects on the trade balance. This model is empirically validated using Argentine data, which shows that commodity price increases not only have a significant impact on spreads but also amplify output shocks, thereby exacerbating economic cycles in emerging markets.

Summary This paper aims to develop and validate a methodology for processing climate model data to detect both positive and negative weather extremes. This approach is designed to accommodate different types of data, including reanalysis, climate models, and meteorological observations, which have distinct characteristics. We propose an advanced signal that can be applied across these data types, enhancing the detection of extreme weather events. Specifically, we utilize ERA5 monthly reanalysis data (Muñoz Sabater, 2019) and agroclimatic indicators from 1951 to 2099, derived from Copernicus climate projection data (Nobakht *et al.*, 2019), to predict the impact of climate variability on agricultural production and commodity prices. The resulting production and price shocks are further analyzed for their effects on financial markets, with particular attention to the propagation of these shocks to inflation.

Our contributions to the literature are threefold. First, we introduce a novel methodological framework that enables the processing and comparison of results across different climate databases. This framework is then applied to assess the market and investor implications, particularly by examining the effects on CPI inflation. Second, to our knowledge, this study represents one of the first attempts to extend climate modeling to the pricing of emerging market bonds, exploring the effects of climate-induced spread changes and their implications for asset managers.

Our findings reveal that climate variables negatively affect crop yields, leading to increased commodity prices. These effects are more pronounced when using reanalysis data compared to climate models, due to differences in their construction. While commodity prices are sensitive to various climate scenarios, the differences between scenarios remain marginal before 2040. This results from the fact that CO2 emissions require decades to manifest their full effects, meaning economies will continue to experience the consequences of past emissions until 2040, regardless of future emission trajectories. Additionally, we find that a 1% increase in commodity prices, driven by yield disruptions, results in an approximate 2% rise in US CPI inflation.

The paper is organized as follows. In Section 2 we present the SERENA data processing methodology for geospatial climate data, which can be adapted for economic analysis across various climate databases. We then propose models to measure the transmission of climate impacts to crop yields, commodity prices, and financial markets. Section 3 provides a description of the results, followed by a discussion on the challenges portfolio managers face in accounting for the future risk of more severe climate events in present-day decision-making.

2 Methodology

Extreme event impacts commodity prices as illustrated by Faccia *et al.* (2021) and Hogan and Schlenker (2024). In this section, we describe the process to model the transmission channels from raw climate variables to production and commodity prices, and then to inflation and bond spreads. The first step is to process the climate metrics and reiterate them on different climate data (from climate models or reanalysis). We reconsider some of the approaches introduced in the literature and illustrate the construction of a climate signal.[2] Then, we estimate the impact of our signal on production (Pagani *et al.* (2017), Sun *et al.* (2023), and Tigchelaar *et al.* (2018)), and the impact of change in production on commodity prices. Finally, we model the propagation of climate to inflation and sovereign spread following Hilscher and Nosbusch (2010) with synthetically constructed commodity sensitivity index.

[2] In the paper, we focus on climate models, but we also introduce processes based on the reanalysis in the appendix. The data coming from reanalysis had advantage to be more consistent with meteorological records, and mid-term projections have interesting applications in operational trading.

2.1 Data

ERA5 reanalysis One of the climate datasets utilized in this study is the ERA5 reanalysis at a monthly frequency (Muñoz Sabater, 2019). Reanalysis data, derived from actual meteorological records, is crucial for establishing realistic connections between weather and production before applying tests on climate models. This provides a robust foundation for comparison. To ensure consistency, we selected similar weather variables available across all datasets under consideration, focusing on average temperatures and total precipitation. However, average weather parameters typically lack statistical significance when correlated with economic data. Therefore, we transformed these variables into extremes or anomalies, using the SERENA methodology, which is outlined in the following section.

Climate Models Reanalysis data are only available for the past, as they rely on meteorological observations. In order to predict future climate, we use athmosphere and ocean general circulation model (AOGCM). These models provide information about the future conditions (sea-surface temperature, air temperature, humidity, precipitation, etc.) on grids pof several resolution, for different altitude (or pressure levels).

From these models, we focus on the Agroclimatic indicators database (Nobakht *et al.*, 2019) allows to model climate impact on commodities in the future, in this case we use the range 2011-2040. It is important to consider that as of today, there are several scenarios - Representative Concentration Pathways (RPC) that project future concentration of greenhouse gases (Table 1), and the names of these scenarios represent radiative forcing targets for 2100 in watts per square mettre ($W.m^{-2}$): 2.6, 4.5, 6.0 and 8.5. The scenarios reflect possible development trajectories based on social, economic and technological criteria (Copernicus Climate Change Service, 2021; Met Office, 2018). In this paper, we will only focus on two scenarios - 2.6 and 8.5 to identify differences in patterns before 2040.

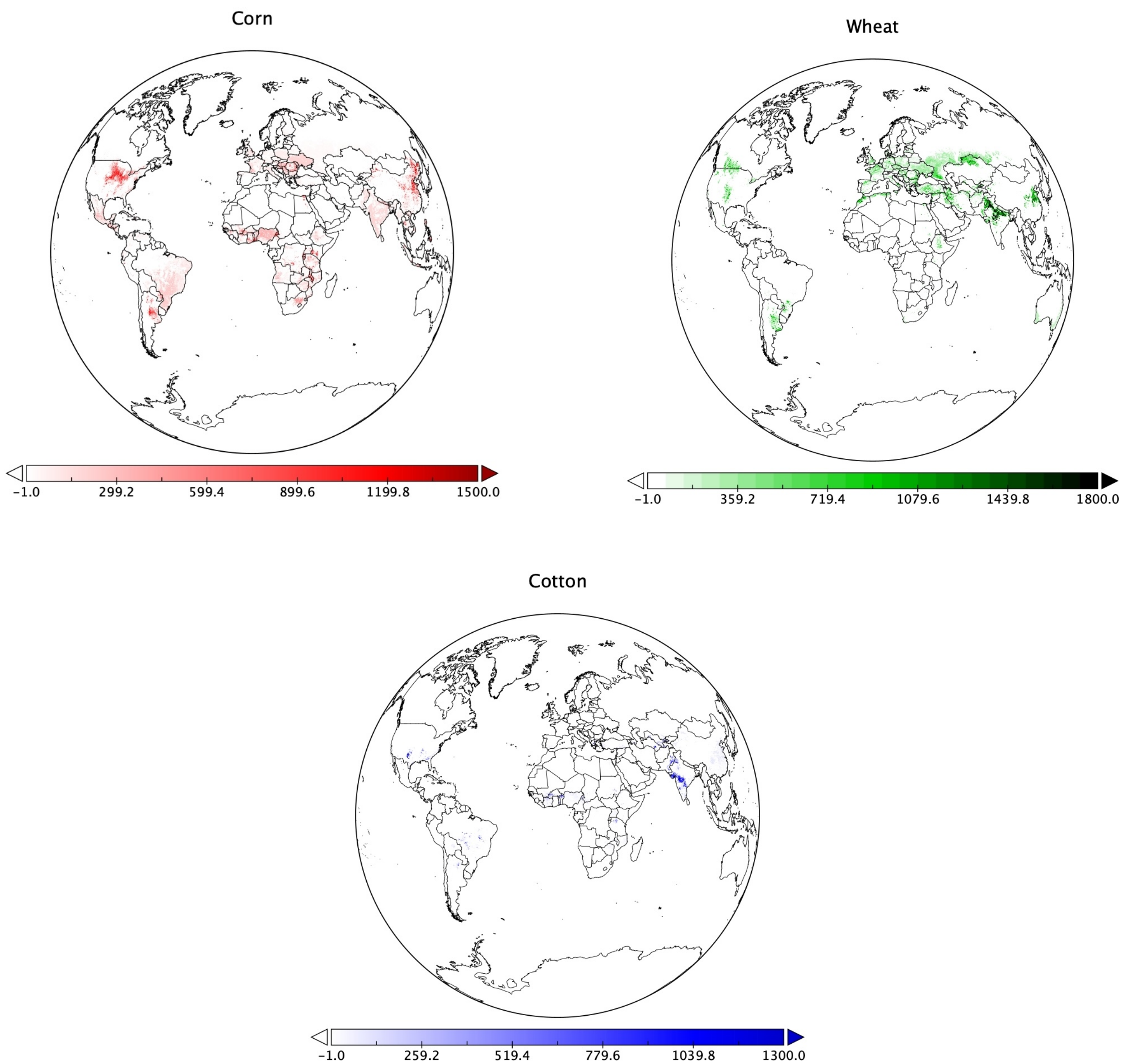
Table 1: Representative Concentration Pathways (RCPs)

RCP 2.6 $W.m^{-2}$
The most sustainable scenario. CO2 emissions are expected to go to zero by 2100, which requires negative CO2 emissions coming from, for example, tree absorption. The global warming is expected to increase by 1°C by the mid-century. This scenario is also associated with massive decrease in methane emission and increased usage of biofuels.
RCP 4.5 $W.m^{-2}$
In this scenario, the emissions will peak by 2045 but decline steadily until 2100, and the temperature increase by 2050 is expected to be 1.4°C. In this middle scenario, there is no deviation from historical socioeconomic trends. Reforestation is possible due to higher yield from cropland and reduced meat consumption.
RCP 6.0 $W.m^{-2}$
The emissions peak by 2080, and decline until 2100, and the temperature increase is expected to be 1.3°C by 2050.
RCP 8.5 $W.m^{-2}$
The worst case scenario where the emissions continue to rise. While this scenario is unrealistic until 2100, it is well representative for more recent analysis and the projections until mid-century. However, this scenario assumes non-implementation of climate policies.

