Three essays on extreme weather, agricultural markets, and international trade

by

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B.B.A. (Hons.), Bahauddin Zakariya University, 2011

M.Sc., Friedrich Schiller University Jena, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics

College of Agriculture

KANSAS STATE UNIVERSITY

Manhattan, Kansas

2026

Abstract

Extreme weather poses risks to agricultural production and food trade, but these effects vary across crops, regions, and markets. This dissertation examines how heat and flood exposure are associated with agricultural production and rice trade in three settings: corn and soybean production in the U.S. Midwest, rice trade in Southeast Asia, and rice trade in South Asia. The three essays combine subnational production data, bilateral and domestic trade flows, weather observations, disaster records, and climate projections.

The first essay examines corn and soybean production value across 12 Midwestern U.S. states from 2000 to 2022. State and year fixed-effects estimates show that extreme heat is associated with significant reductions in production value for both crops, with economic magnitudes varying across states according to historical heat exposure. The chapter also examines the USDA Economic Research Service state export allocation as a secondary cash-receipts-based constructed outcome. Its smaller response to extreme heat is interpreted as a feature of the measure's construction rather than as evidence of independent state export behavior. An exploratory CMIP6 exercise under SSP245 and SSP585 indicates greater future heat exposure and increasing risks to production value through 2100.

The second essay studies rice trade in Southeast Asia from 1986 to 2022 using a structural gravity model estimated with Poisson Pseudo-Maximum Likelihood and exporter-year, importer-year, and bilateral-pair fixed effects. At the global level, the differential response of international shipments relative to domestic flows is not statistically significant. Within Southeast Asia, however, each additional recorded flood is associated with an approximately 15 percent more negative response of international rice shipments relative to domestic flows, with particularly negative estimates for Vietnam and Thailand. Supplementary separate-margin estimates show that, for Thailand, an additional flood is associated with a 6.5 percent

decline in international shipments, equivalent to approximately US$194 million or 0.49 million tonnes, while the domestic-flow response is not statistically significant.

The third essay applies the same framework to South Asia. The aggregate regional response is not statistically significant, but India and Pakistan exhibit sharply different responses. With each additional flood, India's international rice shipments respond approximately 28 percent more negatively relative to domestic flows, whereas Pakistan's respond approximately 17 percent more favorably. A formal Wald test rejects equality of the two coefficients. Supplementary estimates indicate that, for India, an additional flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments; the latter is not statistically significant at the 5 percent level but corresponds to approximately US$56 million or 0.14 million tonnes.

Taken together, the three essays show that weather-related agricultural risks are heterogeneous across production systems and exporters. Extreme heat is associated with lower production value in the U.S. Midwest, while flood exposure is associated with differing international-versus-domestic rice-trade responses across Southeast and South Asia. The findings emphasize the importance of regional and exporter heterogeneity when assessing climate-related risks to agricultural markets and international staple-food supply.

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List of Nomenclature

ERS Economic Research Service

USDA United States Department of Agriculture

PPML Poisson Pseudo-Maximum Likelihood

HDD Heating Degree Days

GDD Growing Degree Days

Acknowledgements

First and foremost, I would like to express my deepest gratitude to my wife, Surriya Wakeel, and our children, Hadi and Haziq, for their love, patience, understanding, and unwavering support throughout my Ph.D. journey. Their encouragement and sacrifices gave me the strength and motivation to continue through the many demanding stages of doctoral study. I am especially grateful to Surriya for standing beside me throughout this journey and for providing the support and stability that allowed me to devote myself to my research and academic responsibilities.

I am equally grateful to my family, especially my father, Rao Muhammad Sultan, whose encouragement, prayers, and belief in me have been a constant source of strength throughout my life. I also sincerely thank my brothers, Rao Asif and Rao Saqib, for their continued encouragement and support. Their confidence in me has meant a great deal throughout this long academic journey.

I am deeply grateful to my major professor, Professor Nelson B. Villoria, for his guidance, mentorship, and academic support throughout the most important stages of my doctoral studies. His guidance helped shape the direction of my research, deepen my intellectual curiosity, and strengthen my development as an applied agricultural economist. I am especially thankful for his patience, thoughtful and constructive criticism, commitment to rigorous scholarship, and willingness to engage in candid and insightful conversations about research. His mentorship over the past three years has influenced the way I approach economic research and has contributed greatly to my growth as a scholar. The lessons I have learned from working with him will remain valuable throughout my academic and professional career.

I would also like to express my sincere appreciation to my committee members, Dr.

Nathan Hendricks, Dr. Jisang Yu, and Dr. Peri Da Silva, for their valuable comments, thoughtful questions, and constructive feedback throughout the development of this dissertation. Their perspectives helped strengthen my research and encouraged me to think more carefully about both its economic motivation and empirical contribution. I am also grateful to Dr. Jesse Tack for his guidance and support during the early stage of my Ph.D. program, which contributed to the foundation of my doctoral training and research.

Finally, I would like to express my sincere gratitude to my friends who supported me throughout this journey. I am especially grateful to Abdur Rub, whose friendship, emotional and academic support, and encouragement have meant a great deal to me. His support played an important role in bringing me to Kansas State University for my Ph.D. and continued throughout the many challenges and milestones of this journey.

I am also deeply thankful to Arslan Hussain and Kinza Emad for their friendship, encouragement, and generous support, particularly during my coursework and qualifiers. Their help and companionship made the demanding early years of the Ph.D. program easier to navigate and considerably more meaningful and memorable.

To everyone who supported, encouraged, taught, and believed in me along the way, I offer my heartfelt gratitude. This dissertation represents not only my academic work, but also the support and generosity of the many people who made this journey possible.

Dedication

This dissertation is dedicated to the loving memory of my mother, Zubaida Sultan. If she were with us today, I know she would be the happiest and proudest mother in the world. Although she could not be here to witness the completion of this journey, her love, sacrifices, and memories have remained with me throughout every step. I pray that she is at peace and happy in Paradise, and I dedicate this achievement to her with all my love and gratitude.

Preface

This dissertation consists of three essays examining the relationships among extreme weather, agricultural production, agricultural markets, and international trade. The chapters are organized as related but distinct research studies, followed by an overall conclusion that summarizes the main findings and contributions of the dissertation.

Chapter 1

Introduction

1.1 Motivation and research context

Agricultural production and agricultural markets are closely exposed to weather and climate conditions. Temperature and precipitation affect biological production processes, while severe weather events can also coincide with disruptions to harvesting, transportation, and market access. These risks are especially important for staple commodities because production and export supply are often concentrated geographically. Weather exposure in a major producing or exporting region may therefore be reflected in market outcomes beyond the location in which the shock occurs. The extent and form of that transmission, however, depend on how production and markets respond and cannot be inferred from weather exposure alone.

This dissertation is motivated by a broad economic sequence: extreme weather can affect agricultural production or supply conditions; agricultural markets then adjust to those conditions; and some of that adjustment may be reflected in domestic and international trade flows. This sequence provides a common conceptual framework for the three essays, but it is not treated as a single causal chain identified by the dissertation. The essays instead enter at different points in that sequence and estimate different response margins using empirical

designs suited to their respective data.

Chapter 2 examines the production side of this framework. It studies how extreme heat is associated with the value of corn and soybean production across the U.S. Midwest. The chapter also examines the Economic Research Service (ERS) state export allocation, but only as a secondary cash-receipts-based constructed outcome. It is not a measure of observed state-level export shipments. Chapters 3 and 4 move to the trade margin. They examine how flood exposure is associated with international rice shipments relative to domestic rice flows in Southeast Asia and South Asia, respectively. Chapter 4 further asks whether this relative international-versus-domestic response differs across major exporters, with particular attention to India and Pakistan. Both rice chapters also report supplementary separate-margin PPML estimates to provide economic scale for selected country responses; these auxiliary estimates complement rather than replace the preferred relative specifications.

The three essays are therefore connected without requiring them to identify the same mechanism. Chapter 2 provides evidence on the agricultural production base under extreme heat. Chapters 3 and 4 provide evidence on a different margin: whether international rice shipments respond differently from domestic rice flows as flood exposure changes. Taken together, the essays study complementary parts of the broader relationship among extreme weather, agricultural production, market adjustment, and international trade.

A central theme throughout the dissertation is careful interpretation of what each empirical design identifies. In Chapter 2, the ERS state export allocation is mechanically constructed from state cash receipts and national export values. With year fixed effects, common national export-value movements are absorbed, so the identifying variation in this secondary outcome comes from within-state changes in state cash receipts, or relative production-value shares, net of state and year effects, rather than from independent state export behavior. In Chapters 3 and 4, exporter-year fixed effects absorb exporter-wide conditions and the main effect of annual flood exposure. The preferred coefficients therefore identify differential international-versus-domestic responses, not absolute changes in exports, domestic flows, or

total rice supply. To provide additional evidence on economic significance, both chapters also report supplementary PPML regressions for the domestic and international margins separately after relaxing the exporter-year fixed-effects structure. Because these auxiliary models use different identifying variation, they are interpreted as complementary magnitude evidence rather than as algebraic decompositions of the preferred relative estimates. These distinctions are maintained throughout the dissertation.

1.2 Literature and conceptual framework

1.2.1 Extreme weather and agricultural production

A substantial empirical literature documents the sensitivity of agricultural outcomes to weather, while also showing that the relevant response differs across crops, locations, outcome measures, and adaptation environments. Schlenker and Roberts (2009) estimate nonlinear temperature–yield relationships for major U.S. crops and show sharp yield losses above crop-specific temperature thresholds. Deschênes and Greenstone (2007) use random year-to-year variation in temperature and precipitation to estimate effects on U.S. agricultural profits, an economic outcome that is distinct from crop yield. Tack et al. (2015) examine the response of U.S. wheat yields to warming temperatures, while Burke and Emerick (2016) study longer-run adaptation in U.S. agriculture and find limited evidence that adaptation has offset the negative short-run productivity effects of extreme heat.

Subsequent studies extend this evidence across crops and production systems. Chen et al. (2016) estimate nonlinear relationships between weather and corn and soybean yields in China. Ortiz-Bobea et al. (2019) examine the climatic drivers of U.S. agricultural yields. Aragón et al. (2021) show that extreme heat reduces agricultural productivity among subsistence farmers in Peru and induces adjustments in planted area and crop mix. For U.S. corn and soybeans, Yu et al. (2021) examine long-run adaptation to temperature and precipitation and document a combination of increased heat and drought tolerance and maladaptation un-

der normal conditions. Hogan and Schlenker (2024a) show that daily temperature extremes recover important nonlinear yield relationships for U.S. corn and soybeans across alternative gridded meteorological data sets. These studies do not estimate a common parameter, but collectively they motivate careful attention to nonlinear and extreme-temperature exposure in agricultural production.

A related literature studies temperature and climate through broader measures of yield and productivity. Zhao et al. (2017) synthesize evidence from four independent analytical approaches and find broadly negative average temperature effects on global yields of major crops, while emphasizing heterogeneity across crops and locations. Chambers and Pieralli (2020) decompose U.S. state-level agricultural total factor productivity growth into technological change, weather-related shifts, input and scale effects, and adaptation. Chancellor et al. (2021) show that measured agricultural total factor productivity in Australia is sensitive to both short-run climate variability and longer-run climate change. Ceballos-Sierra and Dall'Erba (2021) estimate heterogeneous effects of climate variability on coffee productivity across Colombian municipalities, and Ortiz-Bobea et al. (2021) estimate that anthropogenic climate change has slowed global agricultural total factor productivity growth. Together, this literature supports the broader proposition that agricultural yields, output, profits, and productivity can be sensitive to weather and climate, without implying that the magnitude or even the relevant outcome is uniform across settings.

This literature provides the direct foundation for Chapter 2. The chapter focuses primarily on corn and soybean production value in the U.S. Midwest and asks how that outcome is associated with extreme heat and other weather conditions. The ERS state export allocation is retained only as a secondary cash-receipts-based constructed outcome. Because it is mechanically related to state cash receipts and national export values, the chapter does not use it to infer observed state export shipments, independent export behavior, or trade buffering.

1.2.2 Weather shocks, disasters, and agricultural trade

A separate literature examines whether weather shocks and natural disasters are reflected in international trade. Gassebner et al. (2010) use a gravity framework to study major disasters and find that disaster exposure can reduce import and export flows, with effects that vary across countries. Jones and Olken (2010) examine climate shocks and export performance, while Dallmann (2019) studies weather variation in exporter and importer countries and documents heterogeneous relationships with bilateral trade across levels of aggregation. These studies establish that weather-related shocks can be visible in cross-border trade outcomes, but they differ in the shocks considered, the level of aggregation, and the trade margins being estimated.

The literature most closely related to the rice chapters is more specific. Tembata and Takeuchi (2018) use monthly bilateral trade data for Southeast Asia and find that floods are followed by immediate and persistent reductions in export values, including negative associations for agricultural exports. Nes et al. (2025) study growing-season extreme weather using a water-balance measure and find substantial short-run effects on bilateral export values for maize, rice, and soybeans, together with longer-run associations between climate variability and export patterns. These studies motivate Chapters 3 and 4 by showing that weather exposure can affect agricultural export outcomes. At the same time, export-only outcomes do not by themselves identify whether an observed export response reflects an exporter-wide change or a different response of international shipments relative to domestic market flows.

Chapters 3 and 4 address this distinction by incorporating domestic rice flows into the empirical framework. Their contribution is therefore not simply to estimate another export response to weather. Instead, they ask whether the international margin changes differently from a domestic benchmark as annual flood exposure varies. This distinction is central to the interpretation of the rice chapters.

1.2.3 Trade and market adjustment under climate shocks

A broader climate-and-trade literature provides the economic motivation for studying production and trade as related, but distinct, margins of adjustment. Costinot et al. (2016) quantify the consequences of climate-induced changes in crop productivity in a framework that allows production and trade patterns to adjust across locations. Gouel and Laborde (2021) use a quantitative general-equilibrium model to show that climate-induced yield changes generate production and trade adjustments that can reduce global welfare losses. Dall'Erba et al. (2021) examine U.S. interstate crop trade and show that intranational trade can mitigate projected climate-related losses in crop profits in their empirical and counterfactual setting.

These studies support the idea that spatial market integration can be an important margin of adjustment when climate impacts differ across locations. They do not, however, imply that every empirical relationship between weather and a trade-related variable measures adaptation or buffering. That distinction is especially important for this dissertation. Chapter 2 does not identify trade buffering because the ERS state export allocation is not an observed shipment measure. Chapters 3 and 4 identify a different object: whether international rice shipments respond more or less strongly relative to domestic rice flows as flood exposure changes. The rice coefficients therefore should not be interpreted as absolute export effects or as direct evidence of a particular policy, storage, or supply-reallocation mechanism.

1.2.4 Structural gravity and the domestic trade benchmark

The empirical strategy in Chapters 3 and 4 builds on the structural gravity literature. Anderson and van Wincoop (2003) provide a theoretical foundation for gravity models that accounts for multilateral resistance, and Yotov et al. (2016) develop a modern structural-gravity framework for empirical trade analysis. Santos Silva and Tenreyro (2006) show why log-linear gravity estimation can be problematic under heteroskedasticity and motivate Pois-

son Pseudo-Maximum Likelihood (PPML), which also permits trade observations with zero values to enter the estimation in levels.

Domestic flows are central to the interpretation used in the rice chapters. Bergstrand et al. (2015) estimate international border effects using a framework that combines international and intranational trade, while Yotov (2022) develops the case for including domestic trade flows in theory-consistent gravity estimation. In Chapters 3 and 4, domestic rice flows provide the internal benchmark against which international shipments are compared. Exporter-year fixed effects absorb all exporter-specific annual factors, including the main effect of the annual flood count; importer-year fixed effects absorb destination-year conditions; and bilateral-pair fixed effects absorb persistent bilateral trade costs and baseline trade intensity. Identification of the flood coefficient therefore comes from the interaction between exporter flood exposure and the international-flow indicator. The resulting estimate captures a differential international-versus-domestic response. The supplementary economic-significance exercises estimate the domestic and international margins separately under a less saturated fixed-effects structure so that the flood coefficient is directly estimable for each margin; these estimates provide economic scale but do not have the same identifying interpretation as the preferred structural-gravity coefficients.

1.2.5 Positioning of the dissertation

The three essays occupy related but distinct positions within these literatures. Chapter 2 is closest to the weather-and-agricultural-production literature: it estimates how extreme heat is associated with corn and soybean production value and treats the ERS state export allocation only as a secondary constructed-value outcome. Chapters 3 and 4 are closer to the weather-and-trade and structural-gravity literatures: they use domestic flows to identify how international rice shipments respond relative to an internal domestic benchmark as flood exposure changes. Chapter 3 examines the regional and exporter-specific pattern in Southeast Asia, while Chapter 4 focuses on heterogeneity in South Asia and formally tests

whether the relative responses of India and Pakistan are statistically different.

The dissertation therefore does not claim to trace a single shock through a fully identified sequence from weather to production to trade. Instead, it studies complementary empirical margins within a common research program. The organizing logic is that extreme weather can affect the agricultural production base and can also be associated with changes in how staple commodities move across domestic and international markets. The empirical meaning of those changes depends on the outcome and specification used in each essay.

1.3 Research questions

The dissertation is organized around three related research questions. First, how is extreme weather, particularly extreme heat, associated with the value of corn and soybean production across the U.S. Midwest, and how does the cash-receipts-based ERS state export allocation respond relative to production value? This question focuses on the production base of an important U.S. grain-producing region while maintaining a clear distinction between production value and the constructed allocation measure.

Second, how is flood exposure associated with international rice shipments relative to domestic rice flows in Southeast Asia? By incorporating domestic flows into a structural gravity framework, Chapter 3 asks whether international shipments exhibit a differential response to flood exposure relative to an internal domestic benchmark.

Third, do these differential international-versus-domestic responses vary across major rice exporters in South Asia? Chapter 4 focuses particularly on India and Pakistan and tests whether their estimated responses are statistically different. Differences in market institutions and policy environments provide context for interpreting the contrast, but the empirical design does not identify those institutional differences as causal mechanisms.

1.4 Contributions of the dissertation

The dissertation makes four broad contributions. First, it brings together complementary production and trade margins within a single research program on extreme weather and agricultural markets. Chapter 2 studies weather-related variation in the value of agricultural production, whereas Chapters 3 and 4 study differential international-versus-domestic trade responses. The contribution is therefore integrative rather than sequentially causal: the essays illuminate different points at which weather exposure can matter for agricultural markets.

Second, the dissertation combines subnational production evidence with bilateral and domestic trade evidence. The Midwest analysis uses state-level agricultural and weather data to study variation within a major producing region. The Southeast Asian and South Asian analyses use bilateral and domestic rice flows in structural gravity models, providing an internal benchmark for interpreting the international trade margin. This combination of empirical scales connects local production exposure with international market questions without treating the estimates as components of a single structural model.

Third, the dissertation emphasizes heterogeneity rather than assuming a uniform response to extreme weather. In Chapter 2, the economic magnitude implied by a common heating-degree-day coefficient differs across states when scaled by each state's historical year-to-year heat variability. In Chapter 3, the country-level estimates are especially negative for Vietnam and Thailand relative to their domestic benchmarks. In Chapter 4, India and Pakistan exhibit opposite-signed relative responses, and a formal Wald test rejects equality of the two coefficients. These results illustrate why regional averages can conceal important differences across locations and exporters.

Fourth, the dissertation contributes through disciplined empirical interpretation. Chapter 2 distinguishes the cash-receipts-based ERS state export allocation from observed state export shipments and does not attribute the production–allocation difference to an unobserved buffering mechanism. Chapters 3 and 4 distinguish the preferred differential international-

versus-domestic responses from the supplementary separate-margin associations used to provide economic scale. The auxiliary magnitude estimates do not replace or decompose the preferred gravity coefficients. These restrictions make the claims narrower, but they align the economic interpretation with what the data and empirical designs can support.

1.5 Overview of the three essays

Chapter 2, "Weather Extremes, Production Value, and Export Allocations: Evidence from Corn and Soybeans in the U.S. Midwest," studies twelve Midwestern states from 2000 to 2022. Using state and year fixed effects, the chapter estimates associations between weather conditions and corn and soybean production value. Extreme heat, measured using heating degree days, is associated with statistically significant reductions in production value for both crops. The ERS state export allocation is examined as a secondary cash-receipts-based constructed outcome and responds less strongly than production value. Because common national export-value movements are absorbed by year fixed effects, the identifying variation in the allocation comes from within-state changes in state cash receipts. The smaller HDD response of the allocation is therefore interpreted as consistent with the measurement wedge between ERS cash receipts and NASS production value, rather than as evidence of independent state export behavior or trade buffering. The chapter also uses CMIP6 projections under SSP245 and SSP585 in an exploratory, scenario-based exercise through 2100. These projections are used to illustrate how greater future heat exposure may be associated with lower and more volatile production value under the estimated relationships; they are not interpreted as precise causal forecasts.

