Chapter 03: Persistent Climate Impacts on Agriculture and Nutrition

Abstract

This research investigates how the economic effects of climate change persist over time and extend beyond aggregate output, particularly through agricultural and nutritional channels. While prior studies have shown that temperature shocks can lower GDP in the long run, and others have examined the impact of climate variability on crop yields or nutrition outcomes, no empirical work has yet connected these components along a unified causal chain. The study reviews evidence on climate-induced persistence in economic performance, yield variability, and food security, highlighting key limitations in how these relationships are currently modeled. Building on this foundation, it proposes a two-stage empirical strategy: first, estimating the lagged effects of climate anomalies on crop yields; second, examining how these yield changes influence nutrition outcomes such as stunting and wasting. By incorporating persistence into the agricultural pathway leading to food security and nutrition outcomes, this research aims to quantify how climate disruptions impair human welfare through sustained effects on production and consumption.

1 Background and Introduction

The economic impacts of climate change are increasingly observable, measurable, and non-negligible. Far from being only a future concern, anthropogenic climate change has already altered macroeconomic outcomes across many countries (Kotz, Levermann, & Wenz, , ,). These effects are not merely contemporaneous: temperature shocks and climatic anomalies can exert prolonged effects on output through persistent disruptions to labor productivity, capital accumulation, and sectoral reallocation (Nath, Ramey, & Klenow, , ,). Quantitatively, recent estimates suggest that climate change has already led to sizable output losses. Kotz et al. () find that global GDP is approximately 6.3% lower today than it would have been without human-induced warming. Neal, Newell, and Pitman () report that including persistence may increase projected GDP losses by 2100 from about 7% to nearly 40%, depending on the emission scenario. Callahan and Mankin () further attribute substantial historical damages to anthropogenic climate forcing, reinforcing the urgency of quantifying realized impacts. These disparities highlight that both the magnitude and the distribution of climate damages depend critically on whether persistent effects are captured in the modeling framework.

Empirical studies increasingly document how climate shocks influence economic trajectories over multiple years. Temperature anomalies have been shown to depress GDP not only in the year of occurrence but for several years thereafter (Nath et al., ,), with mechanisms ranging from delayed investment and infrastructure loss to health effects and institutional erosion (Chang, Mi, & Wei,). Ignoring these dynamic effects risks underestimating the long-run costs of climate change, especially in vulnerable economies. Yet, many widely used modeling tools—including integrated assessment models (IAMs) and computable general equilibrium (CGE) models—still rely on static damage functions and assume only contemporaneous impacts (Kompas, Pham, & Che, , , ,). These limitations restrict their ability to reflect the true, time-evolving burden of climate change. Conversely, empirical frameworks that account for temporal dynamics yield more realistic damage estimates and offer stronger foundations for policy design (Kotz et al., , ,).

Among the key mechanisms through which climate-induced economic shocks propagate, agriculture plays a central role. Not only is agriculture highly climate-sensitive, but it also directly affects food security, labor productivity, and household welfare, particularly in low-income regions (Ortiz-Bobea et al., ,). Understanding losses in this sector is therefore critical to capturing the broader macroeconomic and human costs of climate change.

Climate change has significantly hindered global agricultural progress, slowing total factor productivity by 21% since 1961 (Ortiz-Bobea et al.,) and causing substantial production losses over recent decades (Lobell, Schlenker, & Costa-Roberts,). These effects are not only historical: under continued warming, model projections point to further declines in global output without effective adaptation (Zhao et al., ,). Between 2008 and 2018, climate-related disasters led to over $108 billion in crop and livestock losses in developing countries, threatening livelihoods and food security for billions (Food and Agriculture Organization of the United Nations,).

In addition to hindering productivity, climate change affects human well-being indirectly by reducing agricultural yields, which in turn undermine food security and nutrition. Declines in crop productivity reduce food availability, disrupt supply chains, and elevate food prices—especially in regions where agriculture is climate-sensitive and subsistence-based (Gregory, Ingram, & Brklacich, ,). These disruptions limit household access to diverse and nutritious diets, often forcing reliance on cheaper, calorie-dense staples and reducing intake of essential nutrients (Devereux & Edwards, ,). The resulting food insecurity has measurable impacts: as of 2016, 23% of children under age five (about 155 million) were stunted globally, and around 7% were wasted, with climate-driven scenarios projecting hundreds of thousands of additional stunted children by 2030 (Gregory et al.,). More recently, approximately 148 million children (23%) remain stunted and 45 million (7%) are wasted, signaling persistent nutrition vulnerabilities (Tirado et al.,). Understanding these interconnected pathways is essential for capturing the full social cost of climate change.

To analyze these links, this study plans to use historical data on GDP, climate conditions (e.g., temperature and rainfall from ERA5), agricultural yields (e.g., FAOSTAT, IFPRI, GAEZ, Harvard Dataverse), and nutrition indicators (e.g., child stunting and wasting from DHS or UNICEF MICS). For the main empirical strategy, we plan to employ fixed-effects panel regressions, incorporating lagged climate variables to capture intertemporal persistence. Firstly, we will estimate the impact of climate anomalies on crop yields, and then trace how these yield changes affect nutrition outcomes.

2 Literature Review

This study is motivated by a central question: how much economic loss has already resulted from anthropogenic climate change? While most existing models emphasize projections of future damages, this research instead estimates realized historical impacts using observed data on climate conditions and economic outcomes. It focuses on the temporal persistence of these losses and their transmission through key sectors—particularly agriculture and nutrition. By linking climate variability to agricultural yields and downstream food security outcomes, the study highlights the long-term channels through which climate change affects economic and human development.