For the main part of the analysis, we use IPSL-CM5A-LR Model (IPSL, France) model origin which provides a generalized approach to simulating climate dynamics. We also verify robustness using the MIROC-ESM-CHEM model with (JAMSTEC, Japan) origin in the Appendix. Again, we focus on average 2-meter temperatures and precipitation sum variables.

Plantation area and production Additionally, we use gridded crop area data for 2020 from newly constructed CROPGRIDS dataframe which is a comprehensive global geo-referenced dataset containing information about the growth and harvest of crops at 0.05° resolution in 2020 (Tang *et al.*, 2024) as illustrated in Figure 2.

Figure 2: Crop areas (ha) of corn, cotton, and wheat in 2020



We merge both datasets (climate raw variables and crop area) by latitude and longitude a 1° resolution to accommodate the computational limitations of available resources where 1° of latitude is equal to approximately 111 kilometers at the equator. Figure 2 represents the crop area of corn, wheat and cotton extracted from CROPGRIDS database. For instance, corn production is visibly diversified globally, and the areas of intense production are the United States, Ukraine, China, Brazil, Argentina, Mexico, European Union, India, and several African countries.

As we further aim to estimate the impact of climate on production or yields, we use PSD (Production, Supply and Distribution) database (U.S. Department of Agriculture, Foreign Agricultural Service, 2024) where variables on production, yield, stocks, imports and exports are available at the country level. Crop yield is a measure of agricultural production harvested per hectare. This variable is often used in literature as it efficiently captures the production efficiency related to available harvest.

Remark 1 *In this process, we assume that planted areas will not change geographically for the whole period 2011-2040. This assumption is unrealistic, as the plantations usually change from year to year only if the weather/soil or even economic conditions make it no longer profitable to exploit that area and it becomes abandoned. In fact, many areas for certain crops might become not fertile which will even further push up the prices. We leave the question of crop areas rotation for further research and focus on the extraction of a significant econometric signal in this paper.*

2.2 SERENA process

Agroclimatic signal processing In this section, we transform weather variables (Nobakht *et al.*, 2019) described in the paragraph above into extremes, and we test their impact on production of commodities and crop yield. The transformation is happening in three main steps. Before the transformations we merge the variables with gridded data of the crop and harvest area in 2020 (CROPGRIDS) (Tang *et al.*, 2024) assuming that geographical distribution of cropland remains largely unchanged year over year. We then associate each coordinate with a country as production database - PSD database (U.S. Department of Agriculture, Foreign Agricultural Service, 2024) is available at the country level.

As first transformation step, we calculate the weight of each crop area for each coordinate per country, so that the weighted weather variables W_t^w is:

$$W_t^w = C^{(\text{country})} \times \left(W_t - \overline{W_{0,t}}^{(\text{country, month})} \right)^2 \tag{1}$$

where W_t is the weather variable, $C^{(\text{country})}$ is the weighted crop area by country, and $\overline{W_t}$ is the average value until today's date per country for each month. Then the values are aggregated by country and average value is taken. Secondly, the weather values are discounted at r=1% on a rolling window for the past 4 months which allows to efficiently capture the past effects of extreme weather on today's yields or prices:

$$W_t^d = W_t^w(\text{country, commo}) + \sum_{i=2}^{4} \frac{W_i^{w,(\text{country, commo})}}{(1+r)^{i-1}} \tag{2}$$

Last, the Z-score for the most recent value in an expanding window for each country, commodity and season is computed as:

$$Z = \frac{|W_t^d(\text{country, commo, season}) - \mu_{0,t}|}{\sigma_{0,t}} \tag{3}$$

Z-score allows us to transform the variables in a form of statistical distribution where higher values indicate extreme events both on the right and left tails as we take the absolute value of the variables. This processing does not allow differentiation between extreme high and low temperatures but it provides a parameter that detects extremes in general since we assume that all types of anomalies are destructive for crops in this context. However, this constraint can easily be relaxed if one wishes to differentiate between the tails.

Yield-weather relationship Crop yield is an important measure that allows to track the amount of agricultural production harvested per hectare, it is measured in MT/HA (Metric ton/hectare). This metric allows to better understand land efficiency that can depend on many factors including amount and quality of fertilizers and pesticides used, soil quality, age, technology, crop genetic modifications and also weather variables. Yield is closely linked to production as it is its derivative variable, but the yield also impacts the prices of commodities.

We use the PSD database (U.S. Department of Agriculture, Foreign Agricultural Service, 2024) to first test the impact of weather variables on yield. We first define the yield return as:

$$R_t^Y = \frac{Y_t - Y_{t-1}}{Y_{t-1}} \tag{4}$$

We assume a relative change in yield as a finite difference approximation of $R \sim \delta Y$. However, given that shocks in yield production may exhibit acceleration effects, we also consider a second-order approximation:[3]

$$\delta Y^2 = 1 + \beta Z \tag{5}$$

where the impact of weather variables is proportional to the Z-score of weather anomalies. To account for the effect of weather shocks, we propose the following non-linear model:[4]

$$R_t^Y = R_{t-1}^Y \times \left(1 + \beta \times \left(Z^{\text{Temp}} + Z^{\text{Prec}}\right)\right) \tag{6}$$

[3] The term '1' in $1 + \beta Z$ is included to account for a baseline level of yield return independent of weather anomalies. If removed, the model would assume that without extreme weather events, yield return would approach zero, which might not be realistic. If we instead fit $\beta_1 + \beta_2 Z$, it might lead to numerical instability when $\beta_1 + \beta_2 Z$ becomes small or negative, causing unrealistic fluctuations in yield.

[4] In this paper, although we use sensibly the same impact variable (temperature), we differ from the approach used in Moore *et al.* (2017), where the response function is estimated with data from a meta-analysis of 56 studies analyzing yield-temperature relationships between 1997-2012:

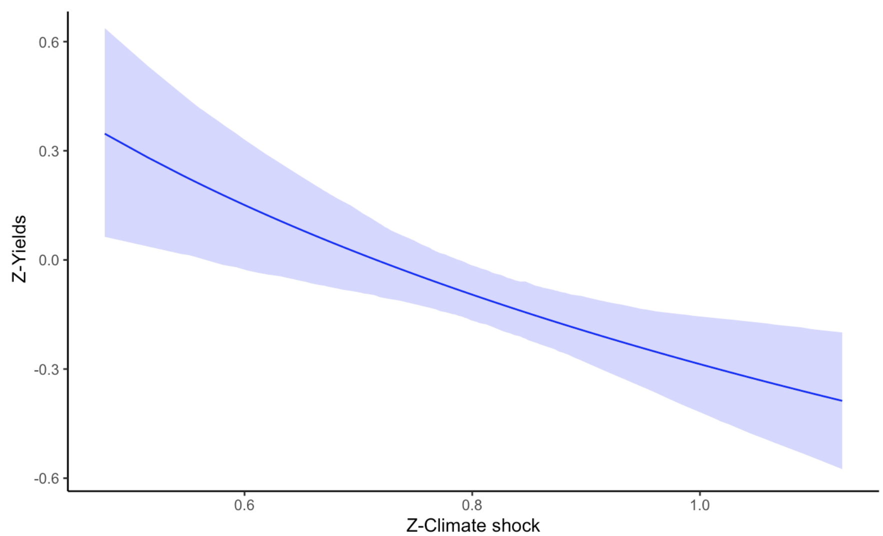
$$\begin{aligned}\Delta Y_{ijk} &= \beta_{1j}\Delta T_{ijk} \times Crop_j + \beta_{2j}\Delta T_{ijk}^2 \times Crop_j + \beta_{3j}\Delta T_{ijk} \times Crop_j * \bar{T}_{jk} \\ &+ \beta_{4j}\Delta T_{ijk}^2 \times Crop_j \times \bar{T}_{jk} + \beta_5 f_1(\Delta CO2_{ijk}) \times C_{3j} \\ &+ \beta_6 f_2(\Delta CO2_{ijk}) \times C_{4j} + \beta_7 \Delta P_{ijk} + \beta_8 \Delta T_{ijk} \times Adapt_{ijk} + \beta_9 Adapt_{ijk} + \varepsilon_{ijk}\end{aligned}$$

where ΔY_{ijk} is the change in yield for crop j in country k (in %). ΔT_{ijk} - changes in temperature, $\Delta CO2_{ijk}$ - CO_2 concentration , and ΔP_{ijk} - rainfall. $\bar{T}_{jk}$ is the baseline temperature for crop j in country k, C_{3j} and C_{4j}, and $Adapt_{ijk}$ are control dummy variables. We base the construction of our model on this Equation with where Y_t is the commodity yield at time t and Z^{Temp} and Z^{Prec} are the transformed weather variables of Temp - mean temperature and Prec - mean precipitation sum. Based on that, it is possible to capture the sensitivity of weather variables to yield. We present the sensitivity of CMIP to yield in Table 2. First, it is observable that the joint combination of temperature and precipitation extremes negatively affects the crop yield. That is, the production worsens when weather anomalies are present where 1 unit increase in Z-score of weather extremes results in around 60% decrease in yields for corn, cotton and wheat. Figure 3 also suggests evidence of a negative relationship between climate shocks and yields, represented by high Z-score for temperatures and precipitation and relative yield degradation.