Chapter 3, "The Impact of Flood Disasters on Rice Trade Flows in Southeast Asia: A Gravity Framework Analysis," examines bilateral and domestic rice flows from 1986 to 2022. The chapter estimates structural gravity models using PPML with exporter-year, importer-year, and bilateral-pair fixed effects. At the global level, the estimated differential response

is not statistically significant. For Southeast Asian exporters, however, each additional flood is associated with an approximately 15 percent more negative response of international rice shipments relative to domestic rice flows. Country-level estimates are particularly negative for Vietnam and Thailand. These preferred coefficients identify relative international-versus-domestic responses. A supplementary separate-margin analysis provides additional economic scale: for Thailand, an additional recorded flood is associated with a 6.5 percent decline in international rice shipments, equivalent to approximately US$194 million or 0.49 million tonnes, while the constructed domestic-flow response is not statistically significant; the corresponding separate-margin estimates for Vietnam are smaller and statistically insignificant. Because the supplementary models use a different fixed-effects structure, these magnitudes complement rather than decompose the preferred relative estimates.

Chapter 4, "Flood Shocks and Rice Trade in South Asia: Contrasting Responses of India and Pakistan in a Structural Gravity Framework," applies the same relative-trade framework to South Asia. The South Asian aggregate response is not statistically significant, but the exporter-specific estimates reveal substantial heterogeneity. With each additional flood, India's international rice shipments respond approximately 28 percent more negatively than its domestic rice flows, whereas Pakistan's international rice shipments respond approximately 17 percent more favorably relative to its domestic flows. A formal Wald test rejects equality of the India and Pakistan coefficients, confirming that the two relative responses are statistically different. Supplementary separate-margin estimates provide economic scale: for India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments, with the latter statistically insignificant at the 5 percent level and equivalent to approximately US$56 million or 0.14 million tonnes; Pakistan's separate domestic and international estimates are both statistically insignificant. These auxiliary results complement the preferred relative estimates. Differences in market institutions and policy environments are discussed as plausible context for the India–Pakistan contrast, not as mechanisms identified by the

model.

Chapter 5 synthesizes the evidence across the three essays. It draws together the implications for extreme-weather exposure, agricultural production, trade adjustment, and the resilience of staple-food markets; discusses policy relevance and limitations; and identifies directions for future research. The synthesis preserves the empirical distinctions developed throughout the dissertation rather than converting the three essays into a single causal claim.

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Chapter 2

Weather Extremes, Production Value, and Export Allocations: Evidence from Corn and Soybeans in the U.S. Midwest

Abstract

This paper studies how extreme weather affects the value of corn and soybean production across 12 Midwestern U.S. states from 2000 to 2022. We also examine the ERS state export allocation as a secondary cash-receipts-based constructed outcome, not as a measure of observed state-level exports or physical shipments. We find that extreme heat, measured by heating degree days, significantly reduces production value for both crops, with larger approximate effects in states experiencing greater year-to-year HDD variability. The ERS state export allocation responds less than production value, a pattern we interpret as a feature of the cash-receipts-based construction of the series rather than as evidence of export behavior. Using CMIP6 climate projections under SSP245 and SSP585, we extend the

analysis to 2100 as an exploratory scenario exercise. The projections point to lower and more volatile production value over time, with implications for the production base that supports U.S. grain exports.

Keywords: Climate change, Weather extremes, Degree days, Farm cash receipts, ERS state export allocation

JEL codes: Q5, Q540; O19

2.1 Introduction

Corn and soybean production in the U.S. Midwest is central to U.S. agricultural markets, farm cash receipts, and the production base that supports national grain exports (USDA FAS 2025). Yields of these crops are sensitive to temperature and precipitation (Schlenker and Roberts 2009). Climate change is expected to increase exposure to extreme conditions in agriculture worldwide (Lobell et al. 2008; Bozzola et al. 2023), and the U.S. Midwest is particularly exposed to these risks. Hultgren et al. (2025) find that, even with farmers' adaptation efforts, corn yields in the region could decline by up to 40 percent and soybean yields by up to 50 percent under high-emission scenarios. These projections increase uncertainty about the future role of the Midwest in supplying corn and soybeans to world markets.

A large literature links weather and agriculture outcomes, including yields (Schlenker & Roberts, 2009; Deschênes and Greenstone 2007; Tack et al., 2015; Burke & Emerick, 2016; Chen et al., 2016; Ortiz-Bobea et al., 2019; Aragón et al., 2021; Yu et al., 2021; Hogan & Schlenker, 2024a), productivity (Zhao et al., 2017; Chambers & Pieralli, 2020; Chancellor et al., 2021; Ceballos-Sierra & Dall'Erba, 2021; Ortiz-Bobea et al., 2021), and trade (Gassebner et al., 2010; Jones & Olken, 2010; Oh & Reuveny, 2010; Zhang et al., 2014; Dallman, 2019; Karlsson, 2021; Osberghaus & Schenker, 2019; 2022; Vital et al., 2022; Nes et al., 2025). However, reliable subnational physical export data are unavailable for the United States, and state-level evidence remains limited on how extreme heat affects the production-value

base underlying national grain-market supply.

We address this gap by combining high-resolution PRISM growing season weather data with state-level production from the USDA's National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) state export allocation for 2000–2022. Using the standard degree day bin specification from the climate and agriculture literature (Schlenker & Roberts, 2009; Burke & Emerick, 2016; Yu et al., 2021; Hogan & Schlenker, 2024a), we construct growing degree days (GDD 0–28 °C) and heating degree days (HDD $\geq$ 29 °C), along with precipitation and freezing variables, to capture productive and damaging heat exposure. Because the ERS series is constructed by allocating national export value to states using farm cash-receipt, or production-value, shares, it is not a record of physical shipments and contains no direct information on export behavior. With year fixed effects, the national export component is absorbed, so the identifying variation in this outcome comes from within-state variation in relative production-value shares. This distinction is important because cash-receipts-based state export allocations are widely used in applied work, but in fixed-effects settings they should be interpreted as relative production-value shares rather than observed export behavior. We therefore refer to this measure throughout as the ERS state export allocation and interpret results on this outcome as evidence on a cash-receipts-based allocated value measure rather than on observed export behavior. Section 2.2.3 provides further details.

Existing studies examined the relationship between climate and trade using structural, partial-equilibrium, or general-equilibrium modeling frameworks (Reilly and Hohmann, 1993; Rosenzweig and Parry, 1994; Mendelsohn et al., 1994). Other contributions emphasize trade and production reallocation as important adaptation mechanisms (Costinot et al., 2016; Baldos et al., 2019; Gouel and Laborde, 2021; Adenäuer et al., 2023). Few studies document volatility in global corn markets under changing climatic conditions, emphasizing the need for region-specific empirical analyses (Villoria and Chen, 2018; Chen and Villoria, 2019). Dall'Erba et al., (2021) provide such subnational evidence for the United States, showing

that interstate trade mitigates climate-induced losses and acts as a domestic adaptation mechanism.

In contrast to these structural or domestic-trade approaches, our study employs an econometric panel framework based on observed weather extremes. Unlike Nes et al. (2025), who study global bilateral agricultural export dynamics using a gravity framework and country-crop water-balance measures, we focus on subnational variation within the U.S. Midwest. We estimate two-way fixed-effects panel models for state-level corn and soybean production value and, secondarily, the ERS state export allocation using PRISM degree-day exposure. We then combine the estimated historical weather–production value relationships with CMIP6 projections under SSP245 and SSP585 to illustrate how future climate scenarios may affect the distribution and volatility of production value, while reporting ERS allocation paths only as secondary mechanical scenario illustrations. We use the future climate exercise as an exploratory scenario analysis, with the full assumptions discussed in Section 2.4.

This paper contributes to the literature in three ways. First, it applies the standard degree-day framework used for yields and physical production to state-level corn and soybean production value in the U.S. Midwest, providing evidence on how extreme heat affects agricultural production-value outcomes across states with different climate exposure. Second, it uses the ERS state export allocation as a secondary constructed-value outcome to document the limitations of cash-receipts-based subnational export measures in fixed-effects settings. Third, it combines the estimated weather–production value relationships with CMIP6 climate projections through 2100 to describe how the distribution and volatility of state production value may change under alternative climate scenarios, holding prices, technology, and adaptation fixed. The corresponding ERS state export allocation paths are reported only as secondary mechanical scenario illustrations, not as forecasts of future exports or physical shipments.

Using historical data, we find that extreme heat significantly reduces production value for both corn and soybeans, with impacts that differ across states: states with greater year-to-

year HDD variability show the largest estimated declines. The ERS state export allocation responds less than production value, but we attribute this gap to measurement differences between ERS cash receipts and NASS production value rather than as evidence of trade buffering. As complementary diagnostics, we examine USDA grain-stocks data and find that heat shocks significantly draw down end-of-season stocks for both crops, a production-side inventory result reported in the appendix. The projections show relatively stable outcomes through the 2040s under the SSP245 scenario, but larger declines and greater volatility in production value under the high-emission SSP585 scenario. Overall, the results suggest that increasing heat exposure may weaken and destabilize the production base that supports U.S. grain exports.

2.2 Data and Methods

This study uses a panel dataset for twelve Midwestern U.S. states Iowa (IA), Illinois (IL), Indiana (IN), Kansas (KS), Michigan (MI), Minnesota (MN), Missouri (MO), North Dakota (ND), Nebraska (NE), Ohio (OH), South Dakota (SD), and Wisconsin (WI) spanning 2000 to 2022. The data combines annual observations of corn and soybean production value and the ERS state export allocation with high resolution measures of weather exposure.

2.2.1 Historical Weather Data

The PRISM daily weather data used to construct our climate exposure variables show wide variation across states and years in the Midwest. Table 2.1 reports summary statistics for the state-year variables used in the estimation: log production value, and export allocation for corn and soybeans, together with the weather indices (GDD, HDD, precipitation, and freezing days). Because the analysis is conducted at the state-year level, we report these aggregated variables in the main text and move the grid-cell PRISM summary statistics to the (Appendix Table A1.1a).

Following Schlenker and Roberts (2009), Burke and Emerick (2016), and Yu et al. (2021), we use daily minimum and maximum temperatures from each 2.5 $\times$.2.5 mile PRISM grid cell and apply a sinusoidal interpolation to compute the time spent in each 1 °C temperature interval during the growing season. We then construct four indices at the grid-cell level before spatial aggregation: growing degree days (GDD, 0 to 28 °C), heating degree days (HDD, $\geq$ 29 °C), precipitation (Prec), and freezing days (Fr). GDD measures exposure to moderate temperatures for crop growth, and HDD measures exposure to damaging high temperatures. Computing the nonlinear degree-day measures before averaging preserves within-state temperature heterogeneity that would be diluted if temperatures were first averaged across grid cells.

We use a single HDD threshold of 29 °C for both corn and soybeans so that heat exposure is defined identically across crops and across the production and allocation equations. This threshold is consistent with Schlenker and Roberts (2009), who report critical temperatures of approximately 29 °C for corn and 30 °C for soybeans. The common 29 °C cutoff coincides with the corn threshold and is slightly conservative for soybeans because it begins counting damaging heat marginally earlier. To confirm that our conclusions do not depend on this cutoff, we re-estimate the model using alternative thresholds of 28 °C and 30 °C; the sign, magnitude, and significance of the HDD effects are unchanged across all three thresholds (Appendix Table A2.11).

Finally, we aggregate the grid-cell weather measures to the state-year level by averaging across PRISM grid cells within each state and summing daily exposures over the growing season. This aggregation matches the resolution of the USDA-NASS production data and the ERS state export allocation series. Because the empirical outcomes are observed at the state-year level, we interpret these variables as broad state-level growing-season exposure measures; additional details on the aggregation procedure are provided in the (Appendix Section 1.3).

The U.S. Midwest shows heterogeneity in heat accumulation during the growing season.

Table 2.1: *Summary Statistics for State-Year Variables Used in Estimation (2000-22)*

Variable	Observations	Mean	Std. dev.	Min	Max
Log corn production value	276	21.63	0.89	18.84	23.52
Log corn ERS allocation	276	6.13	0.87	3.61	8.10
Log soybean production value	276	21.28	0.78	19.23	22.99
Log soybean ERS allocation	276	6.70	0.90	4.25	8.61
GDD (0 to 28 C)	276	3500.87	427.75	2721.87	4429.08
HDD ($\geq$ 29 C)	276	40.97	38.28	1.08	207.37
Precipitation	276	599.11	151.61	249.95	1117.72
Freezing days	276	16.04	9.16	1.73	47.18

Table 2.1 summarizes growing degree days, heating degree days, precipitation, and freezing days at the state year level for the growing season March 1 to September 30. Across the region, Kansas (GDD = 4070) and Missouri (GDD = 4100) accumulate the most productive heat but also experience the highest damaging heat exposure (HDD mean: KS = 128; MO = 71), while northern states show much lower values, illustrating apparent climatic heterogeneity within the Midwest.

2.2.2 Production Value Data

We obtained corn and soybean production data from the USDA's National Agricultural Statistics Service (NASS). Production value is the main outcome in this paper because it measures the state-level economic value of corn and soybean production. We also note that production enters our baseline specifications as a dollar value rather than physical volume. To quantify the price component in the production-value results, we re-estimate the production equation using output measured in bushels rather than dollars; the implied price component is small relative to the quantity response, which supports interpreting the production-value estimates as predominantly quantity-driven (Appendix Table A2.10). Descriptive statistics for the production variables, in logarithmic form, are presented in Table 2.1.

We use USDA quarterly state-level grain stocks data as a complementary production-side diagnostic. March 1 carry-in stocks are predetermined relative to growing-season heat exposure, while December 1 ending stocks capture post-harvest inventory adjustment. Because the ERS state export allocation does not measure physical shipments, these results are not interpreted as evidence of export buffering or trade-flow responses. The corresponding results are reported in the appendix and are used only as diagnostic evidence, not as a baseline mechanism for export behavior.

2.2.3 ERS State Export Allocation Data

The USDA's Economic Research Service (ERS) provides a state-level export allocation series, which is the only consistent subnational allocation of national agricultural export value available for the full sample period. ERS allocates national export value to states using a farm cash-receipts approach based on production value shares. This procedure assumes uniform export propensities and does not account for processing, transportation cost, or final port location. As a result, the series attributes exports to inland crop-producing states rather than to the coastal states containing the ports from which goods are shipped. The series therefore contains no direct information on physical shipments, export timing, destination markets, port location, or state-specific export propensity.

Formally, the allocation for state i in year t is the product of the state's share of national farm cash receipts and national export value. Substituting the cash-receipts share into the allocation formula shows that the national export-value and national cash-receipts components vary only by year and are therefore absorbed by year fixed effects. The remaining identifying variation comes from within-state variation in state cash receipts, net of state and year effects, rather than from independent variation in export behavior. We therefore refer to this variable throughout as the ERS state export allocation, a cash-receipts-based allocation of national export value, and interpret estimates on this outcome as responses of the constructed allocation series rather than as evidence on observed export behavior.

We also note that both production and the ERS state export allocation enter our specifications as dollar values rather than physical volumes. Because the two outcomes share the same price scaling, a common price increase should affect both production value and allocated export value in the same general direction, although residual price effects could still operate if price pass-through differs between production value and ERS allocation. State-level export quantities comparable to the ERS state export allocation are not available, so we state this plainly as a data limitation.

Given these limitations, we do not interpret the ERS state export allocation as a proxy for export capacity or as shipment volume; results on this outcome are reported as descriptive properties of the constructed series. Descriptive statistics for the allocation variables, in logarithmic form, are presented in Table 2.1. Because the allocation is derived from production shares, it is useful to characterize what variation remains once national movements are absorbed by year fixed effects. We therefore report the variance decomposition and production–allocation correlations, and a formal test of equality of the HDD coefficient across the two outcomes in Appendix Table A2.6. The raw production–allocation correlations are high, 0.96 for corn and 0.97 for soybeans, but fall to 0.76 and 0.60 after removing state and year fixed effects, respectively. The ERS state export allocation retains within-state variation in the panel decomposition, with within-state standard deviations of 0.47 log points for corn and 0.64 log points for soybeans. We present these diagnostics to make explicit what the estimates on the allocation do and do not identify: the residual variation is variation in relative cash-receipt shares, and it cannot restore the export information removed by the year fixed effects.

Figure 2.1 describes this residual variation visually. It plots the residualized relationship between the ERS state export allocation and heating degree days after partialling out state fixed effects, year fixed effects, and the remaining model covariates, separately for corn and soybeans. This removes persistent cross-state differences, common annual shocks, and other observed weather controls; the variation that remains reflects within-state movements

in relative cash-receipt shares. The negative fitted relationship in both panels shows that a state's ERS allocation is lower in years when it experiences more growing-season heat, conditional on the controls included in the model, consistent with heat reducing the state's production value relative to the national cash-receipts base.

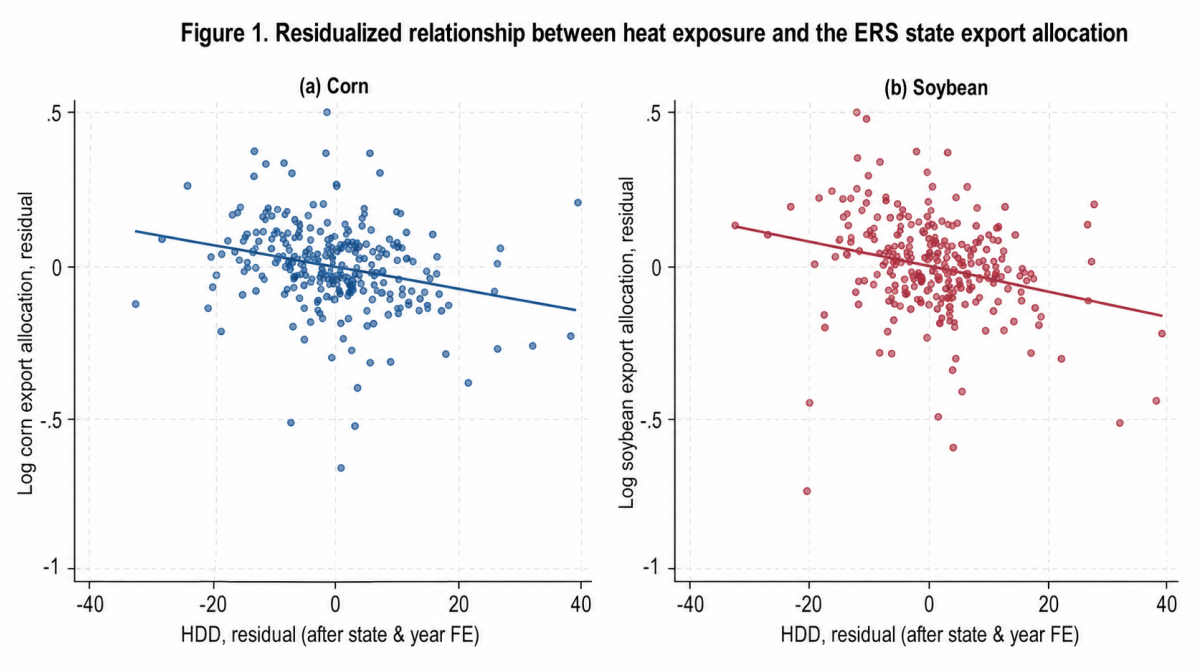


Figure 2.1: *Residualized relationship between heat exposure and the ERS state export allocation. Each point is a state-year observation (N = 276). Both axes are residuals after partialling out state fixed effects, year fixed effects, and the remaining model covariates: GDD, precipitation, and freezing days. The fitted line shows the conditional relationship between HDD and the log ERS state export allocation. The residual variation reflects within-state variation in relative cash-receipt shares, not observed export shipments or export behavior. By the Frisch-Waugh-Lovell result, this fitted relationship corresponds to the HDD coefficient in the allocation regression reported in Table 2.2.*

2.2.4 Future Weather Data for Scenario Analysis and Volatility

Future climate projections data were obtained from two CMIP6 global climate models (GCMs), NorESM-MM2 and CESM2, under the SSP245 (intermediate-stabilization) and SSP585 (high-emission) scenarios. The daily values for the weather variables from both models, including tmin, tmax and Prec are presented in (Appendix Tables A1.1b-A1.1e).

We processed daily minimum and maximum temperatures and precipitation for 2023–2100 to construct the same variables (GDD, HDD, Prec, Fr) using identical methods as for the historical PRISM data.