A growing body of research shows that the economic effects of climate shocks often last for several years rather than being limited to the year of the event. When a country experiences extreme weather, the negative impact on its economy can continue well into the future (Nath et al., , , ,). Studies that take this persistence into account tend to project much higher overall economic damages from climate change. For example, under high-emission scenarios, global GDP could fall by about 7% by 2100, even when only local long-term effects are included (Kahn et al.,). These impacts are not evenly spread: poorer and low-latitude countries are likely to suffer the most, while some cooler, high-latitude regions may even see small gains (Kotz et al., ,).

Methodological advances have contributed to these revised estimates. Recent empirical studies that include temporal interaction terms—capturing how climate shocks affect economies over time—produce substantially larger damage projections than earlier models that only consider immediate impacts (Nath et al., ,). In contrast, integrated assessment models (IAMs) and computable general equilibrium (CGE) models, while useful for global forecasting and policy analysis, often rely on static regional damage functions and fail to capture long-term economic effects (Kompas et al., , ,). Uncertainty remains a major challenge. Monte Carlo simulations and multi-scenario approaches highlight the wide range of possible outcomes due to uncertainty in climate projections and economic responses (Kotz et al., ,). Some estimates suggest that even if emissions stopped today, the economic losses already set in motion could reduce global income by up to 19% over the next 25 years (Kotz et al.,). While adaptation and mitigation can help, they are unlikely to fully offset these damages.

These long-term effects are not limited to macroeconomic aggregates; they are also likely to affect specific sectors—particularly agriculture, where climate impacts are direct and recurring. Several multi-country studies use robust panel econometric models to estimate the effects of interannual climate variability—mainly droughts and heatwaves—on crop yields. For example, Iizumi and Ramankutty () analyze global yield variability of maize, soybean, rice, and wheat between 1981 and 2010 and attribute changes to climate extremes using agro-climatic indices. Similarly, Ray et al. () estimate the historical impacts of observed climate change on the yields of ten major crops across approximately 20,000 political units globally, showing that climate change has likely already reduced global food calories. Vogel, Zscheischler, Wartenburger, Seneviratne, and Frieler () apply machine learning to sub-national yield and climate data, demonstrating that climate extremes explain 18–43% of yield anomalies across crops, with temperature extremes having a stronger impact than precipitation. In contrast, Renard and Tilman () focus on resilience mechanisms, showing that crop diversity significantly buffers climate-driven yield and revenue losses over 58 years of data from 127 countries.

Despite these contributions, few of these studies explicitly model multi-year persistence—such as lagged effects or cumulative climate memory. Most focus on single-year or event-driven shocks, rather than sustained impacts across time, leaving long-term consequences of climate change underexplored in the empirical yield literature (Iizumi & Ramankutty, ; ?, ?; Vogel et al.,). Thus, while the persistence of macroeconomic climate shocks has been well established, there is limited empirical work on how persistent yield shocks unfold across years and propagate into downstream welfare outcomes.

Beyond yield loss itself, a key concern is how climate-induced agricultural shocks affect human development through food security and nutrition. A separate line of research links climate anomalies directly to child health outcomes, particularly stunting and wasting, using geolocated survey data across many countries. For instance, Cooper et al. () examine over 580,000 child-level observations from 53 countries and find that drought exposure significantly increases stunting risks. Thiede and Strube () link temperature and rainfall anomalies to child weight and wasting outcomes across 16 Sub-Saharan African countries using DHS data. Similarly, Dasgupta and Robinson () estimate the global impacts of gradual and acute climate stressors on child stunting, wasting, and mortality in more than 100 countries.Blom, Ortiz-Bobea, and Hoddinott () focus on five West African countries, showing how extreme heat exposure affects child nutrition through panel models with geo-coded data.

These studies apply panel regressions and control for socio-economic and spatial heterogeneity, consistently reporting significant associations between climate extremes and nutrition outcomes. However, none of them include empirical yield loss as a mediator; rather, they model climate shocks as direct predictors of nutrition (Cooper et al., , , ; ?, ?). As a result, current empirical work provides only a partial picture: yield and nutrition outcomes are modeled in isolation, and the causal pathway linking climate shocks to human development outcomes remains incomplete.

Although progress has been made in studying how climate affects yields and, separately, how it affects nutrition, few studies integrate these components into a unified empirical framework. In particular, no study has clearly linked persistent, climate-driven yield losses to changes in nutrition outcomes such as stunting or wasting. Most existing work either examines how weather influences yields or how it affects nutrition, but not how one leads to the other. Nor do current models account for intermediate mechanisms like food prices, household consumption, or access to nutrients. Addressing this gap requires combining detailed data on yields and nutrition outcomes and applying statistical strategies—such as instrumental variables or mediation analysis—that can account for lagged effects and isolate climate impacts from confounding factors. Doing so would offer a clearer understanding of how climate shocks translate into long-term impacts on food security and health.

This study contributes to the literature by providing an empirical estimate of the economic losses already attributable to climate change, with a particular focus on intertemporal persistence. Departing from scenario-based projections, it leverages historical data to examine how past climate shocks have influenced GDP trajectories across countries. By explicitly modeling temporal lags, the analysis extends current macroeconomic impact assessments and offers new insights into the depth of climate-induced economic disruptions.

3 Methodology

3.1 Research Question

This study asks: Do historical climate shocks have persistent effects on agricultural economic performance, and do these effects propagate into long-term food security outcomes? In particular, it investigates whether temperature and precipitation anomalies experienced in the past continue to influence agricultural GDP growth today.

3.2 Hypotheses

- **H1 (Persistence Hypothesis):** Temperature and precipitation anomalies have significant lagged effects on agricultural GDP growth.
- **H2 (Channel Hypothesis):** The impact of climate shocks on food security operates through the agricultural productivity channel.