Table 2: Non-linear model for yield sensitivity to model variables (IPSL AOGCM)

Commodity	Estimate	Std. Error	Statistic	Signif.
Corn	-63.15 %	5.6 %	-11.30	⋆⋆⋆
Cotton	-58.70 %	6.2 %	-9.48	⋆⋆⋆
Wheat	-66.25 %	6.0 %	-11.05	⋆⋆⋆

Figure 3: Relationship between grouped production yield z-scores and average temperatures and precipitation z-score – NLS Curve Fit with Bootstrapped Confidence Interval



The results are also replicated with ERA5 reanalysis and MIROC model variables and the detailed description of it is available in the Appendix.

Price-yield relationship Existing literature has a wide branch related to modeling of commodity prices. The efficient market hypothesis suggests that the expectation of the

a focus on extreme conditions impact on shock - throuhg the use of the acceleration - on yield variation. For example, in this reference model $Crop \times \Delta T$ captures the sensitivity of a location to a temperature variation while we focus on macro sensitivity of extreme conditions with Z^{Temp} and Z^{Prec}. Another difference is that while the authors fit a linear model, we fit a non-linear least squares.

next period realization is the information available at the previous period as no information is neglected in efficient markets, and the estimate of value will only change with income of unanticipated information (Roll, 1970). However, while being too simplistic, this also implies zero net profit. Chambers and Bailey (1996) propose a simple model of commodity prices that is in addition based on supply and demand shocks where the authors relax the assumption that the shocks are independently and identically distributed, contrary to the earlier famous of work of Danthine (1977). Deaton and Laroque (1991) estimate a commodity price model with demand, supply shocks and speculative storage. Although we cannot introduce storage in our equation, we include supply shocks approximated by sensitivity to change in yields.

Commodity prices have a cyclical nature. Kabundi *et al.* (2022) explain that the cycles can either be transitory or permanent, and the permanent component prevails in agricultural prices. Agnello *et al.* (2020) show that inflation, economic uncertainty, interest rates, oil prices, and environmental conditions affect the duration of commodity price cycles, where a rise in average temperature increases the lengths of the cycles, and the rise in precipitation sum reduces them.

To model the relationship between yield and prices, we use the monthly commodity prices from the World Bank (Bank, 2024a). The yield database and prices start in 1960 and while some crops have less data points than others, we use the entire available period for each commodity as the goal is to detect the presence of a general significant relationship. Since the PSD database provides country-level data, and World Bank provides global prices, we sum all yields in all countries to aggregate at a global level. The choice of commodities was limited by the availability of data in both data bases. However, it is still possible to generalize the case of few commodities as all the prices are heavily correlated (Appendix B).[5]. However, we adopt a simplified model to focus on first-order effects and avoid overparameterization:

$$R_t^P = R_{t-1}^P \times \left(1 + \beta_{yield} \times R_t^Y\right) \tag{7}$$

$$R_t^P = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{8}$$

where R_t^P represents the price returns at time t and R_t^Y represents the yield returns at time t. We estimate β parameter using a simple Nonlinear least squares regression. The equation of yield-price relationship yields results displayed in Table 3. The results for most commodities except for palm oil are significant and all coefficients are negative. The weaker significance of results for sorghum and palm oil might be explained not by the absence of the dependency but by the quality of the data where a lot of gaps are present for yield variables.

Negative results indicate that prices decline with a higher yield, and the decline is most pronounced for wheat, corn, and rice. This relationship makes economic sense since higher yield essentially means that it is cheaper to produce the crop. For example, efficient production of sugar in Brazil with highest yields allows their sugar prices to be the cheapest in the world.

[5] A report by the World Bank Bank (2024b) suggests that supply factors are responsible for approximately 20% of commodity price fluctuations.

Table 3: The impact of change variation in yield on price returns (Equation (7))

β	**Std. Error**	**Statistic**	**Signif.**	**Commodity**
-0.10	0.03	-3.22	***	Barley
-0.28	0.05	-5.51	***	Corn
-0.02	0.01	-2.34	**	Cotton
-0.06	0.03	-1.65		Palm Oil
-0.17	0.06	-2.95	***	Rice Thai 5%
-0.08	0.04	-1.86	*	Sorghum
-0.34	0.07	-4.80	***	Wheat

Statistical analysis In this section, we perform a statistical analysis of model scenarios to assess if differences between RCPs are to be expected before 2040. This exercise allows us to determine if the actual difference between the 2.6 and 8.5 RCP scenarios can result in a different impact on commodity prices. Therefore, there is a need to test whether the difference in the same variables of the two scenarios is statistically significant. For each group, indexed by crop c, latitude lat, and longitude lon, we apply a paired t-test between the two related variables $X_{c,lat,lon}$ = `Value 2.6` and $Y_{c,lat,lon}$ = `Value 8.5` for periods before and after 2024.

The paired t-test formula for the group indexed by crop c, latitude lat, and longitude lon is given by:

$$t_{c,lat,lon} = \frac{\bar{d}_{c,lat,lon}}{\frac{s_{d_{c,lat,lon}}}{\sqrt{n}}}$$

Where $\bar{d}_{c,lat,lon} = \frac{1}{n}\sum_{i=1}^{n}\left(X_{i,c,lat,lon} - Y_{i,c,lat,lon}\right)$ is the mean difference between paired values $X_{i,c,lat,lon}$ and $Y_{i,c,lat,lon}$, and $s_{d_{c,lat,lon}} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\left(X_{i,c,lat,lon} - Y_{i,c,lat,lon}\right) - \bar{d}_{c,lat,lon}\right)^2}$ is the standard deviation of the differences.

The paired t-test is applied separately for each group before and after 2024, and t-test statistics and p-value are calculated between the two series at 5% significance. The results are displayed in Table 4. It is observable that the significance of the difference between scenarios increases for sum of precipitation for coffee and sugarcane, and only slightly for cotton, corn and wheat. It is surprising that the statistical significance decreases for the future compared to historical periods for rapeseed and soybeans. This indicates that the difference in total precipitations is expected to not differ significantly for two scenarios until 2040 which still indicates that the precipitation levels will decrease for the majority of commodities.

Nevertheless, the results are completely different for mean temperatures. The percentage of significant series increases for all commodities and is the increase is very strong. The mean temperatures will rise significantly more in the next decades under the 8.5 climate scenario. This shows that when performing further analysis one can expect to see a difference between the scenarios which might not be very pronounced, however, because the statistical difference with precipitation is not strong, and also not for all coordinates for temperature.

Concerning the distribution, Table 5 shows the mean of temperature or precipitation for all coordinates for each commodity, 25th and 75th percentiles. For precipitation, the values

Table 4: Statistical significance of the difference between TG 2.6, TG 8.5 and RR 2.6 and RR 8.5

	Before 2024			**After 2024**		
	Significant	**Non-S**	**% Signif**	**Significant**	**Non-S**	**% Signif**
Precipitation sum (RR)						
Cocoa	4	79	5%	4	79	5%
Coffee	34	200	15%	78	156	33%
Cotton	11	385	3%	14	382	4%
Maize	189	1557	11%	235	1511	13%
Rapeseed	59	489	11%	54	494	10%
Soybean	84	442	16%	45	481	9%
Sugarcane	25	351	7%	56	320	15%
Wheat	121	1053	10%	126	1048	11%
Mean Temperature (TG)						
Cocoa	45	38	54%	81	2	98%
Coffee	60	174	26%	197	37	84%
Cotton	107	289	27%	264	132	67%
Maize	309	1437	18%	1179	567	68%
Rapeseed	40	508	7%	296	252	54%
Soybean	100	426	19%	266	260	51%
Sugarcane	81	295	22%	298	78	79%
Wheat	209	965	18%	728	446	62%

increase for the worst scenario for cocoa, cotton, corn, rapeseed, soybean and wheat, where for cotton and wheat the values are smaller for the 25th percentile and larger for the 75th percentile indicating that the mean increases due to an increase in extremely high values - possibly associate with floods or heavy rains. The mean values decrease for sugarcane and coffee, and it is surprising to notice that the higher percentiles also decrease for these commodities in case of higher carbon emissions scenario. This indicates that there is no homogeneous effect of climate change on precipitation: yes, more extreme values are expected along with more frequent droughts. Coffee and sugarcane grow in tropical regions with already heavy precipitation and climate change might prolong the rainy periods even further.

In case of temperature, the impact is more evident: the temperatures increase for all commodities and for all percentiles in case of RCP 8.5 scenario. That means that the temperature measure is a more suitable comparable when measuring global impact on prices. Nevertheless, it might not be immediately apparent since mean temperature increases do not harm the growth of commodities, but these are the temperature extremes that can disrupt production. Conversely, milder winters may have benefits, such as for corn planting.

Table 6 shows the percentage difference between two climate scenarios for a summer month - July and a winter month - January for the period after 2024. The table confirms that the rise in temperatures will be expected for both winter and summer months for all commodities. In fact, the warming in winter can even be more pronounced than in summer. However, this still does not deny the presence of low temperature anomalies than can disrupt

Table 5: Descriptive statistics for precipitation and temperature (2.6 and 8.5 RCP) across crops

	2.6			8.5		
Precipitation	**Mean**	**25-th**	**75-th**	**Mean**	**25-th**	**75-th**
Cocoa	51.39	16.98	72.59	51.49	17.30	72.92
Coffee	47.26	9.88	69.01	46.32	9.35	68.83
Cotton	23.03	0.96	33.67	23.88	0.90	34.74
Maize	28.71	3.94	41.23	29.14	3.97	41.60
Rapeseed	24.09	6.32	28.22	24.17	6.38	28.75
Soybean	32.09	5.08	44.85	33.63	5.96	47.15
Sugarcane	34.88	2.73	55.10	34.08	2.81	52.77
Wheat	17.50	4.78	22.12	17.90	4.65	22.68
Temperature						
Cocoa	27.13	25.91	28.39	27.38	26.16	28.64
Coffee	24.57	22.27	27.45	24.83	22.46	27.75
Cotton	22.50	17.10	28.87	22.84	17.65	29.06
Maize	19.02	13.93	26.73	19.32	14.29	27.03
Rapeseed	14.61	7.08	22.54	15.02	7.66	23.11
Soybean	18.79	13.62	26.66	19.00	14.03	26.95
Sugarcane	25.50	22.86	28.84	25.83	23.13	29.16
Wheat	13.65	6.08	22.13	14.08	6.57	22.49

crop growth - especially combined with droughts.