GCMs operates at coarse spatial resolution and differ in their physical formulations, introducing model uncertainty in regional climate projections (Burke et al. 2015; Hogan and Schlenker 2024b). To account for this, projections reported below summarize medians and interquartile ranges across models and scenarios in figure 2.2.

Projected distributions of climate exposure variables (GDD, HDD, Prec, and Fr) show significant changes across the twelve Midwestern states under future emissions scenarios. The projections in figure 2.2 show several patterns. Under SSP585, GDD increase in all states, and HDD rise more in southern states such as Kansas, Missouri, and Nebraska. Precipitation differs moderately across models, and freezing days decline over time, which reduces exposure to cold later in the century. CESM2 shows somewhat more dispersion than NorESM-MM2, which points to higher sensitivity to year-to-year variation in temperatures. Overall, these patterns suggest a warmer and more variable Midwestern climate with potential for greater volatility in production value.

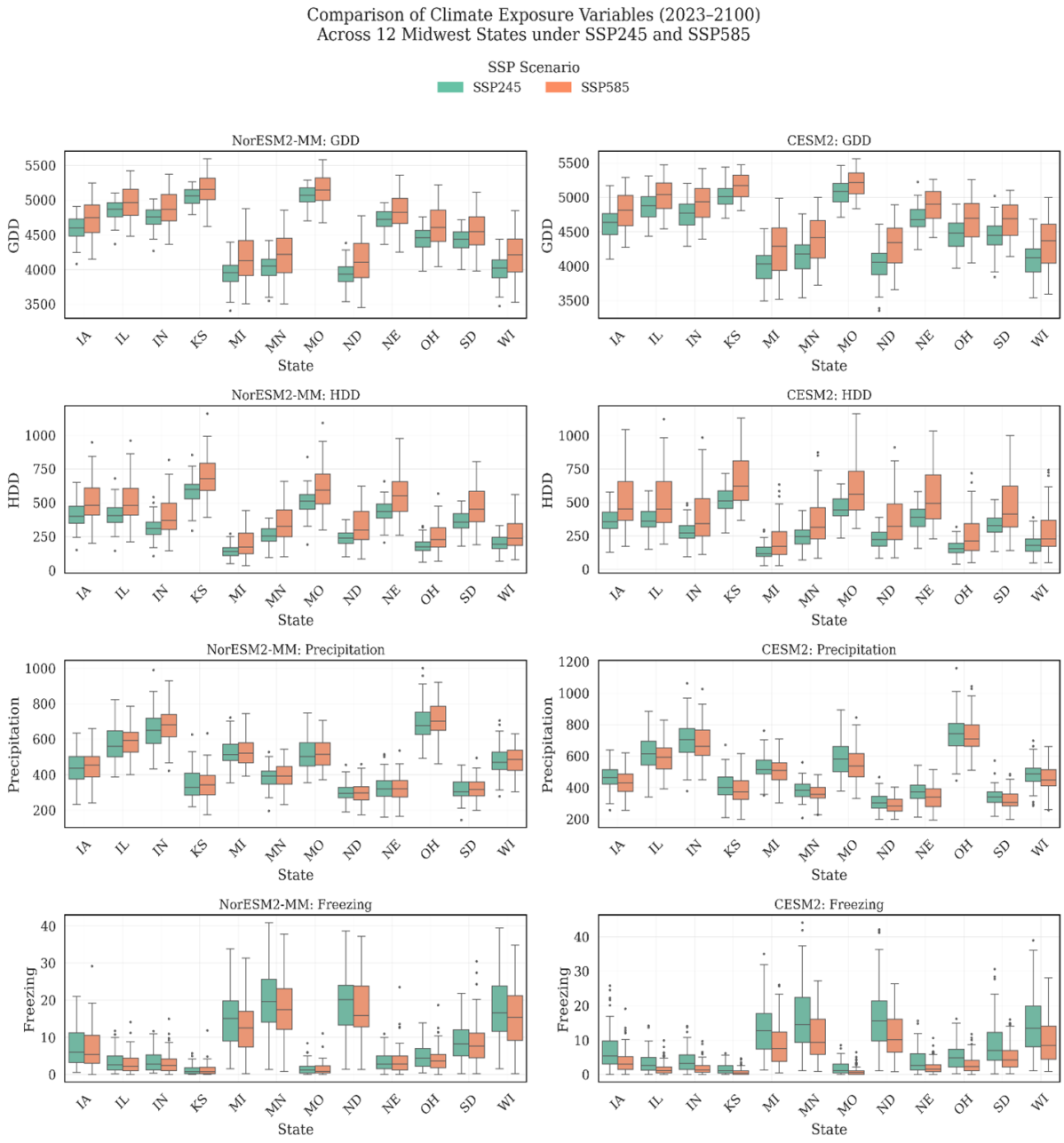


Figure 2.2: *Projected distributions of Growing Degree Days (GDD), Heating Degree Days (HDD), Precipitation, and Freezing Days across twelve U.S. Midwest states under SSP245 and SSP585, simulated by NorESM-MM2 and CESM2 for 2023–2100. HDD values are highest in KS, MO, and NE and lowest in MI, OH, and WI, rising overall under SSP585, consistent with regional warming.*

2.2.5 Methods

We estimate a two-way fixed effects panel model to study how weather extremes affect corn and soybean production value and the ERS cash-receipts-based allocation. The model links annual production value and the ERS allocation to weather variation across states and years and includes state and year fixed effects. Weather is measured using growing degree days, heating degree days, precipitation, and freezing days constructed from daily data following Schlenker and Roberts (2009), Burke and Emerick (2016), Yu et al. (2021), and Hogan and Schlenker (2024a). The model accounts for unchanging regional traits and shared temporal disturbances by incorporating fixed effects for a state and year. The model is articulated in the following manner:

$$ln\ P_{it}^{c} = \beta_0 + \beta_1 GDD_{it\ (0-28)} + \beta_2 HDD_{it\ (29-inf)} + \beta_3 Prec_{it} + Z_{it}\delta + s_i + \delta_t + \varepsilon_{it} \quad (2.1)$$

$$ln\ A_{it}^{c} = \beta_0 + \beta_1 GDD_{it\ (0-28)} + \beta_2 HDD_{it\ (29-inf)} + \beta_3 Prec_{it} + Z_{it}\delta + s_i + \delta_t + \varepsilon_{it} \quad (2.2)$$

We estimate separate log-linear models for production value P_{it}^{c}, and the ERS state export allocation A_{it}^{c} of crop c $\in$ {corn, soybean} in state i and year t. The ERS state export allocation is a cash-receipts-based constructed allocation measure and should not be interpreted as observed exports or physical shipments. GDD_{0-28} measures cumulative exposure to temperatures between 0 and 28°C, while $HDD_{29-\inf}$ measures cumulative exposure $\geq$ 29°C. $Prec_{it}$ *captures* precipitation effects for crop c. Z_{it} includes freezing days and other weather controls; specifications with state-specific trends are reported as robustness checks. Moreover, s_i and δ_t are state and time fixed effects, respectively to control for time and state-level unobserved heterogeneity.

Standard errors are clustered by year, which allows for arbitrary spatial correlation of weather shocks across states within a given year, the dependence the literature on Midwest weather shocks emphasizes. We report robustness to state-only clustering and to two-way clustering by state and year in the appendix.

We report a set of robustness and diagnostic checks in the appendix, including grain-stocks diagnostics (Tables A2.7a–A2.7c), alternative heat thresholds (Table A2.11), alternative clustering of standard errors (Table A2.12), specifications with and without state-specific time trends (Table A2.9), lagged-weather specifications for the ERS allocation series (Table A2.8), and a comparison of production measured in value and quantity (Table A2.10). These checks are used to assess the stability of the production-value results and to describe the behavior of the constructed ERS allocation series; they are not interpreted as tests of observed export behavior.

The grain-stocks analysis is included as a production-side inventory diagnostic. It examines whether heat shocks are associated with changes in carry-in and ending stocks, but because the ERS allocation does not measure physical shipments, the stock results are not interpreted as evidence of export buffering.

A further consideration is timing. Our weather and outcome variables are matched at the annual frequency, which is the finest resolution at which the ERS allocation is reported. More importantly, because the ERS allocation is constructed from cash-receipt shares and contains no shipment information, it cannot be used to study within-year shipment timing. As a descriptive check on the dynamics of the allocation series, we estimate a specification in which growing-season heat enters with a one-year lag (Appendix Table A2.8). For corn, contemporaneous and lagged heat are both negatively associated with the allocation and remain individually significant when entered together; for soybeans, the contemporaneous response dominates. We interpret these patterns as dynamics in the cash-receipts-based allocation series rather than as evidence on shipment timing or export behavior.

2.2.6 Projection and Volatility

Using the estimated parameters from equations (2.1) and (2.2), we simulate future scenario paths for corn and soybean production value P_{it}^{c} for 2023-2100 and report corresponding ERS allocation paths A_{it}^{c} only as secondary mechanical illustrations. We combine the climate projections from CMIP6 models (NorESM-MM2 and CESM2) under the SSP245 and SSP585 scenarios with the historical regression coefficients. For each state i and year t, we construct the projected climate variables, growing degree days $GDD_{it\ (0-28)}$, heating degree days $HDD_{it\ (29-inf)}$, precipitation $Prec_{it}$, and freezing days Fr_{it}, and substitute them into equations (2.1) and (2.2) together with the estimated weather coefficients and state fixed effects, to generate projected production value and ERS allocation paths. These projections should be read as an exploratory scenario exercise rather than as a causal forecast. The coefficients are estimated from modest year-to-year variation over 2000–2022, and applying them through 2100 holds relative prices, technology, and farmer adaptation fixed. The projected paths therefore describe the mechanical consequence of the historical weather–production value relationship under each climate scenario, not predicted future outcomes, and they do not incorporate the price responses or adaptation that would accompany sustained warming.

2.3 Econometric Results

The parameter estimates from equations (2.1) and (2.2) reveal that Heating Degree Days (HDD) have a statistically significant adverse association with both corn and soybean production value and the ERS state export allocation. These results are presented in Table 2.2. The table shows that HDD is consistently negative and statistically significant, while growing degree days (GDD) have weaker and mixed effects, and precipitation and freezing days are generally less robust. The HDD coefficients are larger in magnitude for production value than for the ERS allocation. We therefore describe the production–allocation gap as a property of the constructed series rather than as evidence of export behavior or trade buffering.

The source of this gap is important. As discussed in Section 2.2.3, substituting the cash-receipts share into the allocation formula shows that the national export-value and national cash-receipts components are absorbed by year fixed effects. The identifying variation in the ERS allocation therefore comes from within-state changes in state cash receipts, net of state and year effects. The coefficient gap reflects differences between ERS cash receipts and NASS production value, including marketing-year timing, on-farm marketings, and price weighting, rather than a share-versus-level distinction. These measurement differences can produce a more muted response of the ERS allocation to heat. Appendix Table A2.6 rejects coefficient equality for both corn (wild cluster bootstrap $p = 0.004$) and soybeans ($p = 0.014$). The allocation-to-production coefficient ratios are *0.62* for corn *(95% CI [0.47, 0.76])* and *0.75* for soybeans *([0.54, 0.95])*, and both confidence intervals contain the attenuation benchmark of 0.73 implied by the residual diagnostics. We therefore interpret the coefficient gap as consistent with a measurement wedge between the two series, not as evidence of export behavior or trade buffering.

As complementary commodity-balance diagnostics, we examine USDA quarterly state grain-stocks data, defining carry-in stocks as the March 1 level, which is predetermined relative to March–September heat exposure, and ending stocks as the December 1 post-harvest level. Full results are reported in (Appendix Tables A2.7a – A2.7c). Higher HDD is associated with lower end-of-season stocks for both crops, consistent with inventories being drawn down following heat shocks; we retain this as a production-side result. For the ERS allocation outcome, the HDD $\times$ carry-in interaction is positive and statistically significant for soybeans but close to zero and statistically insignificant for corn. Because the allocation contains no shipment information, these interactions cannot establish export buffering; they show only that the allocation's response to heat varies with stock conditions for soybeans, while for corn state-level carry-in stocks do not moderate the allocation response. We report these results as descriptive heterogeneity of the allocation series.

There is significant regional variability in extreme heat (HDD $\geq$ 29 °C) across the Mid-

Table 2.2: *Weather Effects on Corn and Soybean Production Value and the ERS State Export Allocation, 2000–2022*

	Corn		**Soybean**	
Variables	**Production**	**ERS Allocation**	**Production**	**ERS Allocation**
GDD (0-28)	-0.000087	-0.000141	0.000212	0.000161
	(0.00037)	(0.00022)	(0.000188)	(0.000284)
HDD ($\geq$ 29)	-0.006087***	-0.003753***	-0.005728***	-0.004273***
	(0.00122)	(0.00091)	(0.001158)	(0.001448)
Prec	-0.002045	-0.002221***	-0.000831	-0.001094
	(0.001025)	(0.0006)	(0.000753)	(0.000641)
Fr	-0.004528	0.007862	-0.003354	-0.002623
	(0.007837)	(0.004231)	(0.004099)	(0.005366)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.976271	0.974079	0.978649	0.971341
Adjusted R^2	0.972466	0.969923	0.975226	0.966746

Standard errors clustered by year are reported in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

west. The one-standard-deviation values for each state, presented in figure 2.3, reflect this volatility. Kansas records the highest year-to-year variation in HDD, while Minnesota and Michigan show the lowest.

One Standard Deviation of Heating Degree Days (HDD) by State (2000-2022)

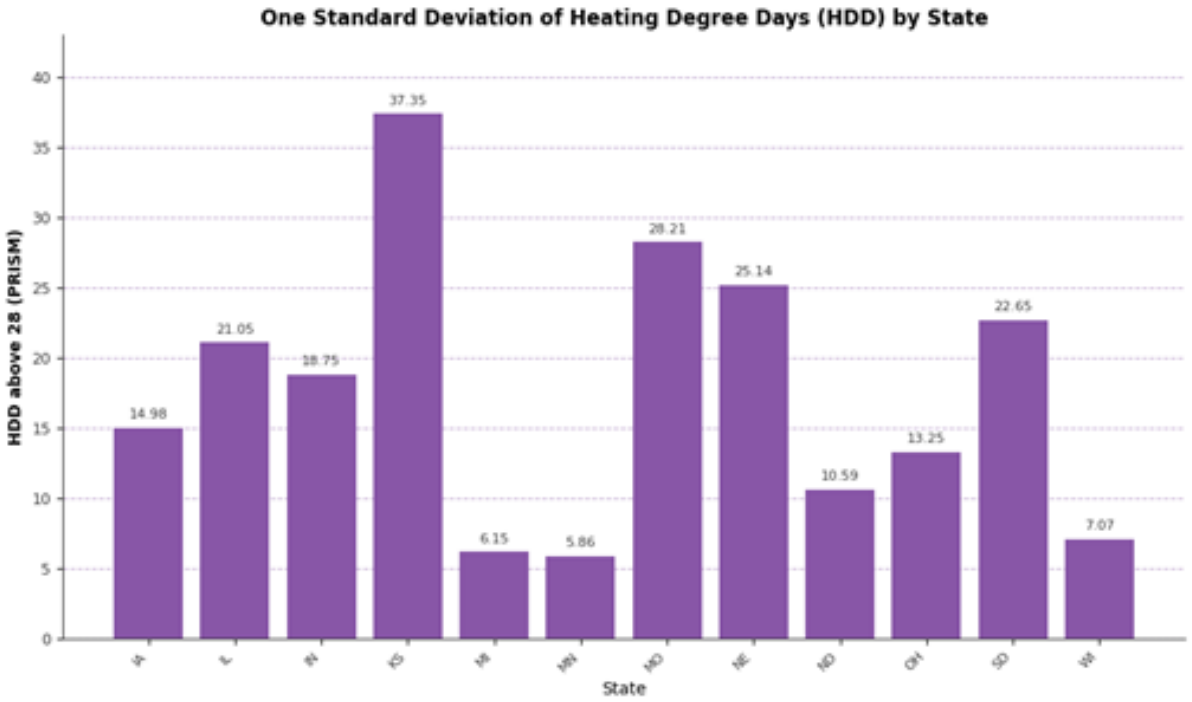


Figure 2.3: *displays the one standard deviation of cumulative Heating Degree Days (HDD) $\geq$ 29°C threshold for each state in the U.S. Midwest. These values describe the year-to-year variation in extreme heat exposure for each state. They are calculated for 2000 to 2022 using data from the PRISM weather dataset.*

The economic impact of a one standard deviation increase in extreme heat differs across states, reflecting weather heterogeneity in the Midwest. Figure 2.4 reports the approximate percentage changes in corn production value and the ERS allocation associated with a one-standard-deviation increase in HDD for each of the twelve states. We calculate these effects as $100 \times \beta HDD \times SD(HDDi)$, where $SD(HDDi)$, is the state-specific standard deviation of heating degree days shown in Figure 2.3. Because the HDD coefficient is common across states, differences in the estimated effects reflect differences in year-to-year HDD variability. States with greater HDD variability, such as Kansas and Missouri, therefore show larger es-

timated declines, while states with lower HDD variability, such as Minnesota and Wisconsin, show smaller declines. Kansas shows an approximate decline of 23 percent in production value and 14 percent in the ERS allocation, while the corresponding estimates for Missouri are approximately 17 percent and 11 percent.

Corn, State-Level Impact of HDD on Production Value and the ERS Allocation (2000-2022)

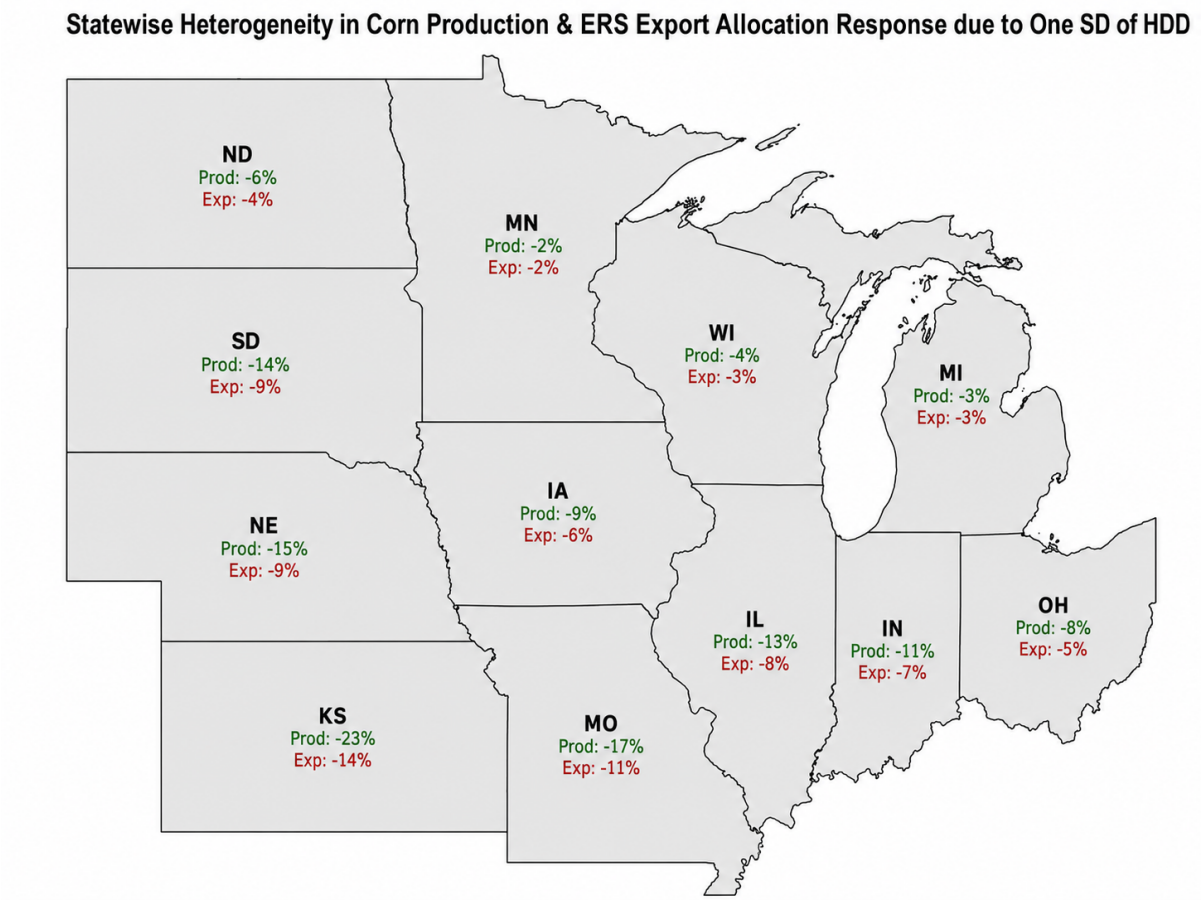


Figure 2.4: *Approximate percentage changes in corn production value and the ERS allocation associated with a one-standard-deviation increase in heating degree days $\geq$ 29°C. The HDD standard deviation is calculated separately for each state. Effects are calculated as* **100 imes etaHDD imes SD(HDDi)**, *using the estimated HDD coefficients of -0.0061 for production value and -0.0038 for the ERS allocation. Because the dependent variables are in logs, these values should be interpreted as approximate percentage changes.*

Figure 2.5 reports the corresponding approximate effects for soybeans. Using the soybean HDD coefficients for production value (-0.0058) and the ERS allocation (-0.0043), we calcu-

late each state's effect as $100 \times \beta HDD \times SD(HDDi)$. States with greater year-to-year variation in HDD, particularly Kansas and Missouri, exhibit larger estimated declines, while states with lower HDD variability, such as Minnesota and Michigan, show smaller effects. Kansas shows approximate declines of 21 percent in production value and 16 percent in the ERS allocation, while the corresponding estimates for Missouri are approximately 16 percent and 13 percent. The consistent gap between the production value and allocation responses reflects the measurement wedge between ERS cash receipts and NASS production value, as discussed in Section 2.3.