3.3 Empirical Strategy

This study investigates the persistent effects of climatic anomalies on agricultural economic performance and subsequent food security outcomes. The empirical strategy adopts a Two-Stage Least Squares (2SLS) framework to estimate the causal impact of climate shocks on agricultural GDP growth and its downstream effects on food insecurity. In the first stage, agricultural GDP growth is instrumented using weather anomalies—specifically deviations in temperature and precipitation. In the second stage, the predicted (instrumented) values of agricultural GDP growth are used to estimate their effects on multiple food security indicators, controlling for time and country fixed effects.

In the first stage, we regress agricultural GDP growth on contemporaneous and lagged temperature and precipitation anomalies, along with a set of control variables that capture economic structure and productivity. Specifically, we include total factor productivity (TFP), labor input (measured as employment multiplied by average hours worked), and capital stock per worker as controls. To absorb unobserved heterogeneity across countries and time, we include fixed effects for country (α_i) and year (δ_t).

The first-stage regression is estimated as:

$$\begin{aligned} \text{AgGDP\_growth}_{it} = & \sum_{l=0}^{5} \beta_l^{(T)} \text{TempAnom}_{i,t-l} + \sum_{l=0}^{5} \beta_l^{(P)} \text{PrecAnom}_{i,t-l} \\ & + \gamma_1 \text{TFP}_{it} + \gamma_2 (\text{EMP}_{it} \times \text{AVH}_{it}) + \gamma_3 \text{RKNA}_{it} + \alpha_i + \delta_t + \epsilon_{it} \end{aligned} \tag{1}$$

Where:

- $\text{TempAnom}_{i,t-l}$: temperature anomaly in country i at lag l,
- $\text{PrecAnom}_{i,t-l}$: precipitation anomaly in country i at lag l,
- TFP_{it}: total factor productivity,
- $\text{EMP}_{it} \times \text{AVH}_{it}$: total labor input (employment times average hours),
- RKNA_{it}: capital stock per worker,

- α_i: country fixed effects (controls for time-invariant country characteristics),
- δ_t: year fixed effects (controls for global or time-specific shocks),
- ϵ_{it}: error term.

The predicted values from this regression give us the part of agricultural growth that is explained by climate shocks and control variables, after removing the influence of other hidden or confounding factors. In the next step, we use these fitted values to see how changes in agricultural growth affect key food security outcomes.

In the second stage of the analysis, we examine the relationship between agricultural growth and food security outcomes. Specifically, we estimate the effect of instrumented agricultural GDP growth on three indicators of food security: the prevalence of undernourishment, the prevalence of moderate or severe food insecurity, and average dietary energy supply adequacy.

Since observed agricultural growth may be endogenous due to reverse causality or unobserved confounders, we use the predicted values from the first-stage regression as an instrumented variable. The second-stage specification is as follows:

$$\text{FoodSecurity}_{it} = \theta \, \text{AgG}\widehat{\text{DPG}}\text{rowth}_{it} + \alpha_i + \delta_t + u_{it} \tag{2}$$

where $\text{AgG}\widehat{\text{DPG}}\text{rowth}_{it}$ is the instrumented agricultural GDP growth in country i and year t, α_i and δ_t are country and year fixed effects respectively, and u_{it} is the error term. Standard errors are clustered at the country level to account for within-country autocorrelation.

This approach helps us understand whether climate-related changes in agriculture actually cause changes in food security. It does so by accounting for differences between countries and changes over time that could otherwise confuse the results.

4 Data

This chapter describes the sources and construction of the datasets used in our analysis. The study relies on annual panel data for a large sample of countries, spanning agricultural output, climatic variables, production factors, and food security indicators.

4.1 Agricultural GDP

Agricultural gross domestic product (AgGDP) data are obtained from the World Bank's World Development Indicators (WDI) database (World Bank,). We extract annual values of agricultural value added (constant 2015 US$) for all available countries from 1961 to 2024. To compute the agricultural output growth rate, we take the first difference of the natural logarithm of AgGDP, defined as:

$$\text{AgGDP\_growth}_{it} = \log(\text{AgGDP}_{it}) - \log(\text{AgGDP}_{it-1}) \tag{3}$$

Figure A.3 visualizes the spatial distribution of agricultural GDP by country in 2000 and 2020, providing a comparative snapshot of changes in agricultural output across regions.

4.2 Climate Anamolies

4.2.1 Temperature Anomalies

Temperature anomaly data are colelcted from the Berkeley Earth Surface Temperature project, which provides monthly and annual deviations from a 1951–1980 baseline for most countries worldwide (Berkeley Earth,). We use annual anomalies from 1961 to 2024 and generate multiple lagged values to capture medium-run effects of temperature fluctuations on agricultural output. These lagged anomalies allow us to assess how past climate conditions influence current economic outcomes in agriculture. Figure A.1 illustrates the spatial pattern of changes in temperature anomalies between 2000 and 2020, highlighting significant warming trends in many regions

4.2.2 Precipitation Anomalies

Annual precipitation anomalies are calculated using reanalysis data from the ERA5 dataset, provided by the European Centre for Medium-Range Weather Forecasts (Hersbach et al.,). Monthly precipitation values are first summed to obtain annual totals. These are then spatially aggregated to the country level using a polynomial interpolation method with spatial weights derived from land-masked administrative boundaries, following the approach implemented using the stagg librray in R (Schwarzwald & Geil,) and the resulting data cover the period from 1965 to 2025. Figure A.2 illustrates the spatial distribution of changes in total annual precipitation between 2000 and 2020, highlighting country-level variation in precipitation trends

4.3 Production Factor Controls

To control for input-side dynamics, we use data from version 10.0.1 of the Penn World Table (Feenstra, Inklaar, & Timmer,), which covers the years 1960–2019. The variables include total factor productivity (TFP), the number of employed persons, average annual hours worked per worker, and capital stock per worker at constant national prices. These indicators capture key aspects of labor and capital inputs that influence agricultural output across countries and over time.