Table 6: The percentage difference between RCP 8.5 and RPC 2.6 for Temperature (TG) variable for the future period after 2024 for July and January

	July			January		
Crop	Mean	25-th	75-th	Mean	25-th	75-th
Cocoa	0.68%	0.78%	0.81%	0.57%	0.68%	0.37%
Coffee	0.66%	0.63%	0.75%	1.14%	1.17%	0.85%
Cotton	0.66%	0.53%	0.83%	1.01%	6.25%	0.76%
Maize	0.98%	1.13%	1.39%	2.47%	-35.40%	1.19%
Rapeseed	1.71%	3.86%	0.91%	5.52%	-13.33%	-1.52%
Soybean	0.52%	0.31%	0.73%	2.98%	-23.34%	1.13%
Sugarcane	0.73%	0.30%	0.86%	1.11%	2.97%	1.49%
Wheat	0.98%	1.16%	0.94%	4.29%	-0.36%	2.37%

The stress tests with Monte-Carlo simulations methodology are used to project how potential climate extremes could make commodity prices evolve. To perform the simulations, the Z-score of weather variables calculated in Equation 3 smoothes the differences that might arise across RCP scenarios, and we provide an alternative calculation of Z-score that allows to compare the future variables with a historical mean and standard deviation:

$$Z = \frac{|W_t^d(\text{country, commo, season}) - \mu_{0,2024}|}{\sigma_{0,2024}} \tag{9}$$

This ensures a better capturing of the climate change in the future compared to historical period than in case of Z-score with expanding adaptation as in equation 3.

However, it is important to keep in mind that while the raw weather variables for two scenarios are statistically different, the transformation methodology might reduce this difference as the Z-score is calculated relative to the same series and extremes can appear for both scenarios at their own scale. Indeed, it is evident that the difference between two scenarios is not statistically significant (Table 7). The table shows if the difference of the transformed weather variables series is statistically different for two climate scenarios, where high positive t-statistics value suggests that the mean of the 2.6 RCP scenario is greater than the 8.5 RCP scenario.

Table 7: Significance of the difference between Z-score series of 2.6 RCP and 8.5 RCP

		Z-score with Adaptation (expanding)				Z-score	
		Before 2024		After 2024			
		T-stat	P-value	T-stat	P-value	T-stat	P-value
Corn	Precipitation	1.45	0.15	1.11	0.27	-0.78	0.43
	Temperature	1.37	0.17	0.16	0.88	-1.24	0.22
Cotton	Precipitation	-2.16	0.03	-0.12	0.91	-0.21	0.84
	Temperature	3.16	0.00	0.79	0.43	-0.44	0.66
Wheat	Precipitation	-0.44	0.66	1.11	0.27	0.31	0.75
	Temperature	-2.09	0.04	1.14	0.26	1.29	0.20

It is, nevertheless, possible to detect a difference in Z-scores calculated with different methodologies, as well as the mean values for the 8.5 RCP scenario are often higher compared to lower emission scenarios.

Monte Carlo simulations To conduct Monte Carlo simulations modeling the spillover effects from weather to yield and prices, we use the betas from previous paragraphs as a sensitivity parameter. The algorithm of the simulation is shown in Algorithm 1. Here, as defined, $W_{i,1}^{(s)}$, $W_{i,2}^{(s)}$ are actual weather variables (Z-scores) at time step i; μ_{W_1}, μ_{W_2} are means of the respective weather variable distributions, and σ_{W_1}, σ_{W_2} are standard deviations of the respective weather variable distributions. β_{weather} is the coefficient for the weather impact $W_i^{(s)}$ on yield that was estimates earlier with a non-linear model, β_{yield} is the coefficient for the yield impact $\Delta Y_{i+1}^{(s)}$ on the price return, $\epsilon_y^{(s)}$ and $\epsilon_p^{(s)}$ are Gaussian noise terms specific to each simulation.

Algorithm 1 SERENA: Simulation of Log-Return of Yield and Price with Weather Impact

Input: Weather variables $W_{i,1}^{(s)}$, $W_{i,2}^{(s)}$, parameters $\mu_{W_1}, \sigma_{W_1}, \mu_{W_2}, \sigma_{W_2}$, $\mu_{\Delta Y}$, $\sigma_{\Delta Y}$, $\mu_{\Delta P}$, $\sigma_{\Delta P}$, β_{weather}, β_{yield}

for each time step i **do**

  for each simulation s **do**

    Compute the combined weather impact:

$$W_i^{(s)} \leftarrow 0.6 \times W_{i,1}^{(s)} + 0.4 \times \mathcal{N}(\mu_{W_1}, \sigma_{W_1}) + 0.6 \times W_{i,2}^{(s)} + 0.4 \times \mathcal{N}(\mu_{W_2}, \sigma_{W_2})$$

    if $i <$ July 2024 **then**

      Compute log-return of yield:

$$\Delta Y_{i+1}^{(s)} \leftarrow \mu_{\Delta Y} + \beta_{\text{weather}} \times W_i^{(s)} + \epsilon_y^{(s)}, \quad \epsilon_y^{(s)} \sim \mathcal{N}(0, \sigma_{\Delta Y})$$

      Compute price log-return:

$$R_{i+1}^{(s)} \leftarrow \mu_{\Delta P} + \beta_{\text{yield}} \times \Delta Y_{i+1}^{(s)} + \epsilon_p^{(s)}, \quad \epsilon_p^{(s)} \sim \mathcal{N}(0, \sigma_{\Delta P})$$

    else

      Compute moving average log-return of yield:

$$\Delta Y_{i+1}^{(s)} \leftarrow \frac{1}{20} \sum_{k=i-20}^{i} \Delta Y_k^{(s)} + \beta_{\text{weather}} \times W_i^{(s)} + \epsilon_y^{(s)}, \quad \epsilon_y^{(s)} \sim \mathcal{N}(0, \sigma_{\Delta Y})$$

      Compute moving average price log-return:

$$R_{i+1}^{(s)} \leftarrow \frac{1}{20} \sum_{k=i-20}^{i} R_k^{(s)} + \beta_{\text{yield}} \times \Delta Y_{i+1}^{(s)} + \epsilon_p^{(s)}, \quad \epsilon_p^{(s)} \sim \mathcal{N}(0, \sigma_{\Delta P})$$

    end if

  end for

end for

Output: Simulated log-returns $\Delta Y_{i+1}^{(s)}$ and $R_{i+1}^{(s)}$ for all i and s

This algorithm allows us to combine the weather-yield and yield-price relationships to simultaneously solve for the price.[6]

2.3 Application

Propagation to inflation As illustrated in the introduction, commodity price increases can be advantageous for asset managers as they allow asset managers to benefit from investments in commodity indices. However, it might come at the cost of inflationary pressures that are detrimental to any returns.

[6]Of course, the propagation demonstrates how prices would behave in a world of constant climate extremes ignoring other price formatting factors. The approach provides a visual demonstration of destructive event on future price evolution while it is by no means a realistic commodity price forecast.

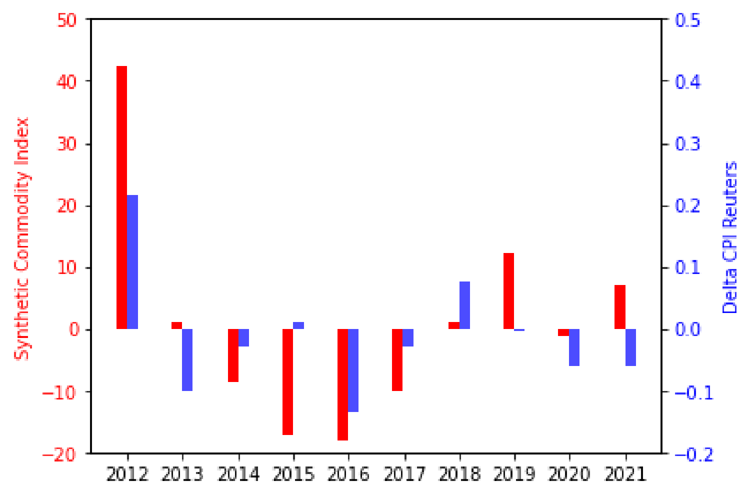
We construct our own commodity price index accounting for sensitivity of commodity yield to commodity prices:

$$\mathrm{CSI}_t = \sum_{i=1}^{n} |\beta_i| \cdot \frac{P_t^{(i)} - P_{t-1}^{(i)}}{P_{t-1}^{(i)}} \times 100 \tag{10}$$

Where CSI_t is the commodity synthetic index, $|\beta_i|$ is the absolute value of the yield sensitivity for commodity i, $P_t^{(i)}$ is the price of commodity i at time t. β_i coefficients are extracted from the estimation described above.