Soybean, State-Level Impact of HDD on Production Value and the ERS Allocation (2000-2022)

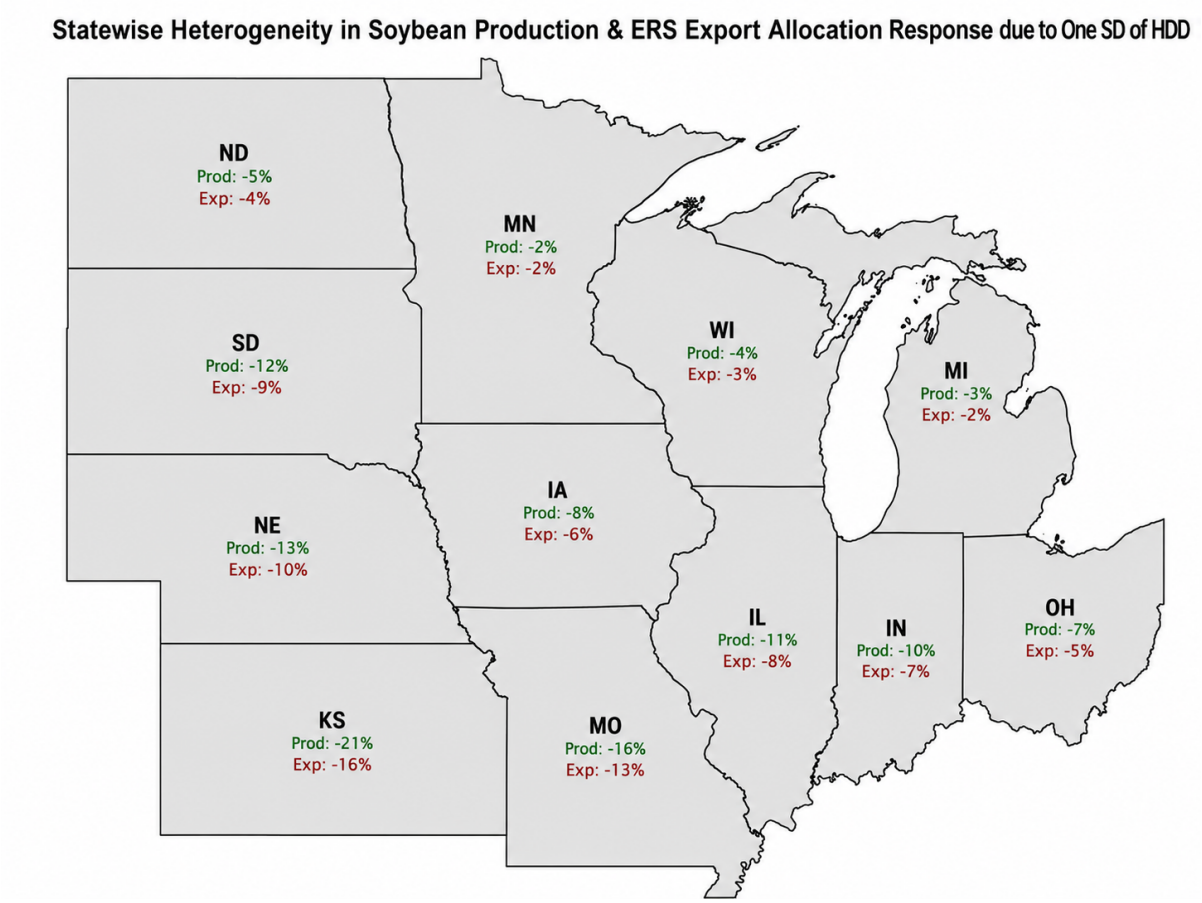


Figure 2.5: *Approximate percentage changes in soybean production value and the ERS allocation associated with a one-standard-deviation increase in heating degree days $\geq 29°C$. The HDD standard deviation is calculated separately for each state. Effects are calculated as $100 \times \beta HDD \times SD(HDDi)$, using the estimated HDD coefficients of -0.0058 for production value and -0.0043 for the ERS allocation. Because the dependent variables are in logs, these values should be interpreted as approximate percentage changes.*

2.4 Climate Scenario Projections and Production-Value and ERS Allocation Volatility, 2000–2100

The results presented in this section are based on projections from the NorESM-MM2 climate model. Corresponding analyses using the CESM2 model are provided in Appendix Section 2.4, where the projected magnitude and volatility of corn and soybean production value are broadly similar. Following the reasoning of Nes et al. (2025), we interpret these long-run paths as exploratory scenario exercises rather than forecasts. They trace the mechanical consequence of applying the historical weather–production value relationship to projected climate exposure while holding relative prices, technology, land use, and farmer adaptation fixed. The paths should therefore not be interpreted as forecasts of future production value, observed exports, or physical shipments. ERS allocation paths, where reported, are included only as secondary mechanical illustrations of the constructed cash-receipts-based series.

2.4.1 Corn Production Value and ERS Allocation Projections and Volatility (2000-2100)

The projected distribution of U.S. Midwest corn production value remains relatively stable in the near term but shifts leftward and becomes more dispersed after mid-century, especially under the SSP585 high-emission scenario. These scenario paths are presented in Figure 2.6, which reports simulations from the NorESM-MM2 model for the historical period, 2000–2022, and future periods through 2100.

In the near term, 2023–2044, medians remain close to the historical baseline and interquartile ranges stay narrow. After mid-century, however, the distributions shift downward. By 2045–2066, the median production value approaches the historical lower quartile, and by 2089–2100, production value declines more sharply and displays wider dispersion. These patterns indicate greater production-value volatility in the scenario exercise. Results using the CESM2 model, provided in Appendix Section 2.4, show similar qualitative patterns.

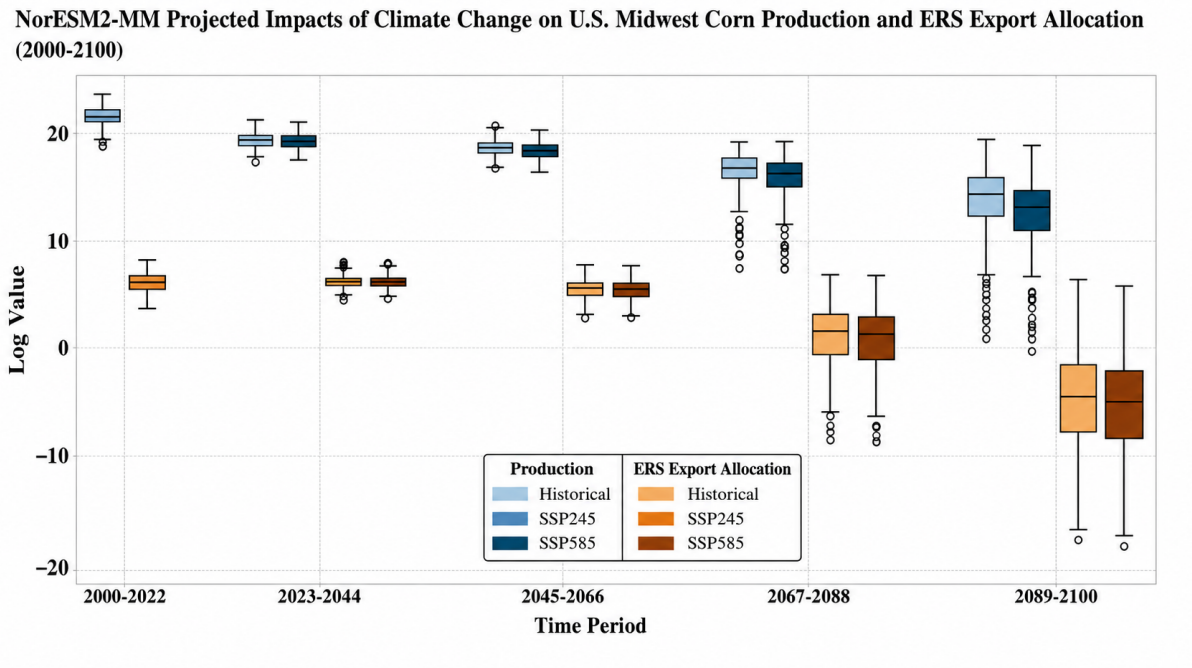


Figure 2.6: *Projected distribution of U.S. Midwest corn production value and ERS state export allocation, 2000–2100. The blue boxes represent corn production value, and the orange boxes represent the ERS state export allocation. Historical values are based on PRISM weather data for 2000–2022, while future scenario values are based on NorESM-MM2 projections under SSP245 and SSP585. The horizontal line within each box indicates the median, the box shows the interquartile range, the whiskers show the range excluding outliers, and the circles indicate outliers. The figure shows that corn production value shifts downward and becomes more dispersed over time, especially under SSP585. The ERS allocation paths are reported as secondary mechanical scenario illustrations of the constructed cash-receipts-based allocation series and should not be interpreted as forecasts of future exports or physical shipments.*

2.4.2 Soybean Production Value and ERS Allocation Projections and Volatility (2000-2100)

Figure 2.7 shows projected changes in soybean production value. Under both SSP245 and SSP585, production value remains close to historical levels until about 2044, after which the distribution shifts downward and becomes more dispersed. Under SSP585, the decline is larger after mid-century, with wider interquartile ranges indicating greater production-value volatility in the scenario exercise.

The corresponding ERS allocation path follows production value mechanically because the allocation is based on cash-receipt shares. We therefore report it only as a secondary scenario illustration of the constructed series, not as evidence on future export levels or physical shipments.

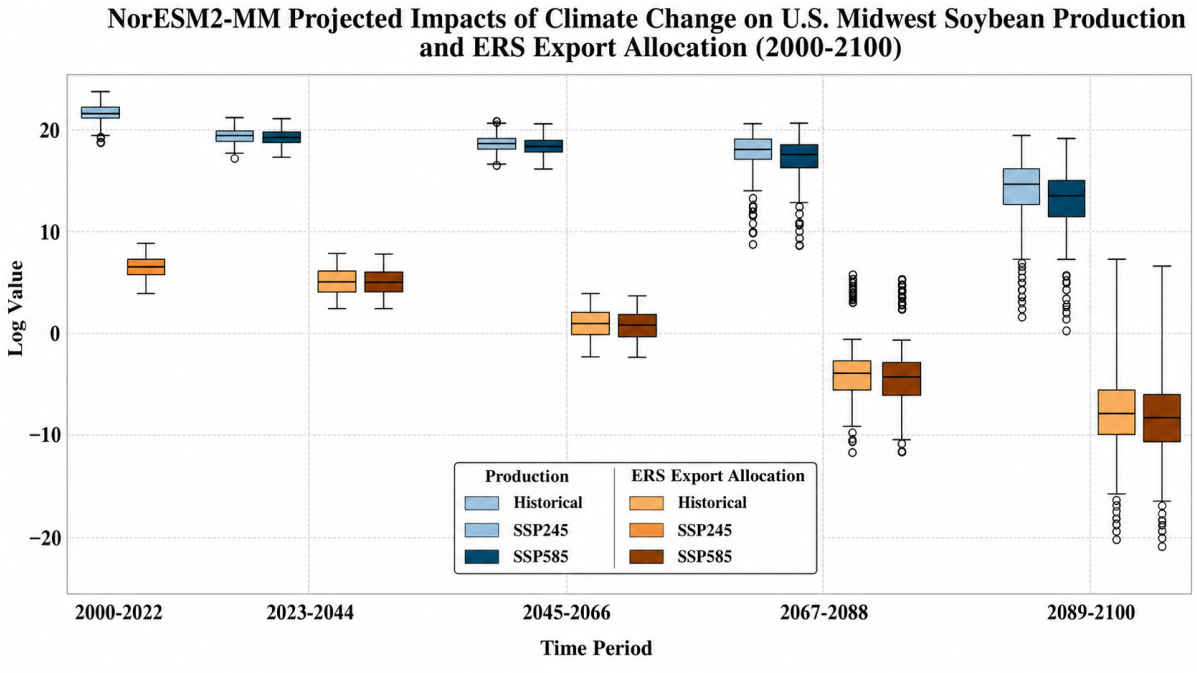


Figure 2.7: *Projected distribution of U.S. Midwest soybean production value and ERS state export allocation, 2000–2100. The blue boxes represent soybean production value, and the orange boxes represent the ERS state export allocation. Historical values are based on PRISM weather data for 2000–2022, while future scenario values are based on NorESM-MM2 projections under SSP245 and SSP585. The horizontal line within each box indicates the median, the box shows the interquartile range, the whiskers show the range excluding outliers, and the circles indicate outliers. The figure shows that soybean production value shifts downward and becomes more dispersed over time, especially under SSP585. The ERS allocation paths are reported as secondary mechanical scenario illustrations of the constructed cash-receipts-based allocation series and should not be interpreted as forecasts of future exports or physical shipments.*

2.5 Discussion

We find that weather extremes are associated with lower production value and a lower ERS state export allocation, the latter interpreted only as a constructed cash-receipts-based outcome. The negative effects of high temperatures are consistent with earlier work on temperature and yields (Schlenker and Roberts, 2009; Burke and Emerick 2016; Ortiz-Bobea et al. 2021). Across specifications, production responds more to heat exposure than the allocation; as discussed in Section 2.3, this ordering reflects measurement differences between ERS cash receipts and NASS production value and is not evidence of trade buffering. Our grain-stocks diagnostics (Section 2.3) show that heat shocks significantly draw down end-of-season inventories for both crops, a production-side result, and that the allocation's response to heat varies with carry-in stocks for soybeans but not for corn. Because the allocation contains no shipment information, these diagnostics cannot establish whether physical exports are buffered; questions about export behavior require shipment-level or trade-cost-adjusted data that are not available in a consistent state-year panel for this setting.

Projections based on CMIP6 climate scenarios SSP245 and SSP585 show greater variability in production value over time, especially under SSP585. These results are in line with Villoria and Chen (2018) and Chen and Villoria (2019), who report higher yield risk and volatility in global corn markets. Higher volatility in production value has implications for farm income stability and for the supply base from which U.S. exports are drawn. Policies that improve risk management, crop insurance, and inventory capacity may help address this production-side risk.

As stated in Section 2.2.3, the ERS series is an allocation of national export value by state production share rather than a record of physical shipments, and it contains no information on export behavior. Shipment-level data would be required to measure state export behavior directly. In their absence, a more trade-theoretic constructed measure could incorporate production shares together with trade-cost components, such as distance to export ports, state-year barge or fuel-cost indices, or local basis measures that capture supply conditions

net of national price movements. These data are not currently available in a consistent state-year panel for our full sample, and we note this only as a data requirement for future research. The present paper does not claim to measure export behavior.

2.6 Conclusion

We study how weather extremes affect the value of corn and soybean production and the ERS state export allocation in the U.S. Midwest using a state-level panel. The models use growing and heating degree days as measures of temperature exposure. We combine PRISM daily weather data for 2000 to 2022 with USDA production data from NASS and the ERS allocation series. The results show that extreme heat significantly reduces production value, with effects that differ across states, reflecting local climate conditions; the ERS allocation responds less than production value, reflecting measurement differences between the ERS and NASS series.

Projections from the CMIP6 models NorESM-MM2 and CESM2 point to higher heat exposure and more volatile production for Midwest corn and soybeans. Under SSP245, production value remains close to current levels until about the 2040s, while under SSP585 it declines after mid-century. The corresponding ERS allocation paths move similarly because they are constructed from production-value shares and are reported only as secondary mechanical scenario illustrations. Corn shows earlier and larger losses, while soybean losses appear later and continue over time. The wider ranges in the projected distributions indicate more uncertainty in future production value, especially under the high-emission scenario. We emphasize that these are exploratory scenarios rather than forecasts. Our coefficients are estimated from modest year-to-year weather variation over a 23-year window and are conditional on the relative prices, technology, and adaptation behavior of that period. Extending them to 2100 holds those conditions fixed, whereas sustained warming would in practice induce price responses and adaptation that our framework does not capture. We therefore

present the long-run paths as scenario illustrations rather than predictions.

Finally, we emphasize the central data limitation of this study. The ERS series is a cash-receipts-based allocation of national export value: with year fixed effects, its identifying variation is within-state variation in production-value shares, and it contains no information on export behavior. The muted response of the allocation relative to production reflects measurement differences between ERS cash receipts and NASS production value and should not be read as evidence of trade buffering. Our grain-stocks diagnostics document a production-side inventory response to heat; whether and how climate shocks pass through from production losses to actual export shipments cannot be answered with these data. Answering that question requires state-level shipment data or consistent trade-cost-adjusted measures that are not currently available for the full state-year panel.

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Chapter 3

The Impact of Flood Disasters on Rice Trade Flows in Southeast Asia: A Gravity Framework Analysis

Abstract

This paper explores how flood shocks affect rice exports in Southeast Asia (SEA) from 1986 to 2022. Using a structural gravity framework estimated with Poisson Pseudo Maximum Likelihood (PPML), we study whether international rice shipments respond differently from domestic rice flows with each additional flood event. The results present no statistically significant differential response of international rice exports relative to domestic flows worldwide. However, each additional flood is associated with an approximately 15 percent more negative response of international rice shipments relative to domestic rice flows in SEA. Country-level results show substantial export sensitivity in Vietnam and Thailand, the region's two largest rice exporters. Supplementary separate-margin estimates provide economic scale: for Thailand, an additional recorded flood is associated with a 6.5 percent decline in international rice shipments, equivalent to approximately US$194 million or 0.49 million

tonnes, while the domestic-flow response is not statistically significant; the corresponding estimates for Vietnam are smaller and statistically imprecise. These auxiliary estimates are complementary associations and do not replace the preferred international-versus-domestic interpretation. The results highlight the importance of accounting for regional export concentration and climate exposure when assessing food security risks in thinly traded staple markets.

3.1 Introduction

More than half of the world's population depends on rice as a staple food, and Southeast Asia plays a central role in the global rice market accounting for over one fifth of global consumption and more than half of net exports (Rezvi et al., 2023; Fadah et al., 2024). Rice is highly vulnerable to flooding and severe floods reduce global rice yields by an estimated 4.3 percent annually (Li et al., 2025). Floods in a major exporting country can lower the amount of rice available for international markets and reduced exports can affect food availability and food security in importing countries. The 2011 Thailand floods provide a useful example. Flooding affected 69 provinces and left more than 41,000 square kilometers of land underwater (World Bank, 2012). Rice paddies across Thailand's central plains, considered the country's main export-oriented production system, were among the hardest hit areas (Haraguchi and Lall, 2015). The Thai government responded with domestic rice price support schemes that helped keep grain available at home, while rice shipments to foreign buyers fell (World Bank, 2012). Thailand supplied around 30 percent of the world's rice at that time, so this event caused implications in many other countries. This paper investigates whether flood shocks reduce an exporter's international rice shipments relative to its domestic rice flows. Export data alone cannot show whether foreign shipments change differently from domestic rice flows. This distinction matters because international and domestic rice flows may respond differently when exporters experience supply disruptions.

An existing literature highlights trade's buffering role in mitigating the adverse effects of climate driven production losses (Costinot et al., 2016; Baldos et al., 2019; Gouel and Laborde, 2021; Adenäuer et al., 2023; Dall'Erba et al., 2021), showing that trade allows food to flow from surplus regions to those experiencing deficits. However, this role depends on exporters' continued supply to international markets during domestic shocks. When major exporters face domestic supply disruptions, political economy pressures often push governments to insulate their domestic markets, prioritize domestic consumers over foreign buyers through export restrictions or domestic price supports (Martin and Anderson, 2012). Amodio et al., (2024) also support that weather shocks reduce agriculture output and affects government trade policy decision. Recent evidence also supports this mechanism, showing that domestic climate shocks lead governments to shift policy in a pro-consumer direction, while foreign shocks induce the opposite response (Hsiao et al., 2026). Building on this evidence, we ask whether flood exposure in major Southeast Asia (SEA) rice exporters is associated with a different response in international rice shipments relative to domestic rice flows.