4.4 Food Security Outcomes

The second stage of our analysis examines the relationship between agricultural shocks and food security outcomes using data from FAOSTAT (FAO,). We focus on three commonly reported indicators: the prevalence of undernourishment (PoU), the Food Insecurity Experience Scale (FIES), and dietary energy supply adequacy. These indicators are reported as three-year moving averages (e.g., 2001–2003), in line with international food security monitoring practices. For consistency with annual agricultural GDP data, we assign each interval to its center year plus one (e.g., 2001–2003 is assigned to 2002). Although food security data cover the period from 2000 to 2023, the final analysis includes only those years for which corresponding agricultural and climate data are also available.

5 Results

5.1 Persistence of Climate Shocks

The first-stage estimates test whether past climate anomalies exert persistent effects on agricultural output. Results indicate that temperature anomalies have strong contemporaneous effects on agricultural GDP growth, with a one-degree Celsius increase reducing AgGDP growth by approximately 3.2 to 3.4 percentage points in the same year (Table 1). However, these effects fade quickly over time: once lagged, temperature anomalies lose statistical significance, and their coefficients become unstable across specifications.

For precipitation anomalies, the evidence is similarly weak. Despite expectations of delayed impacts through water availability, irrigation, or soil replenishment, the effects of lagged precipitation anomalies are small and inconsistent. Even the estimated positive effect at lag 5—previously hypothesized to drive longer-run growth—is not robust across specifications or sample restrictions.

Taken together, these results suggest that climatic shocks influence agricultural output primarily in the short run, with little evidence of persistence in the relationship between climate anomalies and agricultural GDP growth. This motivates the next stage of analysis, which examines whether lagged agricultural growth itself has forward-looking effects, particularly on food security. Figure A.4 visualizes the estimated economic impact of climate anomalies on agricultural GDP across countries, highlighting regional differences in vulnerability based on average anomaly exposure and fixed-effects regression coefficients.

5.2 Link to Food Security

The second-stage estimates assess the relationship between predicted agricultural GDP growth and key food security outcomes. Using climate anomalies as instruments, we estimate the effect of agricultural growth on three indicators: the prevalence of undernourishment (Table 2), the prevalence of moderate or severe food insecurity (Table 3), and dietary energy supply adequacy (Table 4). The results show that higher agricultural growth is consistently associated with improvements in both undernourishment and dietary adequacy. Specifically, a one percentage point increase in predicted agricultural GDP growth is associated with a 0.47 to 0.52 percentage point reduction in the prevalence of undernourishment and a 0.02 to 0.05 percentage point increase in dietary energy adequacy, depending on the lag structure.

These effects are statistically significant and robust across specifications that sequentially include up to five lags of agricultural GDP growth. Notably, the strongest and most consistent effects are observed in the contemporaneous year and at the fifth lag, suggesting both immediate and delayed pathways through which agricultural growth affects nutritional outcomes. In contrast, the estimates for the prevalence of moderate or severe food insecurity—measured using the Food Insecurity Experience Scale (FIES)—are small in magnitude and statistically insignificant across all specifications. This divergence likely reflects conceptual differences in the construction of these indicators: while PoU and dietary adequacy are based on calorie availability and supply, FIES captures experiential and perception-based aspects of access, which may be less directly tied to agricultural performance.

Overall, the evidence indicates that agricultural productivity gains, when instrumented through climate variation, are causally linked to improvements in food security—particularly in reducing undernourishment and enhancing caloric adequacy. These relationships are visualized in Figure A.6 and Figure A.5, which map the projected country-level impacts of climate-induced agricultural growth on undernourishment and dietary energy adequacy, respectively.

5.3 Connecting Climate Anomalies, Agricultural Output, and Food Security

The combined evidence from both stages allows us to trace the transmission of climate variability to food security outcomes through the agricultural sector. The first-stage results indicate that temperature anomalies have statistically significant impacts on agricultural GDP growth in the contemporaneous year, but little evidence of persistence beyond that. Precipitation anomalies, while theoretically capable of producing lagged effects, show weak and inconsistent results across specifications. These findings suggest that climatic disturbances tend to affect agricultural output primarily in the short term.

In contrast, the second-stage analysis reveals meaningful lagged effects in the relationship between agricultural growth and food security. Estimates that sequentially include lags of predicted agricultural GDP growth demonstrate that both contemporaneous and lagged growth—particularly at five years—are associated with significant improvements in food security indicators. For instance, a one percentage point increase in predicted agricultural growth five years earlier is associated with an additional 0.018 percentage point reduction in the prevalence of undernourishment, above and beyond the contemporaneous impact. Dietary energy adequacy exhibits a similar lag structure, with gains accruing gradually over time.

These findings suggest a gap between short-term climate effects and longer-term socioeconomic outcomes. Climate anomalies may affect agricultural output in the short run, but these effects do not persist over time. However, the initial impact on agricultural performance can influence economic conditions beyond the immediate period. In this way, earlier climate shocks set in motion a trajectory that affects future welfare. The persistence in food security, therefore, does not come from the climate shock itself. Instead, it emerges from the economic pathways triggered by that shock.