CSI is well correlated with delta of Reuters commodity index that is used in Le Guenedal *et al.* (2022), and the correlation is 65% that underlines that our commodity index is robust. The time evolution of two indexes is comparable (Figure 4). It is visible that the periods of higher commodity prices were 2012, 2018-19 and 2021.

Figure 4: Price evolution of Synthetic Commodity Index and Reuters Commodity Index



We propose a simple linear regression to the impact of synthetic commodity index on US CPI inflation:

$$\begin{aligned} \text{US CPI}_t = \beta_0 + \beta_1 \mathbf{CSI}_t + \beta_2 \mathrm{TED}_t + \beta_3 r_t^{10Y} + \beta_4 \mathrm{VIX}_t \\ + \beta_5 r_t^{FED} + \beta_6 \text{NYMEX oil}_t + \epsilon_t \end{aligned} \tag{11}$$

Where US CPI_t is Consumer Price Index at time t, TED_t is the difference between the 3-month Treasury bill and 3-month LIBOR, r_t^{10Y} is 10-year US Treasury yield. VIX_t is CBOE Volatility Index, r_t^{FED} is the Federal funds target rate. NYMEX oil_t is NYMEX crude oil futures price.

Weather weighted commodity index to bond spreads In this step, we measure the impact of commodity index for a panel of 73 countries. In this case, emerging bond spread refers to the yield difference between a risky security and a risk-free asset such as an AAA-rated bond. We use the option-adjusted spread (OAS) relative to the U.S. 10-year Treasury bond. The OAS is a measure of the spread that accounts for embedded options in fixed-income securities. Following the approach of Hilscher and Nosbusch (2010), we develop a cross-sectional econometric model for the option-adjusted spread using annual end-of-year data.

$$\begin{aligned}\mathrm{OAS}_t = \alpha + \beta_1 \mathbf{CSI}_t + \beta_2 D_t + \beta_3 \mathrm{VIX}_t + \beta_4 r_t^{10Y} + \beta_5 \mathrm{TED}_t \\ + \beta_6 \frac{L_t}{\mathrm{GDP}_t} + \beta_7 \frac{\mathrm{reserves}_t}{\mathrm{GDP}_t} + \beta_8 R_t + \beta_9 K_t + \epsilon_t,\end{aligned} \tag{12}$$

Where OAS_t is the end-of-year option-adjusted spread, obtained from the JP Morgan EMBI position report in BarraOne. $\mathbf{CSI}_t$ is the constructed yield sensitivity-weighted commodity synthetic index. D_t is the average duration of the bonds (JP Morgan EMBI report). VIX_t is the CBOE volatility index (LSEG), r_t^{10Y} is the 10-year U.S. Treasury bonds rate (LSEG). TED_t is the difference between the three-month U.S. Treasury bill rate and the three-month LIBOR (LSEG), $\frac{L_t}{\mathrm{GDP}_t}$ is the ratio of total external debt stocks (L_t) to GDP, (World Bank). $\frac{\mathrm{reserves}_t}{\mathrm{GDP}_t}$ is the ratio of total reserves, including gold, to GDP (World Bank). R_t is a credit rating dummy variable, which takes a value depending on the country's credit rating, andK_t is a country-specific dummy variable. Le Guenedal *et al.* (2022) reports that this relationship has a strong significance when using the change in LSEG commodity price index.

3 Results and simulations

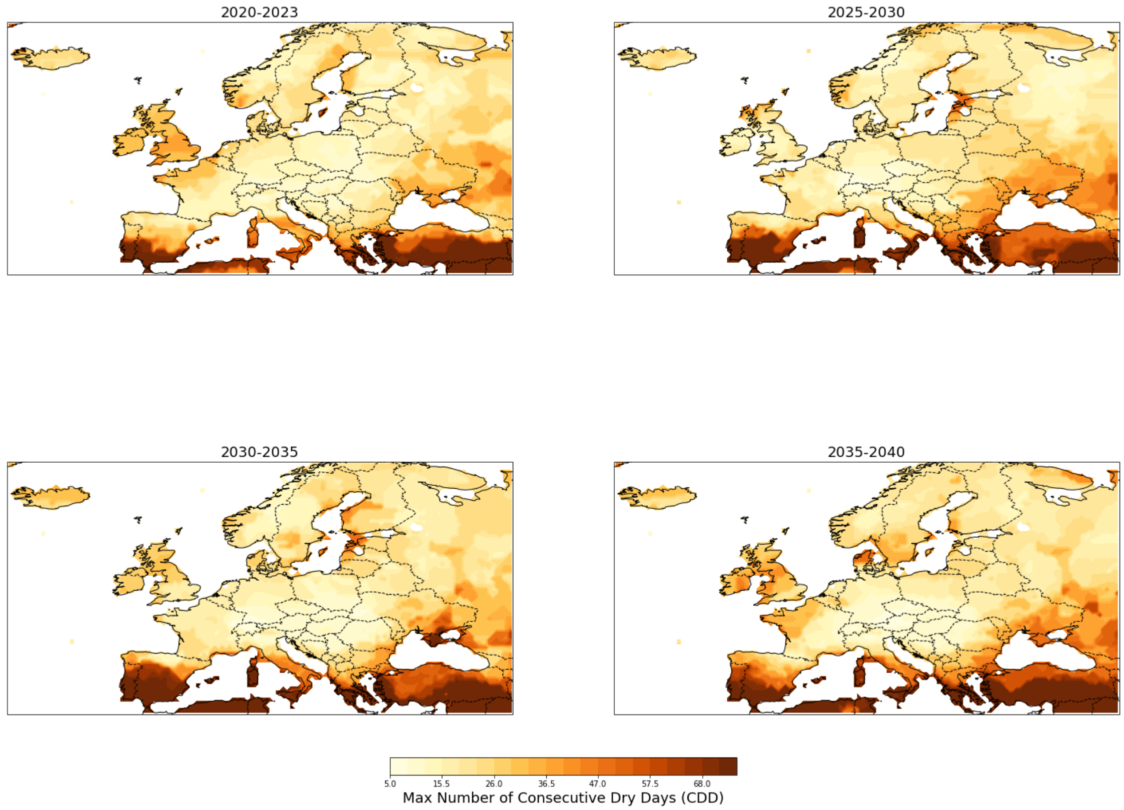
Observation of climate change evolution from models First, we introduce the changes in raw climate data observable directly in climate models. Figure 5 is constructed using the Agroclimatic indicators derived from climate projections Copernicus data (Nobakht *et al.*, 2019) which are used to describe plant-climate interactions for agriculture. The Figure shows the average of the consecutive dry days for the summer months over a period from 3 to 5 years.

This parameter takes into account days where the daily precipitation sum is less than 1mm. Having a precise look, at, for example, France, it is possible to see that even though 2020-2023 were years of abnormal levels of drought (EM-DAT: The International Disaster Database, 2024), the number of consecutive dry days is projected to increase until 2040, particularly in the North-West of France and the French Riviera. The duration of consecutive dry days ranges from 15 to 45 days. Other countries at risk are United Kingdom, Denmark, Sweden, and all countries across Southern Europe.

According to the National Integrated Drought Information System Portal (2024), the drought is third among climate disasters for financial losses behind tropical cyclones and severe storms and its costs average at $9 billion per year. The drought of 2012 impacted 80% of agricultural land in the US, and affected all corn, soybeans, and wheat which accounted for $14.5 billion loss for the federal crop insurance program. In fact, the spread of drought impacts means crop failure and pasture losses. They are aggravated by increasing cases of pests and diseases that are caused by droughts. In addition, there are also indirect impacts such as reduced supply to food processors and lower demand for fertilizers.

Similarly, Figure 6 shows the evolution of the average number of consecutive summer days for the summer season over the years. That is, it shows the longest period, on average, of consecutive days with maximum temperatures exceeding 25°C. This indicator is correlated with drought and might be informative of the optimal growth conditions for crops. The

Figure 5: Mean of maximum number of Consecutive Dry Days for summer season



graph highlights that, in major parts of France, more than 60 consecutive summer days with temperatures exceeding 25°C are expected by 2040. While during 2020-2023 this parameter was around 15 for Northern France, Belgium, Germany, Netherlands and Poland, by 2040 it is projected to be as high as 40 days.

Simulated impact on global prices (by 2030/35/40) We plot the mean value of 1000 Monte Carlo simulations (Figure 7) longside 95% confidence intervals. It is directly evident that weather Z-score without expanding adaptation results in higher sensitivity hence higher prices for commodities. The scenario with more emissions - 8.5 - results in slightly higher price returns for all commodities, while this result depends on the particular simulation and should be interpreted with caution: there are no large differences between the emission scenarios until 2040 as regardless of the socio-economic development path pursued from this point forward, the effects of previously emitted CO2 will continue to influence the planet. In general, the results of both scenarios do not differ significantly before 2040.