Rice is especially relevant to this question and Southeast Asia produces close to one-third of the world's rice and accounts for a large share of global exports, with Thailand and Vietnam among the leading exporters (FAO, 2023). Looking ahead, population growth is expected to drive an approximate 18 percent increase in Southeast Asian rice demand by 2050 (Rejesus et al., 2012; Robinson et al., 2015) adding extra pressure to the region's rice systems already exposed to flood risk. In Southeast Asia, rice cultivation is closely linked to lowland areas where seasonal flooding supports production but also creates a major source of risk. Recent flood events confirm that this exposure remains a serious concern. Heavy rainfall associated with the Vietnam floods, while Thailand also experienced widespread flooding in November 2025 with agricultural impacts (Faranda et al., 2025; ReliefWeb, 2025). Without decisive climate action, global absolute flood damage is projected to increase twentyfold by the end of the century, with Southeast Asian countries expected to be highly vulnerable

(Winsemius et al., 2015). Given that climate change increases the frequency and severity of extreme precipitation throughout the region, similar disruptions are expected to recur with greater regularity (IPCC, 2023).

Previous empirical research has examined how climate anomalies affect agricultural yields (Schlenker and Roberts, 2009; Tack et al., 2015; Burke and Emerick, 2016; Zhao et al., 2017; Hogan and Schlenker, 2024), productivity (Ortiz-Bobea et al., 2021; Chambers and Pieralli, 2020; Nath, 2025), and trade (Gassebner et al., 2010; Jones and Olken, 2010; Dallmann, 2019; Osberghaus and Schenker, 2022). The literature on how floods disrupt rice trade is scarce (Tembata and Takeuchi, 2018; Nes et al., 2025) our analysis builds closely on two studies. The first examines the agricultural export consequences of floods across Southeast Asia (Tembata and Takeuchi, 2018) and the second presents the impact of growing-season water-balance deficits on global rice exports (Nes et al., 2025). Tembata and Takeuchi (2018) use monthly trade data within a gravity framework, estimating that floods decrease agricultural exports by three to five percent in Southeast Asia. However, their specification does not absorb bilateral pair fixed effects, which control for time-invariant trade costs. The estimated flood effect from this specification may therefore be influenced by persistent differences between trading pairs rather than by flood exposure alone. In a recent study, Nes et al. (2025) utilized high-resolution growing-season water balance deficit alongside bilateral trade data for rice to show that extreme water balance deficits reduce rice export values by 53.4 percent. While their specification accounts for bilateral pair fixed effects, they do not include domestic trade flows. The analysis therefore cannot show whether the decline is shared at similar rates across domestic and international flows or is concentrated more heavily in exports. While these studies provide important evidence on the effects of climate shocks on agricultural exports, they cannot distinguish whether international shipments respond differently from domestic rice flows following flood exposure. We address this gap by introducing domestic rice flows into a structural gravity framework. This specification allows us to identify whether floods reduce international rice exports relative to domestic

rice flows in affected exporting countries.

We investigate this question using bilateral rice trade data from 1986 to 2022 for a global sample, with a particular focus on Southeast Asia. We estimate a structural gravity model using Poisson Pseudo-Maximum Likelihood (PPML) with high-dimensional fixed effects (Anderson and van Wincoop, 2003; Silva and Tenreyro, 2006; Yotov et al., 2016). We organize the analysis around three questions. First, do floods reduce international rice exports differently from domestic rice flows at the global level? Second, is this relative response stronger in the SEA region? Third, which countries in SEA drive the regional response with each additional flood?

We contribute to the existing literature (Tembata and Takeuchi, 2018; Nes et al., 2025) by incorporating domestic rice flows into a pair-fixed-effects structural gravity framework, which allows us to identify whether flood shocks affect international rice exports differently from domestic rice flows.

The findings indicate that the export responses are regionally concentrated. We find no statistically significant differential response of international rice shipments relative to domestic rice flows at the global level. In SEA, however, each additional flood is associated with an approximately 15 percent more negative response of international rice shipments relative to domestic rice flows, and this effect remains robust when global and regional measures are estimated jointly. Country-level estimates show that the response is concentrated in Vietnam, Thailand, and Indonesia, while other SEA exporters show no statistically significant response. To assess economic significance, we complement the preferred relative estimates with separate-margin PPML specifications that provide approximate magnitudes for domestic and international responses. For Thailand, the supplementary international-flow estimate corresponds to a 6.5 percent decline, or approximately US$194 million (0.49 million tonnes) per additional recorded flood, whereas the corresponding domestic response is not statistically significant; Vietnam's separate-margin estimates are smaller and statistically imprecise.

3.2 Theoretical Background

3.2.1 Structural gravity framework

Following the structural gravity literature, bilateral rice flows depend on exporter supply conditions, importer demand conditions, bilateral trade costs, and multilateral resistance, which we account for empirically using exporter-year, importer-year, and bilateral pair fixed effects (Armington, 1969; Anderson, 1979; Anderson and van Wincoop, 2003; Yotov et al., 2016).

3.2.2 Flood shocks and rice supply

Floods can reduce rice production in the exporting country by damaging crops, delaying harvests, or disrupting the movement of rice from farms to markets. $Flood_{it}$ denotes the number of flood events recorded in EM-DAT for exporter i in year t, taking a value of zero when no flood event is recorded.

Flood exposure may affect exporter-wide rice supply through crop losses, harvest delays, and transportation disruptions. Because these effects are common to all flows originating from exporter i in year t, they are absorbed by exporter-year fixed effects. Consequently, the direct effect of exporter-year flood exposure is not separately identified. The empirical question is therefore not whether floods reduce total rice supply, but whether international rice shipments change relative to domestic rice flows as flood exposure increases.

3.2.3 Relative response of international and domestic rice flows

Our theoretical framework allows flood exposure to affect international rice shipments differently from domestic rice flows. When floods tighten rice supply, domestic prices may rise. In a well-integrated market, this price increase may dampen domestic demand and weaken export competitiveness, potentially affecting both domestic and international rice flows. However, exports may respond more negatively when governments or market institu-

tions adopt measures intended to stabilize domestic markets. Such responses may include export restrictions, public procurement, stock releases, or other measures intended to stabilize domestic prices and supplies (Martin and Anderson, 2012; Hsiao et al., 2026). These mechanisms provide possible explanations for a differential response, but they are not directly observed in empirical analysis. We therefore interpret the estimates as evidence of a relative international-versus-domestic response rather than as direct evidence of a specific policy intervention or deliberate reallocation.

We define $International_{ij}$ as an indicator equal to one when $i \neq j$, representing international rice shipments and zero when $i = j$, representing domestic rice flows. Interacting this indicator with exporter flood exposure allows international shipments to respond differently from domestic flows. The resulting coefficient measures the change in international rice shipments relative to domestic rice flows associated with one additional flood event. It does not identify the absolute movement of either trade margin. The relative specification remains our preferred model because exporter-year fixed effects absorb exporter-wide shocks and outward multilateral resistance. We use supplementary separate-margin specifications only to provide economic scale; their fixed-effects structure and identifying variation differ from the preferred model, so they are not an algebraic decomposition of the relative coefficient.

3.2.4 Global flood effect

The first empirical specification estimates the average differential response of international rice shipments relative to domestic rice flows across exporters in the global sample.

$$X_{ijt} = \exp\left[\pi_{it} + \chi_{jt} + \mu_{ij} + \beta_1(Flood_{it} \times International_{ij})\right] \varepsilon_{ijt} \tag{3.1}$$

Here, X_{ijt} denotes the value of rice flows from exporter i to importer j in year t. The exporter-year fixed effects, π_{it}, absorb time-varying exporter conditions, including exporter-wide supply shocks and outward multilateral resistance. The importer-year fixed effects, χ_{jt},

absorb destination-year demand conditions and inward multilateral resistance. The bilateral pair fixed effects, μ_{ij}, absorb time-invariant bilateral trade costs, including distance, shared borders, common language, and historical ties. The multiplicative error term is denoted by ε_{ijt}.

The coefficient β_1 does not measure the total effect of floods on rice production or the absolute movement of international or domestic rice flows. Instead, it measures the change in international rice shipments relative to domestic rice flows associated with one additional flood event.

A negative β_1 indicates that international rice shipments respond more negatively than domestic rice flows with each additional flood event. A coefficient equal to zero indicates no differential response between the two margins; both may increase, decrease, or remain unchanged. A positive $\beta_1$indicates that international rice shipments respond more favorably than domestic rice flows as flood exposure increases.

3.2.5 Southeast Asia regional effect

The second specification estimates the differential response of international rice shipments relative to domestic rice flows for Southeast Asian exporters. SEA_i is an indicator equal to one when exporter i is located in Southeast Asia and zero otherwise. The regional specification is:

$$X_{ijt} = \exp\left[\pi_{it} + \chi_{jt} + \mu_{ij} + \beta_{SEA}\left(Flood_{it} \times SEA_i \times International_{ij}\right)\right]\varepsilon_{ijt} \tag{3.2}$$

The coefficient β_{SEA} measures the change in international rice shipments from Southeast Asian exporters relative to their domestic rice flows associated with one additional flood event. A negative and statistically significant β_{SEA} indicates that international rice shipments from Southeast Asian exporters respond more negatively than their domestic rice

flows as flood exposure increases. Because Equation (3.2) does not include the general flood–international interaction, it estimates the Southeast Asian response but does not directly test whether that response differs from the response among exporters outside the region.

To make this comparison, we estimate a combined specification containing both the global interaction and the additional Southeast Asian interaction:

$$X_{ijt} = \exp\big[\pi_{it} + \chi_{jt} + \mu_{ij} + \beta_1 \left(Flood_{it} \times International_{ij}\right) + \beta_2 \left(Flood_{it} \times SEA_i \times International_{ij}\right)\big]\varepsilon_{ijt} \tag{3.3}$$

In Equation (3.3), β_1 measures the differential international-versus-domestic response among exporters outside Southeast Asia, while β_2 measures the additional differential response for Southeast Asian exporters. The total response for Southeast Asian exporters is therefore $\beta_1 + \beta_2$.

A negative and statistically significant β_2 indicates that the relative response of international rice shipments is more negative for Southeast Asian exporters than for exporters outside the region. The magnitude and statistical significance of the total Southeast Asian response should be evaluated using the linear combination $\beta_1 + \beta_2$.

3.2.6 Country-level flood effects

The third specification examines whether the Southeast Asian regional response is broad-based or concentrated in particular exporting countries. The country-level model is estimated using the Southeast Asian exporter sample. $Country_{ic}$ is an indicator equal to one when exporter i is Southeast Asian country c, such as Vietnam, Thailand, or Indonesia, and zero otherwise. The country-level specification is:

$$X_{ijt} = \exp\left[\pi_{it} + \chi_{jt} + \mu_{ij} + \sum_{c \in SEA} \beta_c \left(Flood_{it} \times Country_{ic} \times International_{ij}\right)\right]\varepsilon_{ijt} \tag{3.4}$$

Each β_c measures the country-specific change in international rice shipments relative to domestic rice flows associated with one additional flood event. For example, β_{Vietnam} measures the differential response of Vietnam's international rice shipments relative to its domestic rice flows as flood exposure increases, while β_{Thailand} measures the corresponding response for Thailand.

The specification therefore indicates whether the regional pattern is shared across Southeast Asian exporters or driven by a smaller group of major rice-exporting countries.

3.3 Data and Empirical Methodology

This research uses a panel dataset for global level and 11 countries of Southeast Asia (SEA) region (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, and Vietnam) covering the period 1986–2022. We first examine the relationship between floods and rice trade at a global scale to establish a baseline, before narrowing the focus to the SEA region.

3.3.1 Data Sources and Scope

We obtained bilateral and domestic trade data for rice (industry id = 2) from the United States International Trade Commission (USITC) database (Larch et al., 2025; Borchert et al., 2021). The inclusion of domestic trade flows, where the exporter and importer are in the same country, is a critical component of the structural gravity framework. Including domestic flows provides the within-exporter benchmark needed to identify whether international shipments respond differently from domestic flows in a model with high-dimensional fixed effects. Flood exposure is measured using annual event counts from the Emergency Events Database (EM-DAT). Previous studies frequently employ this database to examine disaster-related socioeconomic shocks (Oh & Reuveny, 2010; Loayza et al., 2012; Anttila-Hughes & Hsiang, 2013; El Hadri et al., 2017).

For the supplementary economic-significance analysis, we also use FAOSTAT rice production quantity and gross production value (GPV) to describe production scale and export orientation (Food and Agriculture Organization, 2023). International-flow value changes are evaluated using mean annual rice-export values from the bilateral ITPD-E panel. Approximate physical-volume equivalents are obtained using an average rice export unit value of about US$400 per tonne. Because the constructed domestic-flow measure represents apparent domestic use rather than observed physical domestic sales, the main text emphasizes its estimated percentage response rather than a production-scaled tonnage interpretation.

Table 3.1: *Descriptive Statistics for Rice Flows and Flood Exposure in Southeast Asia, 1986-2022*

Exporter (ISO3)	**Mean Total Rice Flows**	**Mean Domestic Rice Flows**	**Mean International Rice Shipments**	**Cumulative Flood Events**	**Number of Years**
IDN (Indonesia)	15,778.60	15770	9	228	37
THA (Thailand)	8,474.04	5474	3000	87	37
VNM (Vietnam)	7,624.10	6383	1241	95	36
PHL (Philippines)	3,787.53	3785	2	133	37
KHM (Cambodia)	793.84	622	171	24	31
MYS (Malaysia)	339.72	335	4	65	37
LAO (Laos)	179.90	165	14	21	31
MMR (Myanmar)	160.82	0	161	30	37
TLS (TimorLeste)	44.63	45	0	1	9
SGP (Singapore)	20.96	0	21	0	37
BRN (Brunei)	1.73	1	0	0	26

Table 3.1 presents country-level descriptive statistics for total rice flows, domestic rice

flows, international rice shipments, cumulative flood events, and the number of observed years across Southeast Asian exporters. Indonesia, Thailand, Vietnam, and the Philippines have the highest mean annual rice-flow values and are also among the countries with the greatest cumulative flood exposure. Thailand and Vietnam, the region's dominant global exporters, possess high mean exports international, indicating significant trade volatility that coincides with frequent flood occurrences (87 and 95 events, respectively).

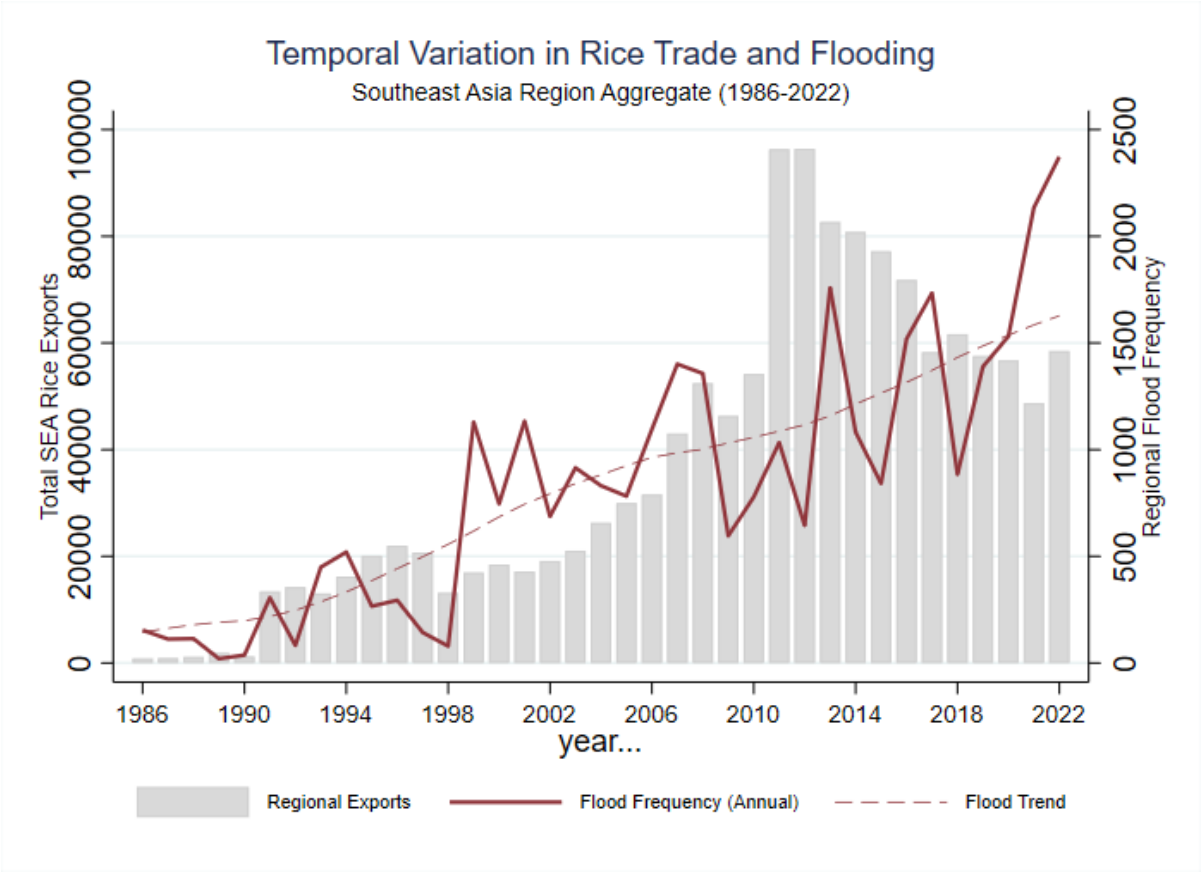


Figure 3.1: *Annual Rice Exports and Flood Events in Southeast Asia, 1986–2022. Bars show total regional rice exports (left axis). The solid line shows the annual count of flood events recorded in EM-DAT (right axis). The dashed line is a linear trend through the flood series.*

Figure 3.1 presents the annual rice exports and flood frequency for the Southeast Asian region between 1986 and 2022. The solid line shows substantial interannual variation in recorded flood events, including elevated exposure during the early 2010s, while the dotted trend line indicates an upward descriptive trend over the sample period. This rising trend

in climate-related disruptions suggests that the regional rice trade is operating under an increasingly risky environment, where the probability of supply-chain shocks is higher today than at the start of the study period. The IPCC (2023) report highlights that the Mekong Delta is becoming increasingly vulnerable. The combined effects of global warming, sinking terrain, and human activity are driving a shift toward more severe flooding in SEA region.

3.3.2 Empirical Strategy

We estimate the effect of floods on global and Southeast Asian rice trade using a structural gravity framework. This approach is consistent with a broad class of trade models and accounts for multilateral resistance, which reflects each country's trade costs relative to all alternative trading partners (Anderson and van Wincoop, 2003). Two features of agricultural trade data require particular care: bilateral rice flows contain many zeros, and the variance of trade grows with its mean. We therefore estimate all specifications using the Poisson pseudo-maximum likelihood (PPML) estimator, which remains consistent under both conditions and allows zero-trade observations to enter the estimation sample directly (Santos Silva and Tenreyro, 2006; Yotov et al., 2016; Correia et al., 2020). We estimate the global, regional, combined, and country-level specifications in Equations (3.1)–(3.4) using PPML with exporter-year, importer-year, and bilateral pair fixed effects. Standard errors are clustered at the bilateral-pair level.

Another feature of our design is the inclusion of domestic trade flows alongside international flows in the estimation sample. The structural gravity literature argues that omitting domestic trade can mix a general supply contraction with a trade-specific response. When a flood reduces a country's rice output, it can affect both the volume sold domestically and the volume shipped abroad. Observing both channels in the same model allows us to distinguish an exporter-wide change in rice flows from a differential response of international shipments relative to domestic flows (Bergstrand et al., 2015; Yotov, 2022).

Identification comes from changes in flood exposure within exporters over time and the

corresponding difference between international and domestic flows, conditional on exporter-year, importer-year, and bilateral-pair fixed effects. The fixed-effect structure controls for time-invariant bilateral trade costs, baseline trade intensity, and exporter-year and importer-year shocks, leaving variation in the international-versus-domestic margin associated with flood events in the exporting country.

We estimate three principal specifications, each designed to identify the flood effect at a different level of aggregation: the global level, the Southeast Asia regional level, and the country-specific level for individual exporters within the region. We also estimate a combined global–regional specification.