Table 1: Climate Anomalies and Agricultural GDP Growth

	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5	Spec 6
Temp lag 0	−3.20*	−3.27*	−3.19*	−3.26*	−3.36*	−3.41*
	(1.41)	(1.45)	(1.43)	(1.48)	(1.39)	(1.39)
Temp lag 1		1.22	0.96	1.03	0.95	1.00
		(1.13)	(1.14)	(1.16)	(1.16)	(1.14)
Temp lag 2			2.12	2.15	2.12	2.12
			(1.25)	(1.27)	(1.30)	(1.31)
Temp lag 3				−0.66	−0.49	−0.53
				(1.28)	(1.33)	(1.32)
Temp lag 4					−0.88	−0.82
					(1.47)	(1.50)
Temp lag 5						0.11
						(1.50)
Precip lag 0	−4473.14	−4912.37	−5436.70	−5352.80	−5703.35	−5578.23
	(2643.92)	(2950.98)	(3381.27)	(3604.87)	(3506.42)	(3409.03)
Precip lag 1		2864.56	3304.36	2861.56	2760.55	2186.74
		(3758.19)	(4106.15)	(4474.93)	(4605.03)	(4606.39)
Precip lag 2			−3321.74	−2889.20	−2452.39	−2419.63
			(2596.19)	(3019.52)	(3024.75)	(2871.62)
Precip lag 3				−2182.79	−2730.91	−2528.49
				(2944.75)	(3198.10)	(3229.82)
Precip lag 4					3796.01	3312.59
					(2309.63)	(2178.97)
Precip lag 5						4796.31**
						(1578.73)
TFP	18.68***	18.35***	17.59***	17.77***	17.93***	17.96***
	(4.65)	(4.63)	(4.66)	(4.67)	(4.67)	(4.67)
Labor	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital	0.72	1.17	1.59	0.90	0.77	1.01
	(6.19)	(6.12)	(6.28)	(6.36)	(6.50)	(6.56)
Num.Obs.	1048	1048	1048	1048	1048	1048
R2	0.158	0.159	0.162	0.162	0.164	0.165
R2 Adj.	0.078	0.077	0.078	0.077	0.076	0.075
R2 Within	0.014	0.015	0.019	0.019	0.021	0.022
R2 Within Adj.	0.009	0.008	0.009	0.008	0.007	0.006
RMSE	17.71	17.69	17.66	17.66	17.65	17.64
Std.Errors	by: iso3c	by: iso3c	by: iso3c	by: iso3c	by: iso3c	by: iso3c
FE: iso3c	X	X	X	X	X	X
FE: year	X	X	X	X	X	X

p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 2: Effect of Agricultural GDP Growth Lags on Effect of Predicted Agricultural GDP Growth (Lags 0-5) on the Prevalence of Undernourishment (PoU)

Dependent Variable:	food_insecurity					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\widehat{\text{AgGDP Growth}}_t$	-0.4639***	-0.4559***	-0.4547***	-0.4341***	-0.4079***	-0.4109***
	(0.1089)	(0.1079)	(0.1075)	(0.1015)	(0.0947)	(0.0934)
$\widehat{\text{AgGDP Growth}}_{t-1}$		-0.0107**	0.0005	0.0003	-0.0356**	-0.0063
		(0.0047)	(0.0008)	(0.0007)	(0.0137)	(0.0042)
$\widehat{\text{AgGDP Growth}}_{t-2}$			-0.0205**	-0.0019	-0.0024	-0.0493**
			(0.0085)	(0.0019)	(0.0019)	(0.0176)
$\widehat{\text{AgGDP Growth}}_{t-3}$				-0.1193**	-0.0799*	-0.0749*
				(0.0536)	(0.0433)	(0.0403)
$\widehat{\text{AgGDP Growth}}_{t-4}$					-0.0509**	-0.0079
					(0.0177)	(0.0050)
$\widehat{\text{AgGDP Growth}}_{t-5}$						-0.0720***
						(0.0235)
Fixed-effects						
iso3	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	566	566	566	566	566	566
R^2	0.87245	0.87255	0.87286	0.87608	0.87725	0.87980
Within R^2	0.14771	0.14840	0.15044	0.17197	0.17978	0.19684

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Effect of Agricultural GDP Growth Lags on Effect of Predicted Agricultural GDP Growth (Lags 0-5) on the Prevalence of Moderate or Severe Food Insecurity (FIES)

Dependent Variable:			food_insecurity			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\widehat{\text{AgGDP}}$ Growth$_t$	0.0206	0.0177	0.0185	0.0314	0.0306	0.0321
	(0.0416)	(0.0397)	(0.0403)	(0.0493)	(0.0493)	(0.0494)
$\widehat{\text{AgGDP}}$ Growth$_{t-1}$		0.0047	1.02×10^{-17}	1.2×10^{-17}	0.0021	-1.63×10^{-17}
		(0.0053)	(1.29×10^{-15})	(1.28×10^{-15})	(0.0039)	(2.22×10^{-13})
$\widehat{\text{AgGDP}}$ Growth$_{t-2}$			0.0089	-4.43×10^{-17}	-4.3×10^{-17}	0.0036
			(0.0100)	(2.69×10^{-16})	(2.68×10^{-16})	(0.0067)
$\widehat{\text{AgGDP}}$ Growth$_{t-3}$				0.0741	0.0716	0.0719
				(0.0782)	(0.0779)	(0.0782)
$\widehat{\text{AgGDP}}$ Growth$_{t-4}$					0.0037	-4.34×10^{-17}
					(0.0068)	(3.82×10^{-13})
$\widehat{\text{AgGDP}}$ Growth$_{t-5}$						0.0063
						(0.0116)
Fixed-effects						
iso3	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	363	363	363	363	363	363
R^2	0.96107	0.96108	0.96112	0.96168	0.96169	0.96170
Within R^2	0.00160	0.00193	0.00285	0.01728	0.01742	0.01776

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Effect of Agricultural GDP Growth Lags on Effect of Predicted Agricultural GDP Growth (Lags 0-5) on Dietary Energy Supply Adequacy