Figure 6: Mean of maximum number of Consecutive Summer Days for summer season

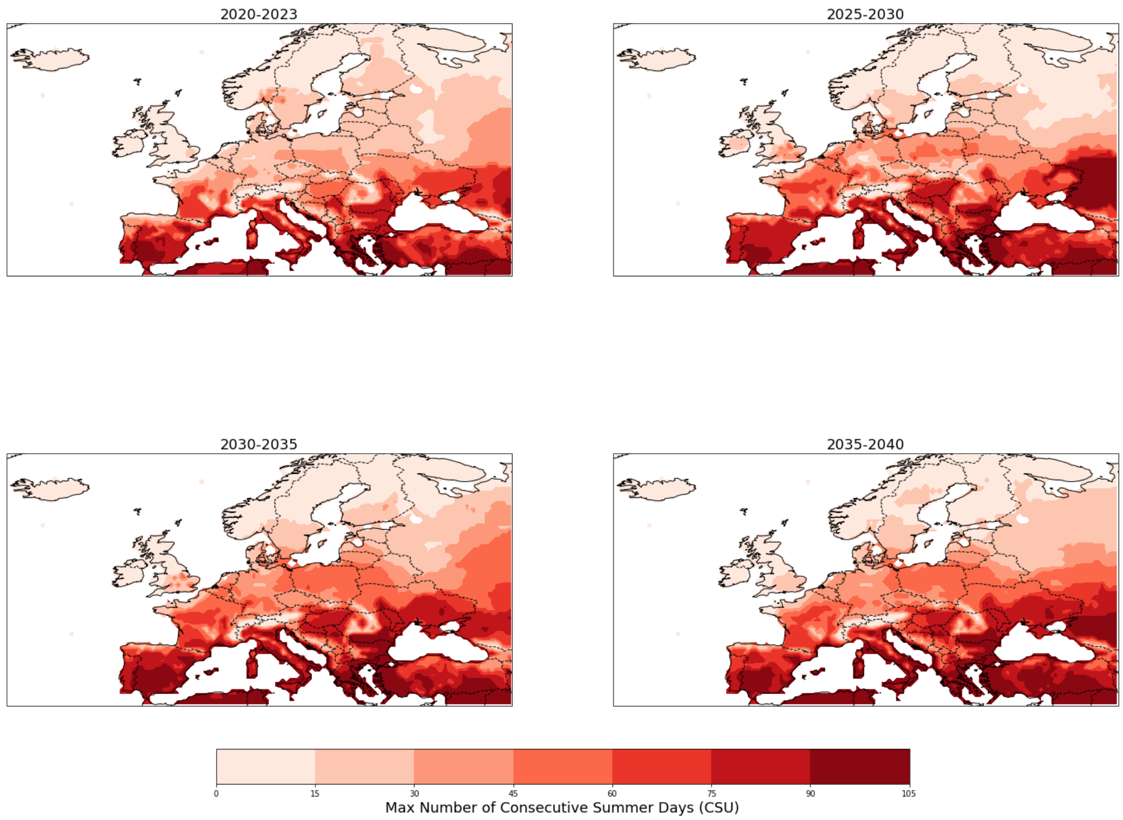
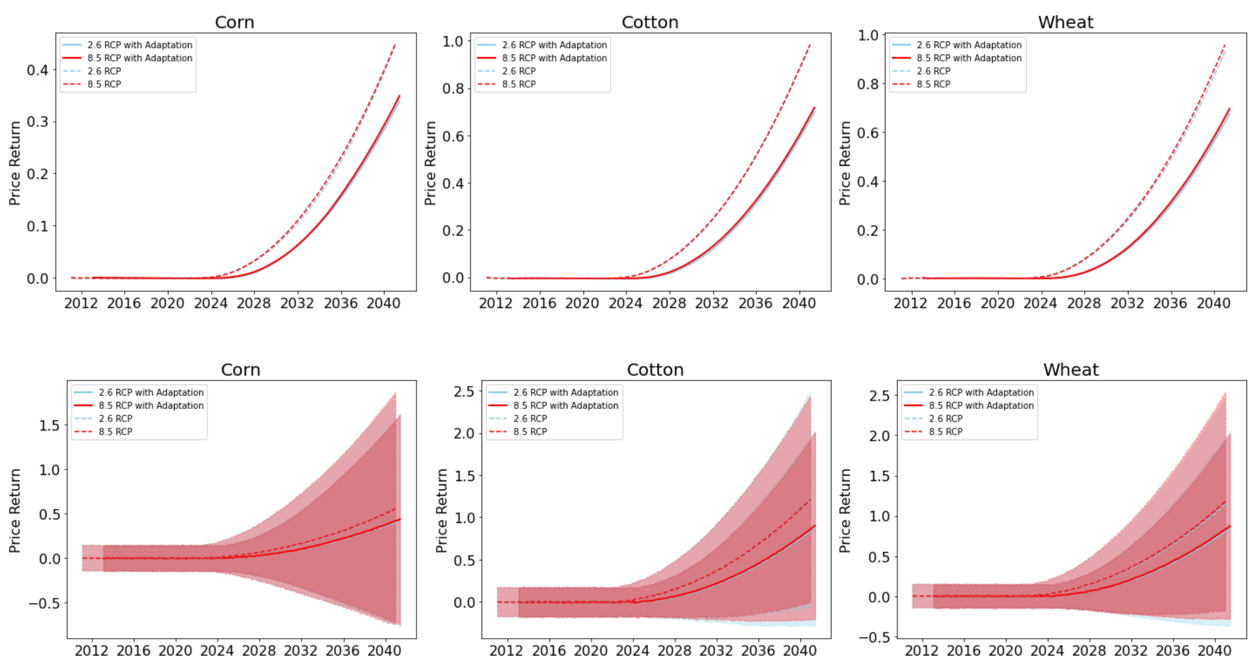


Figure 7: Mean and 95% confidence intervals of Monte Carlo price shock simulations under RCP 2.6 and 8.5 for historical and time-adjusted Z-scores



This analysis stresses the fact what no matter how much the emissions will be cut in the future, investors and producers will already bear negative climate externalities as more frequent extreme weather events will result in increasing expected jumps magnitude of commodity prices.

Inflationary Implications A simple model of the impact of yield-weighted commodity index on US CPI inflation is displayed in Table 8. The results suggest that an average 1% increase in commodity prices is followed by a 2% increase in inflation. The only variable that has a negative effect on inflation is the market volatility index VIX. This result confirms previous studies that commodity prices drive up inflationary pressures (Celasun *et al.*, 2012; Ciccarelli *et al.*, 2023; De Gregorio, 2012; Faccia *et al.*, 2021; Gelos & Ustyugova, 2017; Kotz *et al.*, 2023).

Table 8: The impact of synthetic commodity index on US inflation

	Dependent variable:		
	US CPI		
	(1)	(2)	(3)
CWI	0.013*** (0.005)	0.014*** (0.005)	0.020*** (0.006)
TED	0.002** (0.001)	0.003*** (0.001)	0.003*** (0.001)
US10YTBYC	0.001*** (0.0002)	0.001*** (0.0002)	0.002*** (0.0003)
VIX		−0.007** (0.003)	−0.009** (0.003)
FED target			−0.019 (0.020)
NYMEX crude			0.008*** (0.001)
Constant	−0.373** (0.169)	−0.332* (0.168)	−1.645*** (0.277)
Observations	151	151	100
R^2	0.127	0.153	0.416
Adjusted R^2	0.109	0.130	0.378
Note:			*p<0.1; **p<0.05; ***p<0.01

4 Discussion and conclusion

This section connects the study's findings to existing literature and proposes actionable solutions for investors and policymakers. The paper focuses on the analysis of gridded global weather models, evaluating their strengths and limitations for use in economic studies. We present a data transformation methodology, applying it to selected models to assess the impact of weather on crop yields, commodity prices, and inflation[7].

[7] Global weather datasets, designed using varying methodologies, exhibit significant differences in temporal frequency and spatial resolution. Ideally, high-resolution, high-frequency data should be used to maximize precision, but the sheer volume of such data often requires substantial computational power. Therefore, a balance must be struck between resolution, frequency, and statistical significance. In our analysis, we average the data to a 1° resolution (approximately 111 kilometers at the equator) and choose monthly frequency

Our results indicate that crop yields, measured in metric tons per hectare, are negatively impacted by extreme temperatures and precipitation, on average, across global regions. This finding supports the assertion by Hogan and Schlenker (2024) that the accuracy of data transformation into extreme events is more critical than the selection of specific variables. However, these results should not be misinterpreted to suggest that every increase in temperature uniformly leads to lower yields.

Ritchie (2024) states that some crops, especially wheat and rice, can benefit substantially from higher C02 in the atmosphere, though higher temperatures might also increase yields. This depends on whether the commodity is already grown in optimal climate conditions or if the conditions are lower than optimal. However, water scarcity, such as during droughts, or excess, such as in floods, is always destructive for crops. It is therefore important to be aware that mild climate change can benefit some crops in some geographical areas. Nevertheless, our study focuses on extreme events that are the consequence of higher average temperatures, and they are always destructive for yields on average.