We estimate Equations (3.1) and (3.2) separately as our baseline, and we also estimate a single regression containing both flood interactions as a robustness check. Estimated separately, Equation (3.1) reports the average differential trade response across all global exporters, and Equation (3.2) reports the corresponding response for Southeast Asian exporters within the global sample. The separate estimates provide the empirical headline comparison of the paper, while the joint specification, reported in Table 3.2, formally evaluates whether the regional response differs from that of exporters outside Southeast Asia.

Each β_c is identified from within-country variation in flood exposure over the sample period, so the country-specific estimates share a common interpretation: each coefficient measures how strongly international rice shipments from country $c$respond relative to that country's domestic flows as annual flood exposure changes. As in equations (3.1) and (3.2), the coefficient identifies a relative margin; the descriptive evidence in Figure 3.3 provides separate evidence on the domestic margin. The estimates are not, however, directly comparable in statistical precision: countries with more trading partners and more flood events over the sample period yield more precise estimates, and Southeast Asian exporters that record no flood events in Singapore and Brunei, are not separately identified. We therefore report standard errors alongside each country-level estimate in the results section. Figure 3.2 summarizes the within-exporter variation in annual flood exposure across Southeast Asian

countries from 1986 to 2022, which provides the identifying variation for the country-level estimates.

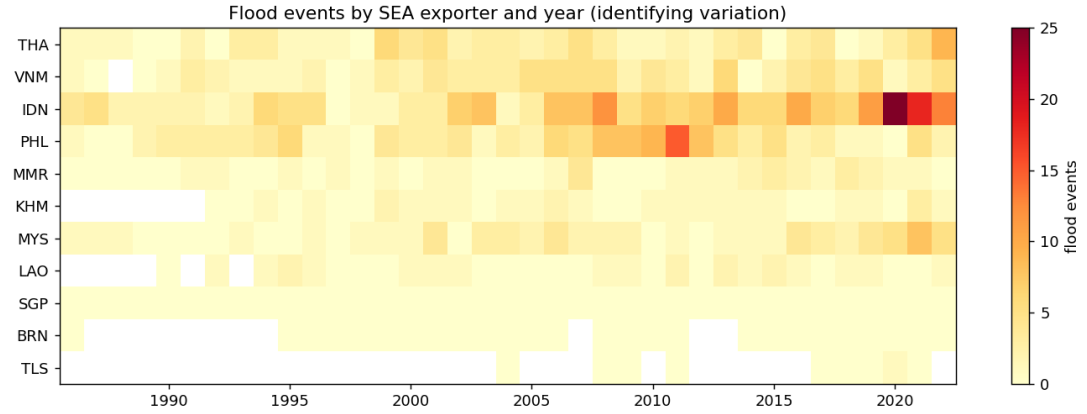


Figure 3.2: *Flood exposure by Southeast Asian exporter and year, 1986–2022. Cell shading reports the number of EM-DAT flood events recorded for each Southeast Asian exporter in each year, with darker cells indicating more events. The figure summarizes the within-exporter, overtime variation in flood exposure that identifies the country-level estimates in Equation (3.4). Singapore and Brunei record no flood events over the sample period and are therefore not separately identified.*

3.3.3 Supplementary economic-significance analysis

The preferred gravity models identify the international-versus-domestic differential but do not identify the absolute movement of either margin because exporter-year fixed effects absorb the flood main effect. To assess the economic scale of the country-level responses, we therefore estimate supplementary PPML models separately for domestic and international observations. These models deliberately relax the exporter-year fixed effects so that the flood coefficient is estimable for each margin. This change also alters the identifying variation, so the resulting coefficients are interpreted as complementary associations rather than as causal decompositions of the preferred gravity coefficients.

For domestic observations, where $i = j$, we estimate

$$\mathbb{E}[X_{iit} \mid Z_{iit}] = \exp\left[\sum_{c \in SEA} \beta_c^D \left(Flood_{it} \times Country_{ic}\right) + \alpha_i + \delta_t\right], \tag{3.5}$$

where α_i denotes exporter fixed effects and δ_t denotes year fixed effects. Standard errors are clustered by exporter. For international observations, where $i \neq j$, we estimate

$$\mathbb{E}[X_{ijt} \mid Z_{ijt}] = \exp\left[\sum_{c \in SEA} \beta_c^I \left(Flood_{it} \times Country_{ic}\right) + \chi_{jt} + \mu_{ij}\right], \qquad i \neq j, \tag{3.6}$$

where importer-year fixed effects χ_{jt} absorb destination-specific demand conditions and inward multilateral resistance, while pair fixed effects μ_{ij} absorb time-invariant bilateral trade costs. Standard errors are clustered by pair. The coefficients β_c^D and β_c^I are not expected to reproduce the preferred relative coefficient algebraically because Equations (3.5) and (3.6) use different samples and a less saturated fixed-effects structure than Equation (3.4).

We convert a supplementary PPML coefficient into percentage terms using

$$\%\Delta_c = 100\left[\exp\left(\widehat{\beta}_c\right) - 1\right]. \tag{3.7}$$

For the international margin, the corresponding value change is evaluated at country c's mean annual international rice-export value, $\overline{V}_c^I$:

$$\Delta V_c^I = \left[\exp\left(\widehat{\beta}_c^I\right) - 1\right] \overline{V}_c^I. \tag{3.8}$$

For ease of interpretation, we also report an approximate physical-volume equivalent by dividing the value change by an average rice export unit value of about US$400 per tonne. These conversions provide scale rather than a new causal estimand. The chapter appendix will document the full data construction, conversion formulas, fixed-effect comparison, and additional regional results; the present chapter reports only the focus-country magnitudes needed to interpret the main findings.

Before turning to the focus-country magnitudes, Figure 3.3 provides a broader descriptive check on the constructed domestic-flow benchmark using exporter and year fixed effects. The domestic-flow estimates show no statistically significant decline under either the flood-

count or any-flood measure. In the global count specification, the estimated response is approximately 1.9 percent per additional flood event. This evidence is consistent with the interpretation that the negative gravity coefficients reflect a more negative international response relative to a domestic benchmark that does not exhibit a statistically significant decline. It should not be interpreted as evidence that floods increase or protect domestic rice availability.

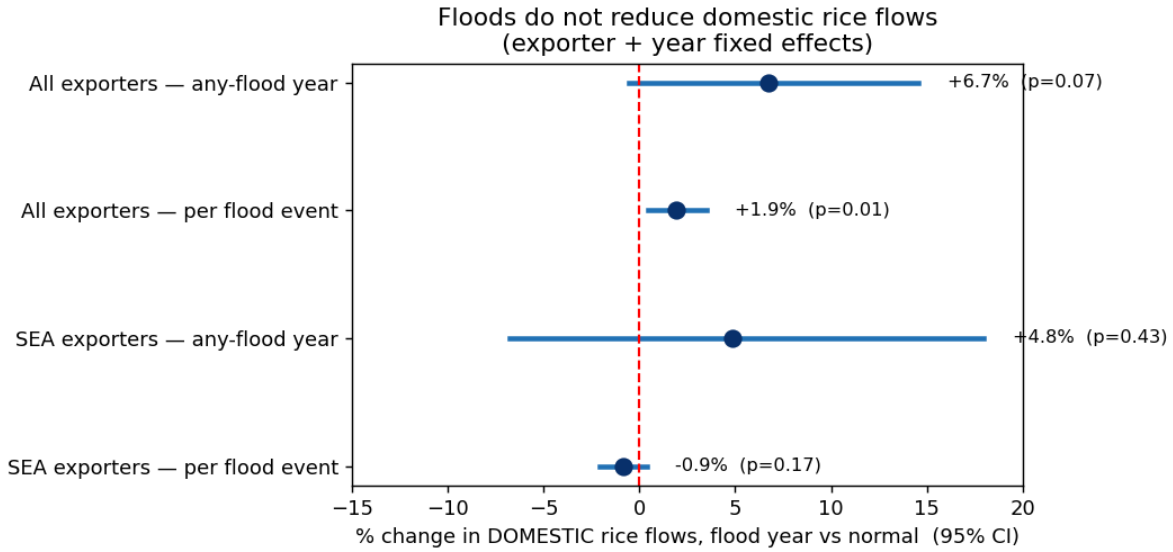


Figure 3.3: *Estimated response of domestic rice flows to flood exposure. Markers report the estimated percentage change in the constructed domestic-flow measure, with horizontal lines indicating 95 percent confidence intervals. Estimates are obtained from exporter-year regressions with exporter and year fixed effects and standard errors clustered by exporter. For the flood-count specification, coefficients measure the response associated with one additional flood event; for the binary specification, they measure the difference between flood and non-flood years. Results are reported for the global sample and for Southeast Asian exporters. Across specifications, none of the domestic-flow estimates is statistically negative, although the Southeast Asian estimates are imprecise because they are based on a relatively small number of exporters. The corresponding gravity coefficients should therefore be interpreted as relative international-versus-domestic responses rather than as evidence of the absolute movement of either margin.*

3.4 Results

Table 3.2: *Global and Southeast Asian Flood Effects on Rice Trade*

Variables	**(1) Global**	**(2) Southeast Asia**	**(3) Combined**
Flood × International	-0.0188 (0.0148)		-0.0121 (0.0152)
Flood × Southeast Asia × International		-0.159** (0.0761)	-0.148* (0.0788)
Constant	9.417*** (0.0050)	9.422*** (0.0057)	9.425*** (0.0067)
Observations	89,092	89,092	89,092
Fixed Effects	Exporter-Year, Importer-Year, Pair	Exporter-Year, Importer-Year, Pair	Exporter-Year, Importer-Year, Pair

Table 3.2 shows the results of the impact of floods on trade at both the global and regional level. In Column 1, no statistically significant differential response at the global level. Column 2 reports a negative and statistically significant coefficient of -0.159, indicating that Southeast Asian international rice shipments respond approximately 14.7 percent more negatively than domestic rice flows[1] with each additional flood event. The additional Southeast Asian interaction remains negative and statistically significant in Column 3, where the global and regional interactions are estimated jointly. The combined specification indicates that the differential international-versus-domestic response is more negative for Southeast Asian exporters than for exporters outside the region. The implied Southeast Asian response in the combined specification is $\widehat{\beta}_1 + \widehat{\beta}_2 = -0.160$, corresponding to an approximately 14.8 percent more negative response of international rice shipments relative to domestic rice flows with each additional flood event.

Table 3.3 reports country-specific estimates of the relative response of international rice shipments to flood exposure across Southeast Asian exporters. Vietnam and Thailand exhibit the largest negative responses, with international rice shipments responding approximately 34 percent and 28.7 percent more negatively than domestic rice flows with each additional

[1]This percentage is calculated using this formula: $(e^{\beta} - 1) * 100$

Table 3.3: *Country-Specific Flood Effects on Rice Trade in Southeast Asia*

Exporter Country	**(4) Flood × Country Indicator × International**
Indonesia	-0.186*** (0.0297)
Cambodia	0.0817 (0.282)
Laos	-0.0879 (0.211)
Malaysia	0.0049 (0.130)
Philippines	-0.0375 (0.0596)
Thailand	-0.338*** (0.116)
Vietnam	-0.416** (0.167)

flood event, respectively. The regional descriptive estimates show no statistically significant decline in the constructed domestic-flow measure. The country-level gravity coefficients therefore indicate a stronger relative response of international shipments, but they do not identify the absolute movement of either margin. For the countries such as Cambodia, Laos, Malaysia, and the Philippines, the estimated differential responses are not statistically significant.

3.4.1 Economic significance of the country-level responses

The preferred country-level estimates in Table 3.3 remain the basis for interpreting flood exposure as an international-versus-domestic differential. The supplementary models in Equations (3.5) and (3.6) provide an additional sense of economic scale by estimating the domestic and international margins separately. Because these models do not retain exporter-year fixed effects, their coefficients should be interpreted as complementary associations rather than as the same estimand as the preferred gravity coefficients.

Thailand is also substantially more export-oriented in the descriptive scaling exercise (about 46 percent of gross production value, compared with about 16 percent for Vietnam). For Thailand, an additional recorded flood is associated with a 1.1 percent increase

Table 3.4: *Supplementary Economic Magnitudes for Thailand and Vietnam*

Country	Domestic response	International response	Approx. value change	Approx. volume change
Thailand	+1.1% (n.s.)	-6.5% ($p < 0.01$)	-US$194 million	-0.49 Mt
Vietnam	-0.7% (n.s.)	-1.7% (n.s.)	-US$21 million	-0.05 Mt

Notes: Responses are per additional recorded flood. Domestic and international responses are from the supplementary separate-margin PPML specifications and provide economic scale; they are not an algebraic decomposition of the preferred relative gravity estimates. International value changes are evaluated at country mean annual international rice-export values in the ITPD-E bilateral panel. Approximate tonnage uses an average rice export unit value of about US$400 per tonne. n.s. denotes not statistically significant at the 5 percent level.

in the constructed domestic-flow measure, but the estimate is not statistically significant. In contrast, the supplementary international-flow estimate indicates a 6.5 percent decline ($p < 0.01$). Evaluated at Thailand's mean international rice-export value, this response corresponds to approximately US$194 million per additional recorded flood. Using the approximate US$400-per-tonne export unit value, the value change is equivalent to about 0.49 million tonnes. This result indicates that the statistically significant international response is economically meaningful in scale.

For Vietnam, the corresponding supplementary estimates are smaller and imprecisely estimated. An additional recorded flood is associated with a 0.7 percent decline in the constructed domestic-flow measure and a 1.7 percent decline in international shipments; neither estimate is statistically significant at the 5 percent level. The international estimate corresponds to approximately US$21 million, or about 0.05 million tonnes using the same approximate unit-value conversion. The auxiliary results therefore provide less evidence of a measurable flood-associated change in either Vietnamese margin.

The supplementary estimates should be interpreted alongside, rather than in place of, the preferred structural-gravity results. In particular, the auxiliary specifications do not retain the full exporter-year fixed-effects structure and therefore do not absorb outward multilateral resistance and other exporter-year shocks as completely as the preferred model. Moreover, the domestic outcome is constructed apparent use rather than observed physical domes-

tic sales. The results therefore do not establish mechanisms such as stock accumulation, deliberate domestic retention, or domestic-price stabilization.

3.5 Discussion

The results show that floods affect rice exports differently across regions. At the global level, floods are not associated with a statistically significant differential response of international rice shipments relative to domestic rice flows. In Southeast Asia, however, international rice shipments respond more negatively than domestic rice flows as flood exposure increases. This finding suggests that the global average masks an important regional response in rice export markets.

This regional response is important because Southeast Asia plays a central role in global rice supply. The region's rice export supply is concentrated in a few countries where floods remain an important risk to rice production and infrastructure. This concentration means that floods in major exporter countries can affect regional rice shipments, even when the global findings remain statistically insignificant.

Our country-level results indicate that the regional response is driven mainly by Vietnam and Thailand, two of Southeast Asia's leading rice exporters. Flood shocks in both countries can affect export availability in importing countries. Indonesia is also informative because it is usually a net rice importer, yet its international rice shipments respond more negatively than its domestic rice flows as flood exposure increases. This suggests that a negative relative export response is not limited to countries with a persistent net-export orientation.

For Thailand and Vietnam, the preferred gravity estimates indicate that international rice shipments respond more negatively relative to domestic rice flows as flood exposure increases. The supplementary magnitude analysis adds scale without changing this interpretation. For Thailand, the separate international-flow specification is associated with a 6.5 percent decline, approximately US$194 million or 0.49 million tonnes per additional recorded

flood, while the domestic-flow estimate is positive but statistically insignificant. For Vietnam, both separate-margin estimates are smaller and statistically insignificant. Because these auxiliary models use a different fixed-effects structure, they do not decompose the preferred gravity coefficients and should not be interpreted as proof of deliberate reallocation, stock accumulation, or policy-induced domestic protection.

These findings extend earlier work on water related shocks and agricultural trade. Tembata and Takeuchi (2018) show that floods reduce agricultural exports in Southeast Asia by 3 to 5 percent, while Nes et al. (2025) show that extreme water balance deficits reduce rice export values more than 50 percent. We contribute to this literature by comparing export flows with domestic rice flows. This distinction is important because export data alone cannot show whether international shipments respond differently from domestic rice flows following flood exposure.

Hsiao et al., (2026) provide one possible policy explanation for the relative export response. They show that domestic climate shocks often push governments toward pro-consumer food policies, such as subsidies or export restrictions, to reduce pressure on domestic prices. In the context of the SEA rice markets, this provides a possible channel for our findings. Policy or market responses may contribute to a weaker performance of international shipments relative to domestic flows as flood exposure changes. However, our results should be interpreted carefully because we do not directly observe the specific policy instruments behind the export response.

Our paper findings also relate to the role of trade in climate adaptation. Previous studies show that trade can help countries adjust to climate shocks by moving food from less affected regions to more affected regions (Costinot et al., 2016; Gouel and Laborde, 2021; Dall'Erba et al., 2021). Our results suggest that this role depends on the reliability of major exporters. A weaker relative response of international shipments from key Southeast Asian suppliers may therefore constrain the ability of trade to buffer climate-related supply stress, particularly for import-dependent countries.

Our study has several limitations. The flood measure is based on country-year disaster indicators and does not capture the intensity of flooding or its location relative to rice-producing areas. Future work could improve this by combining spatial flood maps with rice production data. We also cannot identify which mechanisms drive the more negative response of international rice shipments relative to domestic rice flows, including crop losses, transport disruption, storage losses, policy responses, or market behavior. Linking trade data with information on infrastructure damage and food policy measures would help clarify these channels. Domestic rice flows are measured using apparent domestic use, not observed internal shipments, so the estimates should not be interpreted as changes in household consumption or domestic food availability. In addition, the supplementary economic-significance regressions relax exporter-year fixed effects in order to identify the flood coefficient separately for each margin; those estimates therefore do not control for outward multilateral resistance and other exporter-year shocks as completely as the preferred specification and should be interpreted as associations. The approximate tonnage conversions also rely on an average export unit value of about US$400 per tonne. Our main conclusion is therefore based on the preferred international-versus-domestic differential, while the auxiliary estimates provide economic scale rather than a separate causal result.

3.6 Conclusion

This paper asks whether flood shocks reduce rice exports relative to domestic rice flows, with a particular focus on Southeast Asia. The results show no statistically significant differential response at the global level, while international rice shipments from Southeast Asia respond more negatively than domestic rice flows as flood exposure increases. This finding suggests that flood effects on rice exports are regionally concentrated and that global results can hide important regional sensitivities.

Our main contribution is to identify the international-versus-domestic margin of adjust-

ment following flood shocks. By incorporating domestic rice flows into a structural gravity framework, we identify whether international rice shipments respond differently from domestic rice flows as exporters face more frequent flooding. This distinction is important because international trade data alone cannot reveal whether international shipments respond differently from domestic rice flows following flood exposure.

The country-level results also show that the regional response is heterogeneous across SEA. Vietnam, Thailand, and Indonesia show stronger negative international-versus-domestic responses to flood exposure, while other Southeast Asian exporters show no statistically significant effect. This pattern matters because Vietnam and Thailand are major rice exporters, so their relative export responses may create risks for import-dependent rice markets. Indonesia's case is also informative because its international rice shipments respond more negatively than its domestic rice flows as flood exposure increases, even though it is usually a net rice importer.

Supplementary magnitude estimates further show that Thailand's international-flow response is economically sizable: an additional recorded flood is associated with an approximately 6.5 percent decline in international shipments, equivalent to about US$194 million or 0.49 million tonnes, while the separate domestic-flow response is not statistically significant. The corresponding domestic and international estimates for Vietnam are smaller and statistically indistinguishable from zero. These auxiliary magnitudes provide scale, but the exporter-year fixed-effects gravity estimates remain the basis for the chapter's international-versus-domestic interpretation.

Our findings have broader relevance to food security and climate adaptation. Trade can help countries adjust to climate shocks, but its effectiveness depends on whether major exporters continue supplying international markets during shock years. A more negative relative response of international shipments from key rice suppliers may create additional risks for import-dependent countries when global supply conditions are already stressed. This does not weaken the case for trade as an adaptation tool; it shows that trade-based

adaptation depends on where climate shocks occur and how exporters respond.

Overall, our paper results show that flood exposure is associated with a different response of international rice shipments relative to domestic rice flows in Southeast Asia. For SEA, this is important because the region is central to global rice exports and remains exposed to flood risk. For rice-importing countries, the findings suggest that trade-based adaptation depends not only on market access but also on whether major exporters continue supplying international markets during climate shocks.