Dependent Variable:	food_insecurity					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\widehat{\text{AgGDP Growth}}_t$	0.2688**	0.2590**	0.2599**	0.2617***	0.2405**	0.2496***
	(0.1023)	(0.0999)	(0.0993)	(0.0939)	(0.0884)	(0.0888)
$\widehat{\text{AgGDP Growth}}_{t-1}$		0.0145**	-0.0001	0.0004	0.0349***	0.0049
		(0.0067)	(0.0013)	(0.0012)	(0.0110)	(0.0041)
$\widehat{\text{AgGDP Growth}}_{t-2}$			0.0261**	0.0019	0.0022	0.0502***
			(0.0123)	(0.0019)	(0.0019)	(0.0154)
$\widehat{\text{AgGDP Growth}}_{t-3}$				0.1116*	0.0718	0.0693
				(0.0555)	(0.0462)	(0.0447)
$\widehat{\text{AgGDP Growth}}_{t-4}$					0.0540***	0.0060
					(0.0160)	(0.0048)
$\widehat{\text{AgGDP Growth}}_{t-5}$						0.0782***
						(0.0226)
Fixed-effects						
iso3	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,630	1,630	1,630	1,630	1,630	1,630
R^2	0.94177	0.94180	0.94188	0.94247	0.94273	0.94326
Within R^2	0.04047	0.04097	0.04230	0.05207	0.05635	0.06513

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6 Limitations of this research

This study has several limitations that should be addressed in future research:

1. Precipitation data were aggregated from ERA5 grids without applying land-only masks. As a result, average values may be biased for countries with significant water bodies (e.g., Indonesia, Canada), where grid cells over oceans or lakes were incorrectly included in national means.

2. Temperature anomalies were derived from Berkeley Earth, while precipitation came from ERA5. This introduces inconsistencies in temporal resolution and spatial coverage.

3. While the model includes productivity-related controls (TFP, labor input, capital stock), it does not capture other potential channels—such as trade shocks, disaster relief, or price mechanisms—that may mediate the climate–food security relationship.

7 Next Steps

In light of the limitations outlined above, several concrete steps are planned for future work:

- Reprocess the precipitation data using land-only masks to exclude ocean and lake grid cells, particularly for countries with substantial water bodies, ensuring more accurate country-level aggregates.

- Replace the Berkeley Earth temperature anomalies with ERA5-based estimates to ensure consistency in spatial and temporal coverage across all climate variables.

- Broaden the empirical framework to account for additional potential mechanisms through which climate shocks may affect long-term food security outcomes.

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A Appendix

A.1 ANOVA

Table A.1: Stepwise Wald Tests for Additional Climate Lags

Compared Model	Tested Terms	Wald Stat	p-value	Significant
Lag 0 vs Lag 1	TempAnom_lag1 & tp_lag1	0.82	0.439	No
Lag 1 vs Lag 2	TempAnom_lag2 & tp_lag2	2.50	0.082	Marginal
Lag 2 vs Lag 3	TempAnom_lag3 & tp_lag3	0.63	0.532	No
Lag 3 vs Lag 4	TempAnom_lag4 & tp_lag4	1.51	0.221	No
Lag 4 vs Lag 5	TempAnom_lag5 & tp_lag5	5.43	0.0045	Yes

A.2 Figures

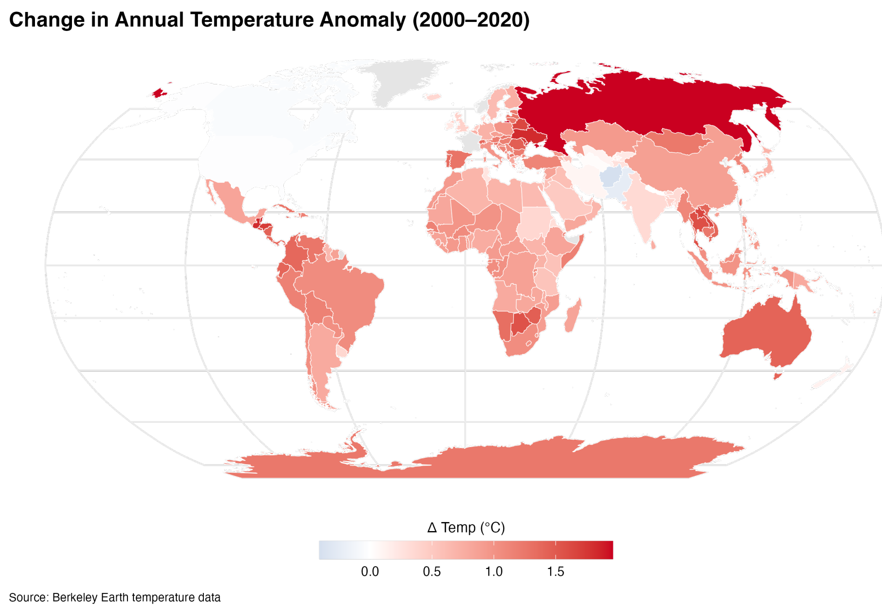

Figure A.1: Change in annual temperature anomalies between 2000 and 2020. The map illustrates differences in country-level temperature anomalies using data from Berkeley Earth. Red shades indicate increased warming, while blue shades reflect relative cooling over the two-decade period. Source: Berkeley Earth temperature data