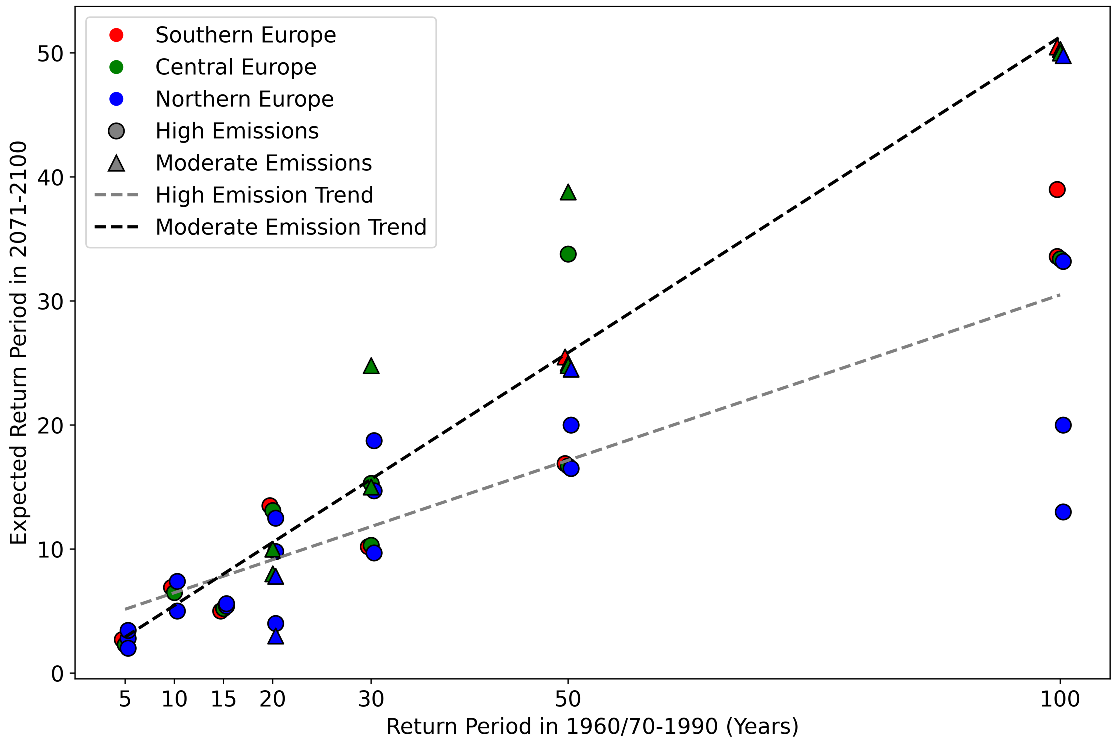
To look deeper into that, we perform a meta study that allows us to track the evolution of return periods of extreme precipitation events (Figure 8). Return period is a statistical measure that permits to estimate the average time between two extreme weather events of a certain intensity. Figure 8 assembles the results of 11 studies that use years 1960/70-1990 as a base historical period, and simulate the changes for the period 2071-2100 in Europe. The results depend on the exact methodology to calculate return period, the climate model used and the scenario, and on precise geographical locations that we divide into three categories: Southern, Central and Northern Europe. For example, (Semmler & Jacob, 2004) use REMO 5.1 climate model, high emissions SRES-A2 scenario, and find that return periods for precipitation events increase by 50% for most European regions and by 100% in Baltic Sea. The result of higher extreme events frequency in Northern Europe compared to Southern Europe is also found in Beniston *et al.* (2007), Larsen *et al.* (2009), and Nikulin *et al.* (2011). May (2008) explain this result with the fact that Mediterranean region sees fewer wet days since it will also have higher frequency of droughts, but extreme precipitation events will, however, appear with higher intensity.

Kyselỳ *et al.* (2011) finds that increases in return periods of precipitation events are particularly pronounced in winter compared to summer. In addition, the magnitude of the increases in average duration between two events also depends on climate scenario, where high emission scenarios might have the double of the change with low emission scenario (Hosseinzadehtalaei *et al.*, 2020; Rajczak & Schär, 2017). Last, the change in return period will be higher for more rare high intensity events (Fowler *et al.*, 2007; Sedlmeier *et al.*, 2018). In general, Figure 8 shows with linear regression analysis that high emission scenarios will indeed result in more frequent extreme events by the end of the century.

On another note, biodiversity loss due to climate change negatively impacts pollination of crops like coffee, soybeans, oil crop and others (Gallai *et al.*, 2009; Potts *et al.*, 2010).

for consistency. The data sources used include ERA5 climate reanalysis and the MIROC climate model. Climate reanalysis integrates historical observations with models to generate consistent climate time series, offering a detailed account of observed conditions in recent decades. In contrast, climate models like MIROC simulate the entire climate system, making them suitable for future weather predictions. Robustness checks for these models are provided in the Appendix.

Figure 8: The expected change in return period of precipitation events



Artificial pollination increases production costs, potentially leading to project abandonment or adverse price shifts. However, new crop-breeding technologies make plantations more resistant to drought and heavy rains, thereby improving yields.

Our finding of price spikes is straightforward: lower yields mean higher prices due to supply shocks. However, the propagation to financial markets may not always be evident in particular cases. First, crop stocks can offset poor harvests in any given year, and some crops are harvested multiple times per year. Also, the production does not always match the demand as the demand for certain crops also depends on consumer preferences, and the demand for, for example, cotton might decline as the preferences towards cheaper synthetic fabrics increase. Therefore, we find an overall negative propagation of yield to prices, but the analysis of commodity stock levels could enrich and provide more details into the price-yield relationship, although this is beyond the scope of this study.

Next, our analysis focuses on the transmission of price shocks to the broader economy, with particular emphasis on US CPI inflation. As discussed in the introduction, commodity shocks are known to create inflationary pressures (De Gregorio, 2012; Faccia *et al.*, 2021; Gelos & Ustyugova, 2017), and our result confirms that the index weighted by yield sensitivities to prices is relevant, and it is possible to assume that the inflationary pressures indeed comes from physical markets disruptive processes such as climate change. While inflation is a macroeconomic phenomenon, investors should be aware of the fact that higher temperatures can thus not only decrease the attractiveness of commodity index investing strategies, but financial returns overall. Indeed, agricultural commodity markets are know to be connected to energy markets, currency, equity and bonds (Nekhili *et al.*, 2021; Wang & Wang, 2019).

Last, we provide the results of the EMEA bond spreads panel regression in the Appendix. Similarly as in Le Guenedal *et al.* (2022) we find that increase in synthetic commodity index decreases the spreads. Much of previous literature confirms this result Arezki and Brückner (2012) and Bastourre *et al.* (2012). While this is insightful for asset managers who engage in speculative spread strategies, this result does not mean that emerging countries benefit from extreme climate events. Although there is a slight fall in sovereign spreads, the decline in yields and following supply shock might erode revenues, and the costs of debt needed will exceed any financial benefits of the spread.

On that note, it is important to stress the differences between market actors. Climate change is a hazardous process that in most cases brings extreme unpredictable events that cause harm to plantations and farmers. Of course, the effects are transmitted to local economies and inflation is expected to remain elevated until the mid-term. Nevertheless, where there are losers there are also winners: first, some crops already need warmer conditions, and Scandinavian countries and Russia will certainly benefit from milder climate change. Secondly, a poor harvest in one country might increase demand for imports from other countries that were not affected by weather, and these exporting countries will only benefit from higher commodity prices. Thirdly, the predictions of prices and spread will allow investors to take advantage of speculative strategies in some cases. Nonetheless, asset managers should remain cautious, as while higher returns may appear favorable, the broader economic consequences—such as inflationary pressures—are likely to have more widespread negative effects.

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A Robustness to climate data

Climate yield relationship with ERA5 reanalysis data The methodology of the results below is described in Section 2. The results of the non-linear regression for ERA5 reanalysis are presented in Table 9. The estimates show more variation between themselves and the coefficients are larger. This may be due to differences in data construction, as reanalysis uses real data, which can capture greater variability and extreme weather events. Furthermore, the impact of weather variables on yield appears to be stronger than the influence predicted by climate models.

Commodity	Estimate	Std. Error	Statistic	Signif.
Corn	-0.982	0.0986	-9.95	***
Cotton	-2.87	0.293	-9.78	***
Wheat	-1.58	0.195	-8.11	***

Table 9: Coefficients of the joint impact of temperature and precipitation on yield

It is noteworthy to observe the response of weather to yield for individual weather parameters - temperature and precipitation (Table 10). The coefficients increase in magnitude even further, and this is possible because the impact of temperature and precipitation on yields is not the strongest when combining the variables: extreme temperatures are usually associated with drought while extreme precipitation events usually decrease mean daily temperatures. Nevertheless, these results prove the point that we detect the same patterns for different types of weather data.

Commodity	Var	Estimate	Std. Error	Statistic	Signif.
Corn	temp	-1.89	0.202	-9.35	***
Cotton	temp	-6.64	0.659	-10.1	***
Wheat	temp	-2.71	0.341	-7.94	***
Corn	prec	-1.78	0.191	-9.35	***
Cotton	prec	-4.72	0.532	-8.87	***
Wheat	prec	-3.54	0.448	-7.91	***

Table 10: Coefficients of weather variables temperature and precipitation impact on yield

Climate yield relationship with MIROC model data As in the main analysis using the IPSL climate model, we employ the MIROC-ESM-CHEM model, developed by JAMSTEC, Japan. Compared to the French model, the Japanese is more focused on atmospheric chemistry which also allows its usage to test for aerosols, gases, and other chemical processes (Watanabe *et al.*, 2011). Aside from these differences, both models are similar and use low-resolution configurations, and their results are expected to be comparable.

As shown in Table 11, all coefficients are negative and significant similarly to the case of IPSL and ERA5 tests. It is, however, interesting to observe that while with ERA5 the largest negative coefficient is for cotton, here, the cotton coefficient is smaller (in absolute values) in comparison to corn and wheat. In general, the coefficients are very similar to those from the IPSL model, with IPSL showing only slightly higher magnitudes.

Commodity	Estimate	Std. Error	Statistic	Signif.
Corn	-0.625	0.05505	-11.35	***
Cotton	-0.5655	0.0607	-9.32	***
Wheat	-0.6175	0.0565	-10.9	***

Table 11: Averaged regression results across commodities

Similarly, Figure 9 shows that the price evolution in the future is comparable to the IPSL model. However, the expected return increases with MIROC are smaller for cotton and wheat, and slightly larger for corn. This analysis estimates the approximate impact on prices caused by yield disruptions. Similarly, there is not much difference between socio-economic development scenario outcomes before 2040.