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Chapter 4

Flood Shocks and Rice Trade in South Asia: Contrasting Responses of India and Pakistan in a Structural Gravity Framework

Abstract

This paper examines how flood exposure is associated with international rice shipments relative to domestic rice flows in South Asia and whether responses differ across exporters. Using bilateral and domestic rice flows from 1986 to 2022, we estimate a structural gravity model with Poisson Pseudo Maximum Likelihood and exporter-year, importer-year, and bilateral-pair fixed effects. Floods show no statistically significant differential response at the South Asian aggregate level, but country estimates reveal substantial heterogeneity. India's international rice shipments respond about 28 percent more negatively than its domestic rice flows with each additional recorded flood, whereas Pakistan's respond about 17 percent more favorably relative to domestic flows; a formal coefficient-equality test confirms that

the two responses are statistically different. Supplementary separate-margin estimates add economic scale: for India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments, corresponding to approximately US$56 million or 0.14 million tonnes on the international margin, while Pakistan's separate-margin estimates are small and statistically insignificant. These auxiliary estimates use a different fixed-effects structure and do not replace the preferred international-versus-domestic interpretation. The findings show that flood exposure need not translate uniformly into rice trade and that exporter-specific market responses matter for the reliability of international staple markets.

4.1 Introduction

International rice markets depend heavily on a relatively small number of major exporters, making disruptions in supplying countries potentially consequential for food-importing economies. India accounted for more than 40 percent of global rice exports in 2022, while Pakistan was also among the world's major suppliers (USDA Economic Research Service, 2023). Rice production in both countries is closely linked to the summer *kharif* and monsoon season, exposing production and marketing conditions to weather and water-related shocks (USDA Foreign Agricultural Service, 2020, 2022). The 2022 Pakistan floods illustrate the scale of this vulnerability: the Post-Disaster Needs Assessment estimated approximately US$3.7 billion in damage to agriculture, food, livestock, and fisheries (World Bank, 2022). Yet the implications of such shocks for international food markets depend not only on their effects on agricultural production, but also on how major exporters distribute adjustment between domestic and international markets.

India and Pakistan provide an informative setting for examining this question because they combine common exposure to monsoon-related risks with important differences in their rice-market institutions. India has used the export margin as an instrument of domestic rice-

market policy; in September 2022, for example, the government prohibited exports of broken rice and imposed a 20 percent export duty on several other rice categories amid concerns over domestic supply and prices (USDA Foreign Agricultural Service, 2022). Pakistan's rice trade, by contrast, is largely private-sector led and strongly connected to international markets, including through basmati and other rice exports (USDA Foreign Agricultural Service, 2020). These institutional differences do not imply that flood shocks necessarily trigger particular trade policies, but they suggest that similar exposure need not be transmitted in the same way between domestic and international markets. This paper therefore asks whether flood exposure changes international rice shipments relative to domestic rice flows and whether this relative response differs across South Asian exporters, particularly India and Pakistan.

Export data alone cannot answer this question. A change in international shipments following a flood year is consistent both with a contraction in total rice supply and with a reallocation of available supply toward domestic buyers, and export values do not distinguish between them. Structural gravity models that incorporate domestic flows supply the internal benchmark this comparison requires (Bergstrand et al., 2015; Yotov, 2022). Exporter year fixed effects absorb exporter wide conditions, including production, prices, and outward multilateral resistance, while importer year and bilateral pair fixed effects control for destination conditions and persistent trade costs. The coefficient of interest is therefore relative: it measures whether international rice shipments change relative to domestic rice flows as annual flood exposure varies, not whether exports, domestic flows, or total rice supply move in levels.

That relative margin is what climate adaptation and food security depend on, because geographically concentrated production shocks are in principle what international trade is best positioned to absorb: food moves from less affected to more affected markets, and the welfare gains from this reallocation are substantial (Costinot et al., 2016; Gouel and Laborde, 2021; Dall'Erba et al., 2021). The relative margin is where that adjustment shows up, which is why it matters for climate adaptation and food security. Whether the adjustment occurs

at all depends on exporting country behavior. Under domestic supply or price pressure, governments have several stabilization instruments available, including export restrictions, procurement, and stock releases, each of which retains supply within the exporting country (Martin and Anderson, 2012). Recent evidence further shows that weather shocks can influence agricultural trade policy and that domestic climate shocks can shift food policy toward domestic consumers (Amodio et al., 2025; Hsiao et al., 2026). These mechanisms imply that exposure to the same class of climate hazard may generate different relative export responses across countries.

A related empirical literature documents important effects of weather and climate shocks on agricultural yields, productivity, and international trade (Schlenker and Roberts, 2009; Jones and Olken, 2010; Burke and Emerick, 2016; Dallmann, 2019; Ortiz Bobea et al., 2021; Nath, 2025). Natural disasters can also disrupt international trade more broadly (Gassebner et al., 2010), while studies focused on floods and agricultural trade document important export effects in Asia (Tembata and Takeuchi, 2018; Nes et al., 2025). Less is known about whether major exporters exposed to similar climate hazards adjust their international shipments in the same direction relative to their domestic markets. South Asia provides an informative setting because India and Pakistan are important rice exporters but differ substantially in their market organization and policy context.

We address that gap by combining bilateral and domestic rice flows from the International Trade and Production Database for Estimation with annual flood counts from EM-DAT over the period 1986–2022. The estimation sample is restricted to South Asian exporters and includes their domestic flows and international shipments to observed destinations. We estimate the preferred model using Poisson Pseudo Maximum Likelihood with exporter-year, importer-year, and bilateral-pair fixed effects (Anderson and van Wincoop, 2003; Santos Silva and Tenreyro, 2006; Yotov et al., 2016; Correia et al., 2020). To assess economic significance, we complement the preferred relative estimates with supplementary PPML models estimated separately for domestic and international observations after relaxing exporter-year

fixed effects. These auxiliary estimates provide economic scale rather than an algebraic decomposition of the preferred coefficients; the full data construction, conversion formulas, fixed-effect comparison, and broader South Asian results are reserved for the chapter appendix. The empirical analysis focuses directly on exporter-specific responses within South Asia.

This paper design supports two contributions. The first is empirical. Incorporating domestic flows into a structural gravity framework allows us to ask whether each exporter's international shipments respond differently from its own domestic benchmark, and the answer differs sharply between India and Pakistan, the region's two principal rice exporters. We further place these relative effects in economic scale using supplementary separate-margin PPML estimates for domestic and international flows, while keeping the preferred exporter-year fixed-effects specification as the basis for identification. The second contribution is interpretive. India has restricted rice exports repeatedly during periods of domestic supply and price pressure, which offers a plausible reading of its more negative international response, while the export orientation of Pakistan's rice sector, and of basmati in particular, is consistent with a more favorable one. We treat these institutional differences as candidate mechanisms rather than as identified causes.

In the country estimates, India's international rice shipments respond about 28 percent more negatively than its domestic rice flows with each additional recorded flood; Pakistan's respond about 17 percent more favorably. A Wald test rejects equality of the India and Pakistan coefficients at the one percent level. The two estimates are also relative: they locate each country's international margin against its own domestic benchmark rather than establishing whether exports or domestic flows rise or fall in absolute terms. The supplementary analysis adds scale to this contrast. For India, the separate domestic-flow estimate is +3.6 percent ($p = 0.01$), while the international estimate is -1.7 percent ($p = 0.07$), corresponding to approximately US$56 million or 0.14 million tonnes on the international margin per additional recorded flood. Pakistan's separate domestic and international estimates are small

and statistically insignificant. For rice-importing countries, this suggests that the reliability of international supply during climate shocks turns on how the markets and institutions of major exporters transmit exposure, not on exposure alone.

4.2 Theoretical Background

4.2.1 Structural gravity and the domestic benchmark

Following the structural gravity literature, bilateral rice flows depend on exporter supply conditions, importer demand conditions, bilateral trade costs, and multilateral resistance (Armington, 1969; Anderson, 1979; Anderson and van Wincoop, 2003; Yotov et al., 2016). We account for these factors using exporter year, importer year, and bilateral pair fixed effects. Including domestic flows is important because it provides an internal benchmark against which the international margin can be compared (Bergstrand et al., 2015; Yotov, 2022).

Exporter year fixed effects absorb the direct effect of annual flood exposure and other exporter conditions common to all destinations in a given year. Consequently, the model does not identify whether floods reduce total rice production or total rice availability. The empirical question is narrower: does the international margin change relative to the domestic margin as flood exposure increases?

4.2.2 Flood exposure and relative market adjustment

Floods may affect rice markets through crop damage, harvest delays, transportation disruptions, storage losses, or other supply chain effects. In the main rice producing areas of India and Pakistan, the principal rice crop overlaps substantially with the summer monsoon. Flood exposure may therefore affect rice supply conditions, but our country year flood count does not identify the exact location, severity, or crop area affected by each event.

International and domestic flows may adjust differently when supply conditions change.

Governments may use export restrictions, public procurement, stock releases, or other food market measures to stabilize domestic prices and availability (Martin and Anderson, 2012; Hsiao et al., 2026). Weather shocks may also alter trade policy choices more generally (Amodio et al., 2025). Conversely, an exporter with a strongly export oriented rice sector may have commercial incentives to maintain foreign market relationships. These mechanisms motivate heterogeneous relative responses, but they are not directly observed in our regression. We therefore treat policy and market structure as interpretations of the estimated heterogeneity rather than as separately identified causal channels.

Let $Intl_{ij}$ equal one when exporter i and importer j are different countries and zero when $i = j$, which represents the constructed domestic flow. Let $Flood_{it}$ denote the annual number of EM DAT flood events recorded for exporter i in year t.

Let X_{ijt} denote the value of rice flows from exporter i to importer j in year t. We write $E\left[X_{ijt} \mid Z_{ijt}\right]$ for the expected value of rice flows conditional on the regressors and fixed effects collected in Z_{ijt}.

4.2.3 Global, regional, and SA countries specifications

We first estimate the average relative flood response across exporters in the global sample:

$$E[X_{ijt} \mid Z_{ijt}] = \exp\{\beta_1 \left(Flood_{it} \times Intl_{ij}\right) + \delta_{it} + \delta_{jt} + \delta_{ij}\}. \tag{4.1}$$

Here, X_{ijt} is the value of rice flows from exporter i to importer j in year t. The exporter year fixed effects, δ_{it}, absorb time varying exporter conditions and outward multilateral resistance. The importer year fixed effects, δ_{jt}, absorbs destination year demand conditions and inward multilateral resistance. Bilateral pair fixed effects, δ_{ij}, absorb time invariant bilateral trade costs and persistent differences in trade intensity.

To test whether South Asian exporters differ from exporters outside the region, we estimate a combined specification:

$$E[X_{ijt} \mid Z_{ijt}] = \exp\{\beta_1 (Flood_{it} \times Intl_{ij}) + \beta_2 (Flood_{it} \times Intl_{ij} \times SA_i) + \delta_{it} + \delta_{jt} + \delta_{ij}\}. \tag{4.2}$$

SA_i equals one for South Asian exporters and zero otherwise. In Equation (2), β_1 measures the relative flood response for exporters outside South Asia, while β_2 measures the additional response for South Asian exporters. The total South Asian response is therefore $\beta_1 + \beta_2$.

Because the paper focuses on heterogeneity within South Asia, the estimation sample is restricted to South Asian exporters and the main specification estimates country specific flood responses jointly:

$$E[X_{ijt} \mid Z_{ijt}] = \exp\left\{\sum_{k \in K} \beta_k (Flood_{it} \times Intl_{ij} \times Country_{ik}) + \delta_{it} + \delta_{jt} + \delta_{ij}\right\}. \tag{4.3}$$

K denotes the set of South Asian exporters for which sufficient domestic and international flow variation is available. $Country_{ik}$ equals one when exporter i is country k. Each coefficient β_k measures exporter k's international response relative to its own domestic flow benchmark for one additional recorded flood event.

For each estimated country coefficient, we report the relative percentage response using the following transformation:

$$\%\Delta = 100\,[\exp(\beta) - 1]. \tag{4.4}$$

The sign of β_k has a relative interpretation:

$\beta_k < 0$: international rice shipments respond more negatively than domestic rice flows as flood exposure increases.

$\beta_k = 0$: there is no differential response between international and domestic rice

flows. Either margin may still rise, fall, or remain unchanged.

$\beta_k > 0$: international rice shipments respond more favorably than domestic rice flows as flood exposure increases.

The sign alone does not identify the absolute change in exports or domestic flows. For example, a positive coefficient is consistent with exports falling less than domestic flows, exports remaining stable while domestic flows fall, or both margins increasing with international shipments increasing more. This distinction is especially important for interpreting Pakistan's positive estimate.

The supplementary economic-significance analysis introduced below relaxes the exporter-year fixed effects and estimates the domestic and international margins separately. Because this changes both the fixed-effects structure and the identifying variation, those coefficients are used only to provide economic scale and are not treated as an algebraic decomposition of the preferred relative estimates.

4.2.4 Institutional context for interpreting heterogeneity

The country coefficients can differ because the international and domestic margins need not adjust in the same way across exporters. India has repeatedly used rice export restrictions when domestic supply or price concerns intensified. In September 2022, the government prohibited broken rice exports and imposed an export duty on other non basmati rice categories. Further restrictions followed in 2023, after the 1986–2022 estimation window, and are cited only as subsequent institutional context (USDA Foreign Agricultural Service, 2022, 2023). These interventions provide a plausible institutional basis for a more negative international response relative to the domestic benchmark.

Pakistan presents a different market context. Rice is an important export commodity, and Pakistan is a major supplier of basmati and other long grain rice to foreign markets (USDA Foreign Agricultural Service, 2020; Pakistan Bureau of Statistics, 2024). This export orientation provides a plausible reason why its international margin may respond more

favorably relative to domestic flows. We do not interpret this as evidence that the government deliberately reallocates rice toward exports during floods. Rather, the contrast provides institutional context for interpreting the estimated country heterogeneity.

4.3 Data and Empirical Methodology

4.3.1 Data sources and scope

The estimation sample restricts exporters to eight South Asian countries: Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka. For these exporters, the sample includes domestic rice flows and international shipments to destinations observed in the International Trade and Production Database for Estimation. We obtain rice trade data, industry id 2, from Release 3 of ITPD E (Borchert et al., 2021; Larch et al., 2025).

ITPD E includes international flows, where exporter and importer are different countries, and constructed domestic flows, where exporter and importer are the same country. Domestic flows are derived from production and international trade information rather than observed internal shipments. They should therefore be interpreted as a constructed domestic market benchmark, not as household consumption or directly observed internal distribution. This distinction is important because the gravity coefficients compare international shipments with this domestic benchmark rather than identifying absolute domestic availability.

For the supplementary economic-significance exercise, international value magnitudes are evaluated using mean international rice-export values from the ITPD-E bilateral panel. Approximate physical-volume equivalents use an average rice export unit value of about US$400 per tonne and should therefore be read as scaling exercises rather than as directly observed quantity responses. Additional FAO production and gross-production-value variables used for descriptive scaling and export orientation will be documented in the chapter appendix; they do not enter the preferred gravity regressions.

Flood data come from the Emergency Events Database, EM DAT, which is widely used

in studies of disaster related economic shocks (Oh and Reuveny, 2010; Loayza et al., 2012; Felbermayr and Groschl, 2014). Our main measure is the annual number of recorded flood events for each exporter. The count preserves variation in annual flood exposure that would be lost in a simple any flood indicator. It should be interpreted as an exposure measure rather than a measure of flood intensity because it does not capture event severity, spatial overlap with rice producing areas, or the acreage affected.

Table 4.1 summarizes international rice observations and flood exposure for South Asian exporters. Mean trade values are measured in millions of current US dollars, consistent with the ITPD E trade variable.

Table 4.1: *Descriptive Statistics for International Rice Flows and Flood Exposure, South Asian Exporters, 1986 to 2022*

Exporter	International rice flows (obs.)	Mean rice export value	Cumulative flood events	Years observed
India	4,334	28.3	243	37
Pakistan	3,988	10.3	93	37
Sri Lanka	1,010	0.16	68	37
Bangladesh	592	0.27	75	37
Nepal	73	0.20	45	36
Afghanistan	50	0.17	96	37
Bhutan	51	0.06	3	29
Maldives	7	0.30	2	20

Flows are international rice observations in the ITPD E sample. Mean values are average international flow values per observation, measured in millions of current US dollars. Cumulative floods sum annual EM DAT flood event counts over the sample period. India and Pakistan account for the largest international rice samples in the region. Country estimates for very small exporters are interpreted cautiously because international trade and the domestic benchmark are sparse.

4.3.2 Empirical strategy

We estimate all specifications using the Poisson Pseudo Maximum Likelihood estimator with high dimensional fixed effects (Santos Silva and Tenreyro, 2006; Yotov et al., 2016; Correia et al., 2020). PPML accommodates zero trade flows directly and avoids the inconsistency that

can arise from log linear estimation under heteroskedasticity when the conditional mean is correctly specified. All preferred structural-gravity specifications include exporter-year, importer-year, and bilateral-pair fixed effects, with standard errors clustered at the bilateral-pair level. The supplementary separate-margin models described below intentionally use a different, less saturated fixed-effects structure so that the flood main effect can be estimated for each margin.

Identification follows the structural gravity literature incorporating domestic trade flows (Bergstrand et al., 2015; Yotov, 2022). Exporter year fixed effects absorb the main effect of flood exposure because the annual flood count is common to all flows from exporter i in year t. Identification therefore comes from the interaction between flood exposure and the international flow indicator: the model asks whether international shipments change relative to the domestic benchmark as annual flood exposure changes. Importer year fixed effects absorb destination specific demand conditions and inward multilateral resistance, while bilateral pair fixed effects control for persistent bilateral trade costs and baseline trade intensity.

Country specific flood interactions are estimated jointly for identified South Asian exporters. These estimates are informative only where a country has sufficient variation in flood exposure together with both international and domestic flow observations. The main empirical comparison focuses on India and Pakistan because they have the largest international rice samples in the region and their estimated responses are both economically large and statistically significant. Estimates for smaller exporters are reported for completeness but interpreted cautiously.

Figure 4.1 displays this identifying variation directly. It reports the number of EM-DAT flood events recorded for each South Asian exporter in each year, with darker cells indicating more events. India is the most flood-exposed exporter, with especially high counts in the mid-2000s, whereas Bhutan and the Maldives record almost no floods and are therefore not separately identified. This within-exporter variation in flood exposure over time, combined

with the presence of both domestic and international rice flows, is the variation that identifies the country-specific coefficients reported in the next section.

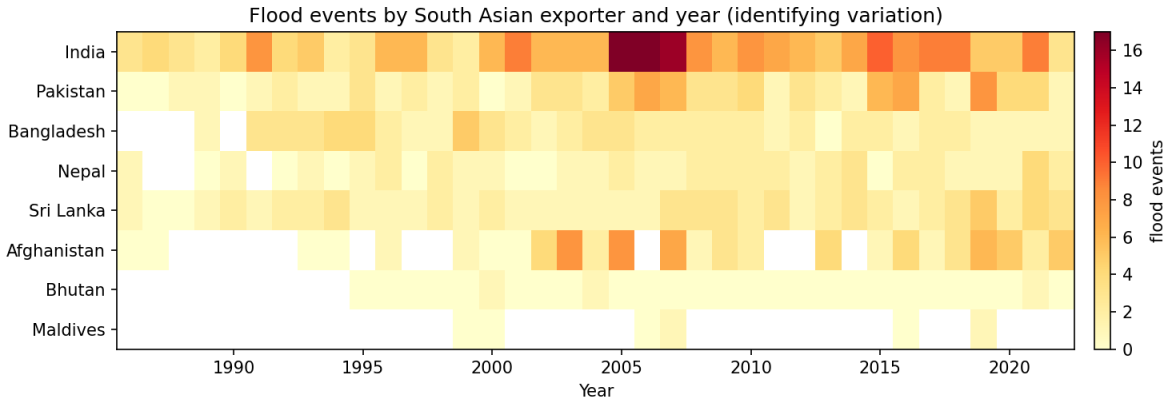


Figure 4.1: *Flood events by South Asian exporter and year, 1986 to 2022. Cell shading reports the number of EM-DAT flood events recorded for each exporter in each year; darker cells indicate more events. The figure summarizes the within-exporter, over-time variation in flood exposure that identifies the country-level estimates. Bhutan and the Maldives record almost no floods and are not separately identified.*

4.3.3 Supplementary economic-significance analysis

The preferred gravity specifications identify the international-versus-domestic differential but do not identify the absolute movement of either margin because exporter-year fixed effects absorb the flood main effect. To assess the economic scale of the India–Pakistan responses, we therefore estimate supplementary PPML models separately for domestic and international observations. These models relax the exporter-year fixed effects so that the flood coefficient is directly estimable for each margin. This change also alters the identifying variation, so the resulting coefficients are interpreted as complementary associations rather than as causal decompositions of the preferred gravity coefficients.