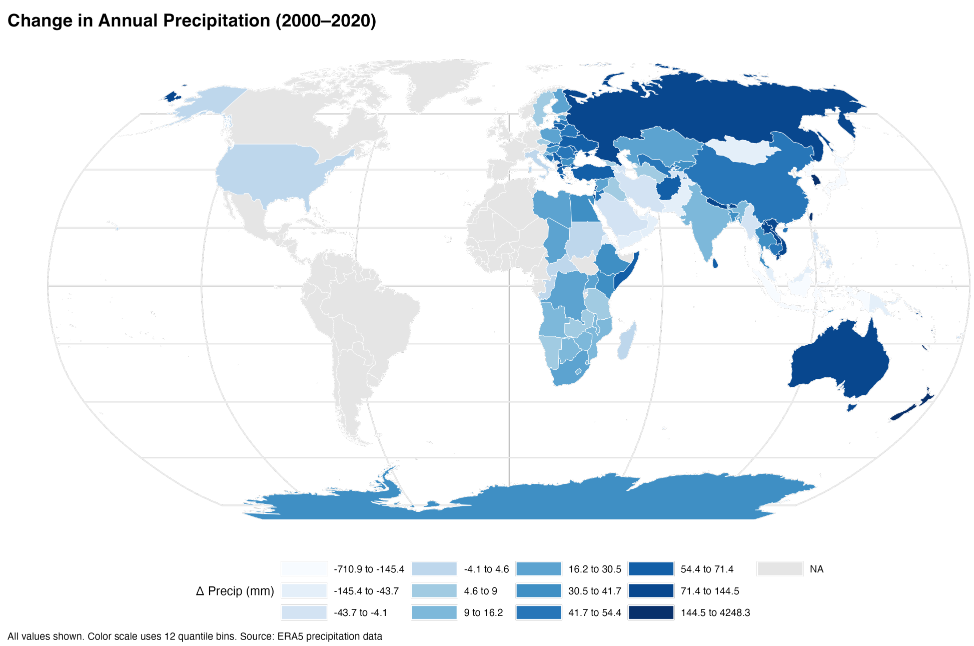

Figure A.2: Change in annual precipitation between 2000 and 2020. The map displays country-level changes in total annual precipitation using ERA5 data. Twelve shades of blue represent quantile-classified changes in millimeters, with darker shades indicating greater increases. Source: ERA5 aggregated precipitation data.

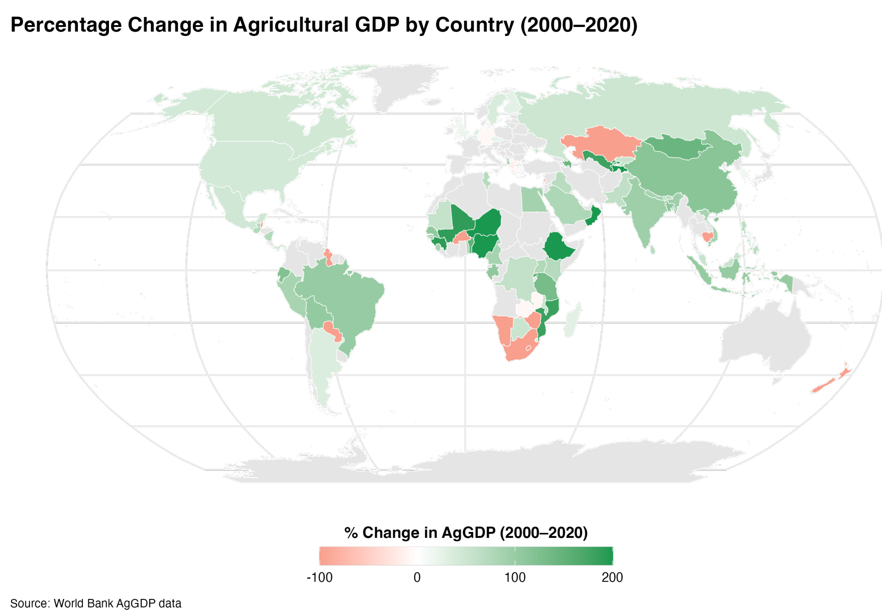

Figure A.3: Agricultural GDP by country in the years 2000 and 2020. The maps display the spatial distribution of agricultural GDP. Data source: World Bank.

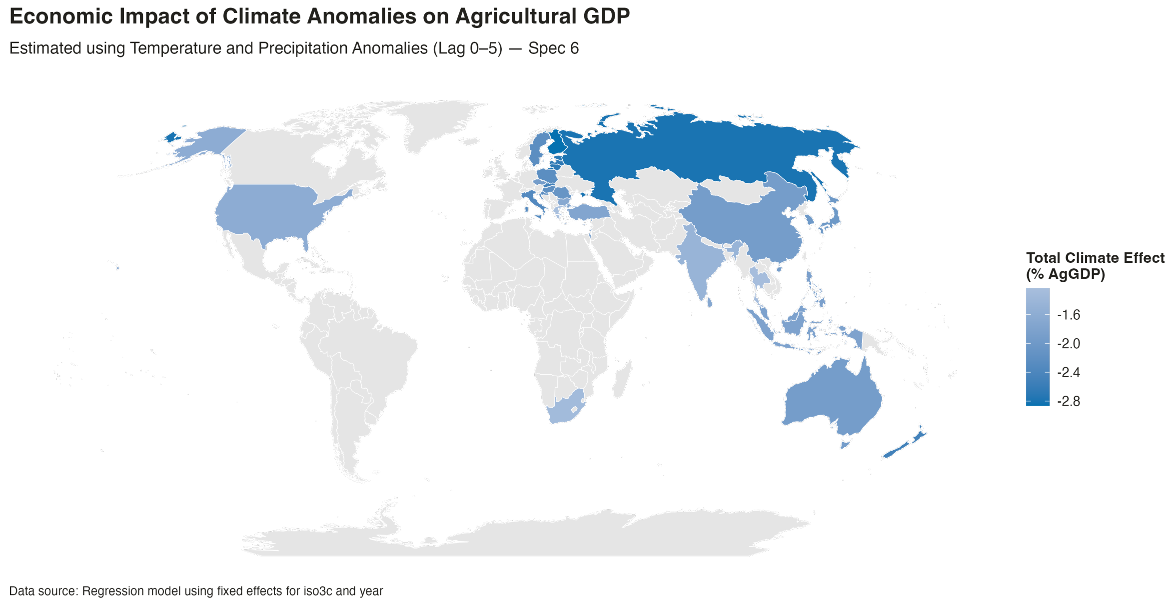

Figure A.4: Economic Impact of Climate Anomalies on Agricultural GDP. Estimated using temperature and precipitation anomalies (lag 0–5), based on a fixed-effects regression model with country and year controls (Spec 6). Country-specific effects are computed by applying globally estimated coefficients to each country's average climate anomalies. Darker shades indicate greater negative impacts on agricultural GDP.