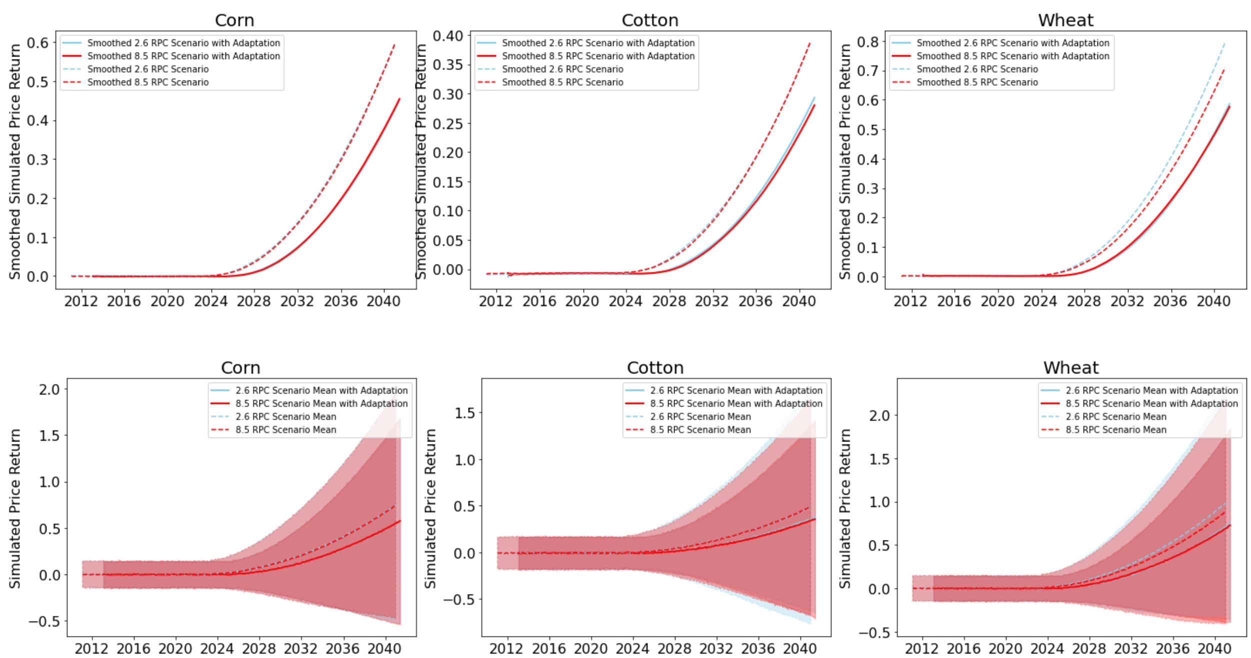

Figure 9: Mean and 95% confidence intervals of Monte Carlo price simulations under RCP 2.6 and 8.5 for historical Z-score and time-adjusted; Robustness check

B Complementary materials

Implications for bond spreads The results of the panel regression are displayed in Table 12. The synthetic commodity index is significant at 1% for both models. In comparison to the results of Le Guenedal *et al.* (2022), our results show a better R^2 for the last two models (0.542 vs 0.55 and 0.723 vs 0.729 respectively) indicating that the synthetic commodity price index explains the OAS even better. Indeed, the index is negative - hence when commodity prices increase the spread decreases suggesting that emerging country risk decreases as higher commodity prices are beneficial to some commodity exporters. The adjustment for yields allows for the identification of commodities whose yields are especially sensitive to prices, and thus the accuracy of the model improves.

Table 12: Weather propagation to Option-Adjusted-Spread model

	Dependent variable:			
	OAS (bp)			
	(1)	(2)	(3)	(4)
CSI			−6.620***	−6.126***
			(0.931)	(0.747)
Duration				8.834***
				(1.640)
VIX			31.346***	28.771***
			(3.164)	(2.582)
TED			381.969***	334.421***
			(131.378)	(104.728)
US,10y			−17.040***	−14.998***
			(2.481)	(1.988)
L/GDP	367.461***	229.629***	339.893***	425.952***
	(26.060)	(21.319)	(25.548)	(78.158)
reserves/GDP			−247.038***	−1,047.854***
			(40.635)	(184.851)
Rating < B-		−1,692.843***	−1,693.795***	−1,389.004***
		(42.121)	(41.326)	(35.894)
Countries	No	No	No	Yes
Constant	207.254***	1,915.443***	3,838.487***	3,586.721***
	(15.583)	(44.361)	(340.932)	(292.239)
Observations	2,212	1,860	1,832	1,832
R^2	0.083	0.509	0.550	0.729
Adjusted R^2	0.082	0.509	0.549	0.721
Note:			*p<0.1; **p<0.05; ***p<0.01	

It is important to note that, due to data availability, we only use seven commodities - barley, corn, cotton, palm oil, rice, sorghum and wheat - and the list does not contain important for emerging markets commodities - sugar, coffee, cocoa, cotton etc. On the other side, the model's significance confirms the usefulness of adjusting prices for yield impacts, even with a limited selection of commodities.

Interactions with other commodities This paper concentrates of three commodities: corn, wheat and cotton due to data availability. However, we want to assess if this study is expected to show similar results with other agricultural crops. Indeed, most World Bank commodity prices show a strong correlation with corn, cotton, and wheat prices (Table 13). For corn, the lowest correlation is with EU sugar of 24% and there is more than 90% correlation with soybean oil, barley, sorghum and wheat. Cotton shows slightly lower correlations on average, with the lowest at 33% for EU sugar and the highest at 80% for palm kernel oil.

Index	**Corn**	**Cotton**	**Wheat**
Coffee Arabica	0.69	0.76	0.67
Coffee Robusta	0.34	0.51	0.32
Coconut oil	0.78	0.71	0.75
Palm oil	0.89	0.76	0.88
Palm kernel oil	0.72	0.80	0.68
Soybean oil	0.93	0.74	0.92
Soybean meal	0.89	0.66	0.89
Rapeseed oil	0.86	0.73	0.88
Sunflower oil	0.86	0.68	0.85
Barley	0.92	0.61	0.92
Corn	1.00	0.75	0.94
Sorghum	0.98	0.70	0.93
Rice thai 5%	0.81	0.63	0.79
Rice thai 25%	0.83	0.54	0.76
Rice thai A.1	0.84	0.52	0.78
Rice vietnam 5%	0.65	0.46	0.55
Wheat US HRW	0.94	0.73	1.00
Orange	0.69	0.50	0.73
Sugar EU	0.24	0.33	0.34
Sugar US	0.73	0.73	0.71
Sugar World	0.67	0.64	0.64
Cotton A index	0.75	1.00	0.73

Table 13: Correlation Matrix of World Bank monthly commodity prices 1960-2024

The same is also observable in the price evolution plot (Figure 10. This shows that agricultural commodity markets are closely linked and that increases of one asset price due to weather extremes might put upward pressure on other prices via spillovers. A more profound study of spillover effects is beyond the scope of this research.

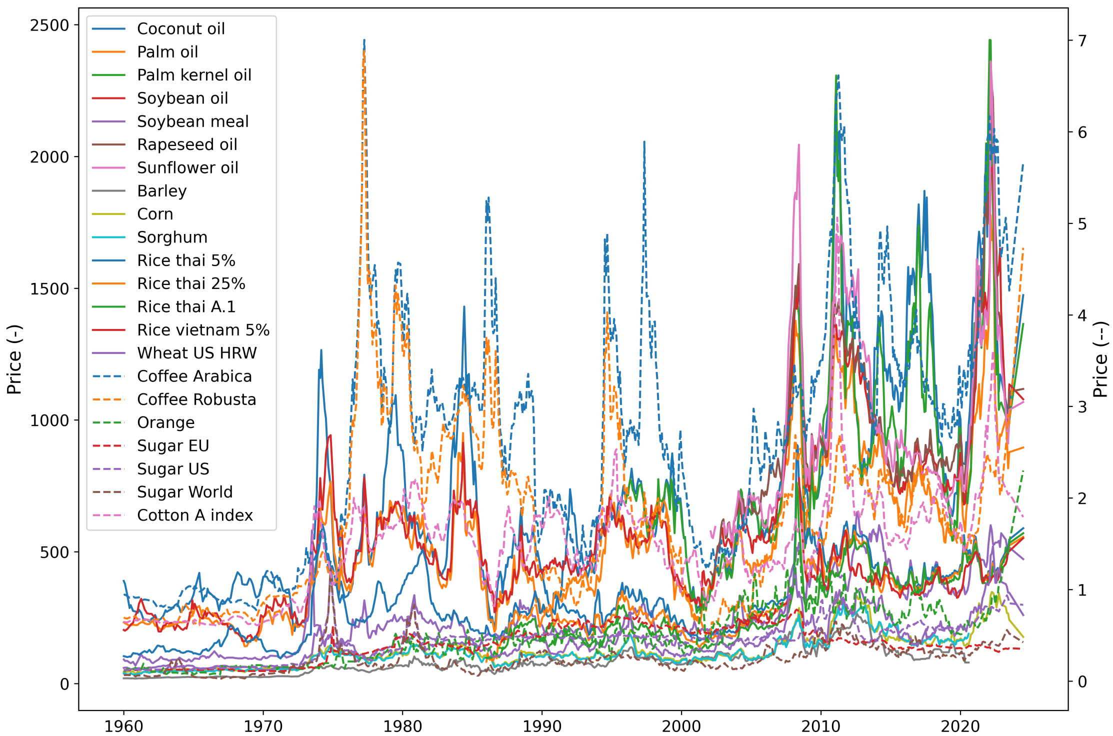

Figure 10: Price evolution of World Bank commodity prices