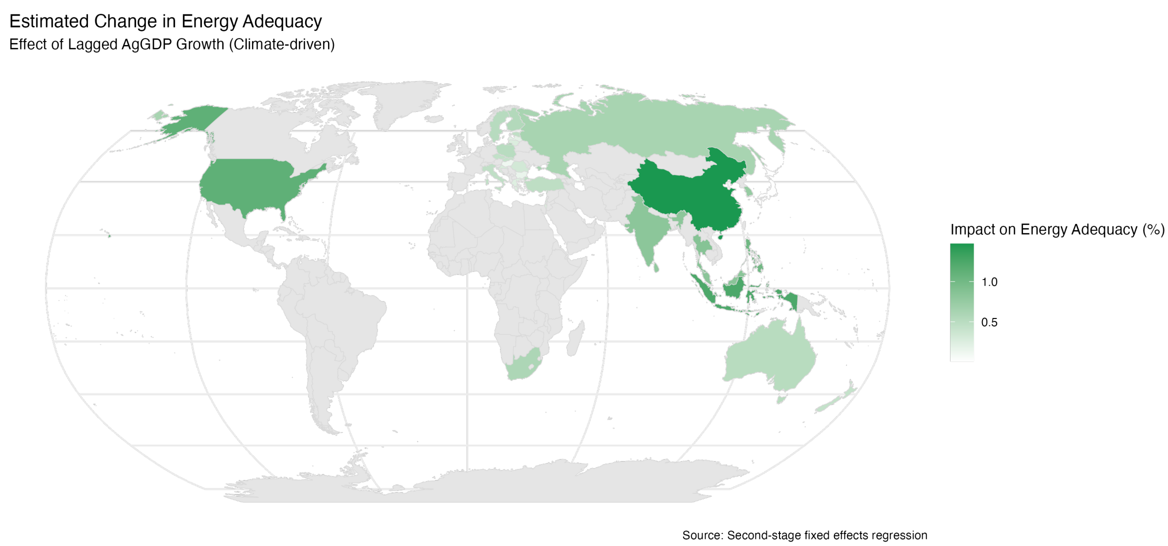

Figure A.5: Country-level estimates are based on the effect of lagged, climate-driven agricultural GDP shocks on dietary energy adequacy, using globally estimated coefficients from a second-stage regression. Green shades indicate projected improvements.

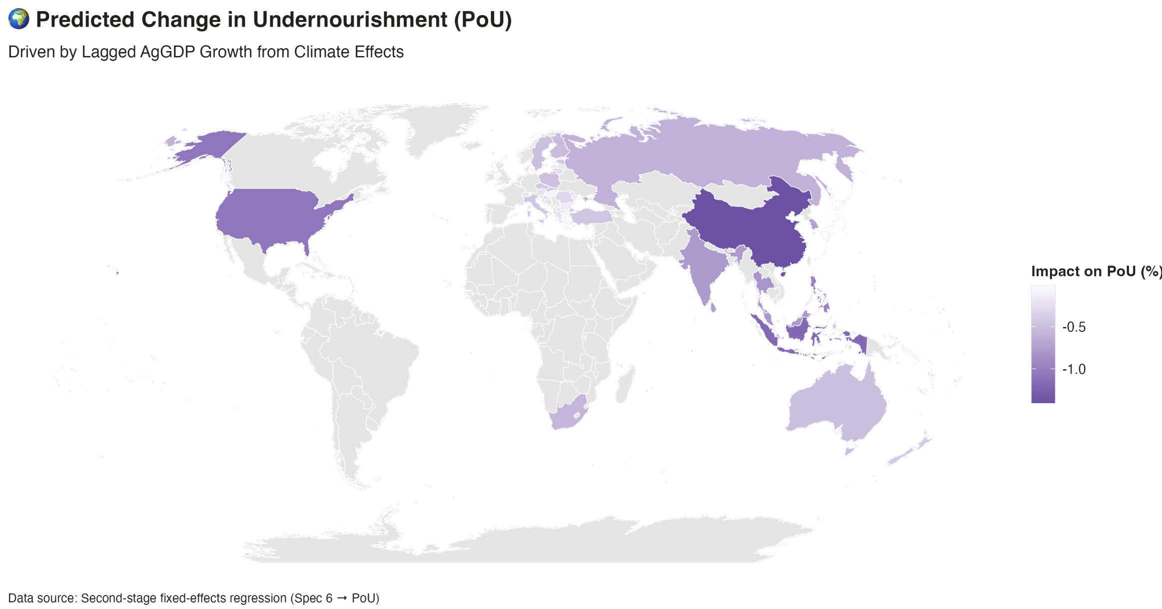

Figure A.6: Country-level estimates are derived by applying a globally estimated coefficient linking lagged agricultural GDP growth to undernourishment. Climate-induced AgGDP shocks were computed using global regression coefficients on temperature and precipitation anomalies (lags 0–5). Purple shades reflect projected reductions in undernourishment; white indicates no significant change.