For domestic observations, where $i = j$, we estimate

$$\mathbb{E}[X_{iit} \mid Z_{iit}] = \exp\left\{\sum_{k \in K} \gamma_k^D \left(Flood_{it} \times Country_{ik}\right) + \alpha_i + \tau_t\right\}, \tag{4.5}$$

where α_i denotes exporter fixed effects and τ_t denotes year fixed effects. Standard errors are clustered by exporter. For international observations, where $i \neq j$, we estimate

$$\mathbb{E}[X_{ijt} \mid Z_{ijt}] = \exp\left\{ \sum_{k \in K} \gamma_k^I \left(Flood_{it} \times Country_{ik} \right) + \delta_{jt} + \delta_{ij} \right\}, \qquad i \neq j, \tag{4.6}$$

where importer-year fixed effects δ_{jt} absorb destination-specific demand conditions and inward multilateral resistance, while pair fixed effects δ_{ij} absorb time-invariant bilateral trade costs. Standard errors are clustered by pair. The coefficients γ_k^D and γ_k^I are not expected to reproduce the preferred relative coefficient algebraically because Equations (4.5) and (4.6) use different samples and a less saturated fixed-effects structure than Equation (4.3).

The auxiliary coefficients are converted to percentage terms using the same PPML transformation in Equation (4.4). For the international margin, the corresponding value change for country k is evaluated at its mean annual international rice-export value, $\overline{V}_k^I$:

$$\Delta V_k^I = \left[\exp\left(\widehat{\gamma}_k^I \right) - 1 \right] \overline{V}_k^I. \tag{4.7}$$

For ease of interpretation, we also report an approximate physical-volume equivalent by dividing the value change by an average rice export unit value of about US$400 per tonne. These conversions provide scale rather than a new causal estimand. The chapter appendix will document the full data construction, additional conversion formulas, the fixed-effect comparison, production-scaled domestic-flow equivalents, de-trended production comparisons, and the full South Asian auxiliary results; the present chapter reports only the India–Pakistan magnitudes needed to interpret the main findings.

4.4 Results

4.4.1 Global, regional, and country responses

Table 4.2 reports the flood interactions at the global, regional, and country levels. At the global level, the coefficient is small and statistically insignificant. In the combined specification, the additional South Asia interaction is also statistically insignificant. The implied combined point estimate for South Asian exporters is close to zero in magnitude, which is consistent with offsetting country responses rather than a common regional pattern.

The country estimates reveal substantial heterogeneity. India's international rice shipments respond about *28* percent more negatively than its domestic rice flows with each additional recorded flood. Pakistan exhibits the opposite sign: its international rice shipments respond about *17* percent more favorably relative to domestic flows. Both estimates are statistically significant, but they describe relative international versus domestic responses and do not identify the absolute movement of either margin.

To assess whether these two responses differ from one another, and not merely in sign, we conduct a Wald test of the null hypothesis that the Indian and Pakistani coefficients are equal, $\beta_{\text{India}} = \beta_{\text{Pakistan}}$. The test rejects equality at the one percent level ($\chi 2(1) = 15.8$, $p < 0.001$); the estimated difference between the two coefficients is -0.49 with a standard error of 0.12. India's and Pakistan's international rice shipments therefore respond to flood exposure in statistically distinct ways, which supports the paper's emphasis on their contrasting responses rather than on the sign or significance of either coefficient alone.

The remaining country estimates are less informative. Sri Lanka's estimate is near zero and statistically insignificant, while Nepal's is negative but imprecisely estimated. Bangladesh has a large positive estimate, but it is a net rice importer with comparatively thin and sporadic exports, so we do not emphasize it. The central empirical finding is therefore the contrasting relative responses of India and Pakistan.

Table 4.2: *Country Specific Flood Responses of International Rice Shipments Relative to Domestic Flows*

Exporter	Coefficient	% Δ per additional recorded flood	p value
Global: Flood × International	-0.019	-1.9	0.20
South Asia	+0.024	+2.4	0.79
India	-0.331	-28.1	0.001
Pakistan	+0.161	+17.4	0.03
Sri Lanka	-0.010	-0.9	0.90
Bangladesh	+0.660	+93.5	< 0.01
Nepal	-0.253	-22.4	0.65

Percentage responses are computed using Equation (4.4), $100 \times [\exp(\beta_k) - 1]$. *Coefficients identify the response of international rice shipments relative to the exporter's constructed domestic flow benchmark for one additional recorded flood event. They do not identify the absolute movement of either margin. Standard errors are clustered by bilateral pair. Bangladesh's estimate should be interpreted cautiously because its international rice exports are comparatively thin and sporadic. A Wald test rejects the null hypothesis of equal Indian and Pakistani coefficients* ($\chi^2(1) = 15.8,\ p < 0.001$).

4.4.2 Economic significance of the India–Pakistan responses

The preferred country estimates in Table 4.2 and the formal coefficient-equality test remain the basis for interpreting the contrasting India–Pakistan international-versus-domestic responses. The supplementary models in Equations (4.5) and (4.6) provide an additional sense of economic scale by estimating the domestic and international margins separately. Because these models do not retain exporter-year fixed effects, their coefficients should be interpreted as complementary associations rather than as the same estimand as the preferred gravity coefficients.

For India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure ($p = 0.01$). The supplementary international-flow estimate is -1.7 percent ($p = 0.07$), which is not statistically significant at the conventional 5 percent level. Evaluated at India's mean international rice-export value, the international estimate corresponds to approximately US$56 million per additional recorded flood. Using the

Table 4.3: *Supplementary Economic Magnitudes for India and Pakistan*

Country	Domestic response	International response	Approx. international value change	Approx. international volume change
India	+3.6% ($p = 0.01$)	-1.7% ($p = 0.07$)	-US$56 million	-0.14 Mt
Pakistan	-0.4% (n.s.)	+1.3% (n.s.)	+US$15 million	+0.04 Mt

Notes: Responses are per additional recorded flood. Domestic and international responses are from the supplementary separate-margin PPML specifications and provide economic scale; they are not an algebraic decomposition of the preferred relative gravity estimates. International value changes are evaluated using mean annual international rice-export values from the ITPD-E bilateral panel. Approximate tonnage uses an average rice export unit value of about US$400 per tonne. n.s. denotes not statistically significant at the 5 percent level.

approximate US$400-per-tonne export unit value, this value change is equivalent to about 0.14 million tonnes. The positive domestic association and the negative international estimate are directionally consistent with the preferred negative international-versus-domestic differential, but the auxiliary estimates do not establish deliberate domestic retention or reallocation.

For Pakistan, the corresponding separate-margin estimates are -0.4 percent for the constructed domestic-flow measure and +1.3 percent for international shipments; neither estimate is statistically significant at the 5 percent level. The international estimate corresponds to approximately US$15 million, or about 0.04 million tonnes using the same approximate unit-value conversion. Thus, the auxiliary models do not identify a statistically detectable absolute change in either Pakistani margin even though the preferred structural-gravity model identifies a positive international-versus-domestic differential.

Taken together, the supplementary estimates provide economic scale without changing the interpretation of the main model. The exporter-year fixed-effects specification and the formal India–Pakistan equality test remain the central evidence on heterogeneous relative responses. The separate-margin regressions are useful for showing the approximate magnitude of the domestic and international associations, but they do not isolate the policy or institutional mechanisms that generate the cross-country difference.

4.4.3 Contrasting responses of India and Pakistan

Figure 4.2 provides the descriptive backdrop for this contrast. It plots the two countries' rice exports and their annual flood exposure over the sample period. India is both the larger rice exporter and the more flood-exposed of the two, which is why adjustment on its international margin has implications for the world rice market; Pakistan's exports are smaller and more consistently export-oriented, consistent with its opposite-signed response.

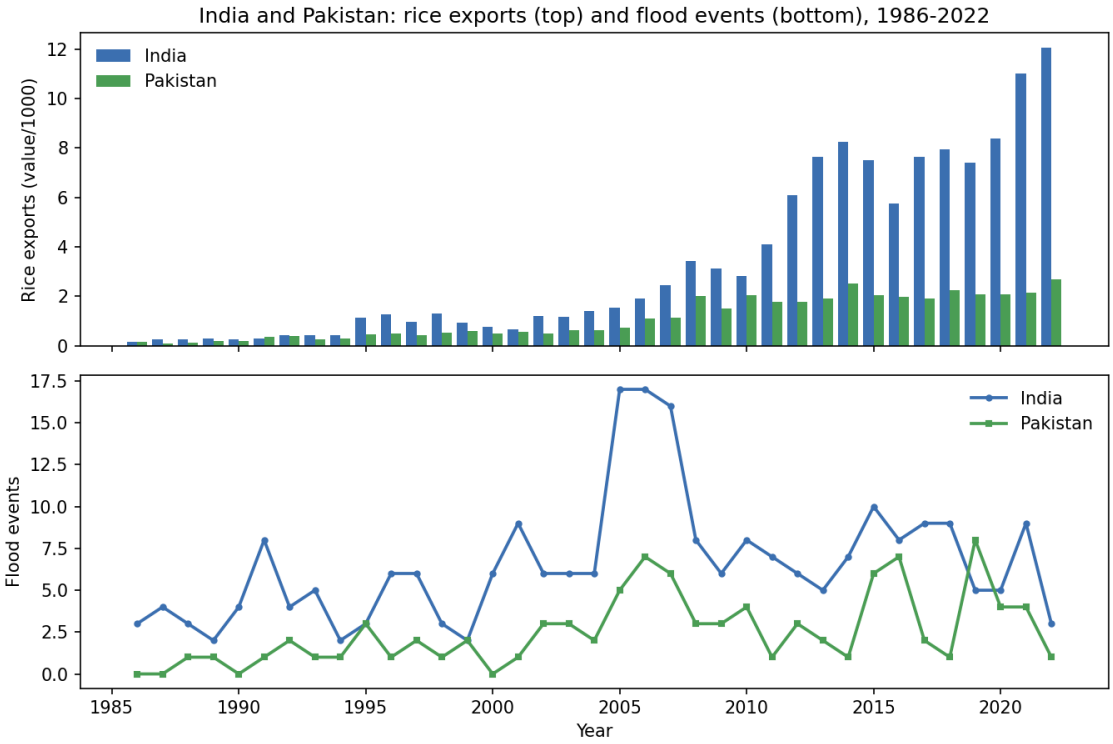


Figure 4.2: *India and Pakistan rice exports (top panel, export value) and annual flood events (bottom panel), 1986 to 2022. India is both the larger exporter and the more flood-exposed of the two.*

India's negative coefficient is consistent with an institutional setting in which domestic market stabilization can place greater adjustment on the international margin. The interpretation is supported by documented policy behavior rather than by a policy variable in our regression. In September 2022, India prohibited exports of broken rice and imposed a 20 percent export duty on white rice other than basmati and parboiled rice amid tighter do-

mestic supply conditions (USDA Foreign Agricultural Service, 2022). Additional restrictions followed in 2023, after the estimation sample, including a prohibition on non basmati white rice exports (USDA Foreign Agricultural Service, 2023). The 2023 measure is therefore cited only as post-sample institutional context. These episodes show that the Indian government has actively used the export margin when domestic rice market conditions become a policy concern. They make a negative international relative to domestic coefficient economically plausible, but they do not prove that the estimated flood coefficient is caused by a particular restriction.

Pakistan's positive coefficient has a different interpretation. It does not mean that floods increase rice exports in absolute terms or that domestic flows necessarily decline. It means only that the international margin responds more favorably relative to the domestic benchmark as flood exposure increases. Pakistan is a major exporter of basmati and other rice varieties, and basmati accounts for substantial export value (USDA Foreign Agricultural Service, 2020; Pakistan Bureau of Statistics, 2024). This stronger export orientation provides a plausible market based explanation for a more favorable relative international response. However, unlike the documented Indian restrictions, our evidence does not establish a specific Pakistani policy that deliberately protects exports during flood years.

The two estimates therefore illustrate the relative interpretation of the gravity coefficient. India's negative coefficient indicates a more negative international response relative to domestic flows, while Pakistan's positive coefficient indicates a more favorable international response relative to domestic flows. These are market response comparisons, not estimates of absolute export changes.

4.5 Discussion

The results show that flood exposure does not generate a uniform rice trade response across South Asian exporters. India's international rice shipments respond substantially more neg-

atively relative to domestic flows, while Pakistan's respond more favorably. This exporter heterogeneity is the central finding of the paper.

The supplementary economic-significance exercise sharpens the magnitude of this contrast without changing its interpretation. For India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments; the latter is statistically insignificant at the 5 percent level but corresponds to approximately US$56 million or 0.14 million tonnes in the scaling exercise. For Pakistan, the separate domestic and international estimates are -0.4 percent and +1.3 percent, respectively, and neither is statistically significant. Because these auxiliary models relax exporter-year fixed effects, they are used to characterize economic scale rather than to replace the preferred relative estimates or the formal India–Pakistan equality test.

Policy and market structure provide a plausible interpretation of the contrast, but they should not be treated as identified causal mechanisms. India's documented use of rice export restrictions during periods of domestic supply and price pressure is consistent with a more negative international margin. Pakistan's export oriented rice sector, especially basmati, is consistent with a more favorable international response. The evidence therefore suggests that the transmission of flood exposure into trade can depend on exporter specific institutions and market incentives, even among countries facing the same broad class of climate hazard.

These findings extend the literature on climate shocks and agricultural trade. Existing studies show that weather shocks and natural disasters can affect trade and agricultural exports (Gassebner et al., 2010; Tembata and Takeuchi, 2018; Nes et al., 2025). Our contribution is to show that the international response relative to domestic flows can differ sharply across major exporters, including in sign. This matters for trade based adaptation because importing countries rely on a limited number of exporters to continue supplying international markets during climate stress.

Several limitations qualify the interpretation. Flood exposure is measured as a country-

year event count and does not capture severity, location, or spatial overlap with rice-producing areas. Domestic flows are constructed from production and international trade data rather than observed internal shipments. The preferred gravity coefficients identify a relative international-versus-domestic response and do not identify the absolute movement of either margin. The supplementary separate-margin regressions relax exporter-year fixed effects in order to identify the flood coefficient directly for each margin; they therefore do not absorb outward multilateral resistance and other exporter-year shocks as completely as the preferred specification and should be interpreted as associations. The approximate tonnage conversions also rely on an average export unit value of about US$400 per tonne. Finally, policy mechanisms are inferred from institutional context rather than directly estimated, and the 2023 Indian export restriction is outside the 1986–2022 estimation period and is used only as post-sample context. Future work combining spatial flood exposure, crop production locations, and time-varying trade policy measures could distinguish more directly between production damage, supply-chain disruption, and policy responses.

4.6 Conclusion

This paper examines whether flood exposure changes international rice shipments relative to domestic rice flows across South Asian exporters. Using a structural gravity framework with domestic flows and Poisson Pseudo Maximum Likelihood, we find substantial exporter heterogeneity. India's international rice shipments respond about 28 percent more negatively than its domestic flows with each additional recorded flood, while Pakistan's respond about 17 percent more favorably relative to domestic flows.

The supplementary separate-margin estimates add economic scale to this relative contrast. For India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments, equivalent to approximately US$56 million or 0.14 million tonnes on the international

margin; the international estimate is not statistically significant at the 5 percent level. Pakistan's separate domestic and international estimates are small and statistically insignificant. These auxiliary magnitudes are complementary to the preferred model: the exporter-year fixed-effects estimates and the formal coefficient-equality test remain the basis for the conclusion that India and Pakistan exhibit statistically different international-versus-domestic responses.

The opposite signs provide a useful framework for interpreting market adjustment after climate shocks. India's negative response is consistent with its documented use of the export margin to stabilize domestic rice markets, while Pakistan's positive response is consistent with the stronger export orientation of its rice sector. These mechanisms are plausible interpretations, not directly identified policy effects.

For import dependent economies, the broader implication is that the reliability of international rice trade during climate shocks depends not only on flood exposure but also on how major exporters' markets and policies transmit that exposure across domestic and foreign margins. More spatially detailed flood data and explicit measures of trade policy would be natural next steps for identifying those mechanisms more directly.

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Chapter 5

Conclusion

5.1 Summary of findings

This dissertation brings together three essays that examine complementary margins through which extreme weather is associated with agricultural market outcomes. Chapter 2 studies the relationship between extreme heat and corn and soybean production value in the U.S. Midwest. Chapters 3 and 4 study a different margin: whether international rice shipments respond differently from domestic rice flows as flood exposure changes in Southeast Asia and South Asia. The dissertation therefore does not identify a single causal sequence running from weather to production and then to trade. Instead, the three essays provide evidence on distinct production and trade-response margins within a common research program on extreme weather, agricultural markets, and international trade.

Chapter 2 finds that extreme heat, measured using heating degree days, is associated with statistically significant reductions in corn and soybean production value across twelve Midwestern states from 2000 to 2022. The economic magnitudes implied by the common HDD coefficient differ across states when the coefficient is scaled by each state's historical year-to-year variation in heat exposure. The chapter also examines the Economic Research Service (ERS) state export allocation as a secondary cash-receipts-based constructed outcome. Be-

cause the ERS series allocates national export value across states using state cash-receipt shares, it is not a measure of observed state-level export shipments. With year fixed effects, common national export-value movements are absorbed, so the identifying variation in the allocation comes from within-state changes in relative cash-receipt or production-value shares. The smaller estimated HDD response of the ERS allocation relative to production value is therefore interpreted as a measurement difference between the ERS cash-receipts-based series and NASS production value, not as evidence that physical exports are buffered from heat.

Chapter 2 also uses CMIP6 climate projections under SSP245 and SSP585 in an exploratory scenario exercise through 2100. The scenarios indicate greater heat exposure and increasing dispersion in projected production value, particularly under SSP585. These exercises extend historical weather–production relationships while holding prices, technology, and adaptation behavior fixed. They should therefore be interpreted as scenario-based illustrations of future production risk rather than as precise forecasts of future production or exports.

Chapter 3 examines bilateral and domestic rice flows from 1986 to 2022 using a structural gravity framework estimated with Poisson Pseudo-Maximum Likelihood and exporter-year, importer-year, and bilateral-pair fixed effects. At the global level, the estimated differential response to flood exposure is not statistically significant. For Southeast Asian exporters, however, each additional flood is associated with an approximately 15 percent more negative response of international rice shipments relative to domestic rice flows. Country-level estimates are particularly negative for Vietnam and Thailand. These preferred coefficients identify a differential international-versus-domestic response rather than the absolute movement of either margin. To provide economic scale, supplementary separate-margin PPML estimates show that Thailand's international rice shipments are associated with a 6.5 percent decline, approximately US$194 million or 0.49 million tonnes per additional recorded flood, while its constructed domestic-flow response is not statistically significant. The corre-

sponding separate-margin estimates for Vietnam are smaller and statistically insignificant. Because these supplementary models relax the exporter-year fixed-effects structure, they are interpreted as complementary magnitude evidence rather than as a decomposition of the preferred gravity coefficient.

Chapter 4 applies the same relative-trade framework to South Asia. The aggregate South Asian response is not statistically significant, but the exporter-specific estimates reveal substantial heterogeneity. With each additional flood, India's international rice shipments respond approximately 28 percent more negatively than its domestic rice flows, whereas Pakistan's international rice shipments respond approximately 17 percent more favorably relative to its domestic flows. A formal Wald test rejects equality of the India and Pakistan coefficients, confirming that the two estimated relative responses are statistically different. Supplementary separate-margin estimates provide additional scale: for India, an additional recorded flood is associated with a 3.6 percent increase in the constructed domestic-flow measure and a 1.7 percent decline in international shipments, with the latter estimate statistically insignificant at the 5 percent level and corresponding to approximately US$56 million or 0.14 million tonnes. Pakistan's separate domestic and international estimates are both statistically insignificant. These auxiliary estimates complement, rather than replace, the preferred relative results. India's documented use of rice export restrictions during periods of domestic supply and price pressure and Pakistan's export-oriented rice sector provide plausible institutional context for interpreting the contrast, but the empirical design does not identify these institutional differences as the causes of the estimated flood responses.

5.2 What the three essays collectively show

Taken together, the three essays illuminate two related but empirically distinct margins of weather-related agricultural risk. The first is the production-value margin: Chapter 2 shows that extreme heat is associated with lower corn and soybean production value in the U.S.

Midwest. The second is the relative trade-response margin: Chapters 3 and 4 show that flood exposure can be associated with different responses of international rice shipments relative to domestic rice flows. The dissertation connects these margins conceptually, but it does not estimate a structural transmission mechanism linking the Chapter 2 production response to the trade responses estimated in Chapters 3 and 4.

A second common finding is heterogeneity. In Chapter 2, a common estimated HDD relationship translates into different one-standard-deviation economic magnitudes across states because historical heat variability differs across locations. In Chapter 3, the global average conceals a statistically significant Southeast Asian relative response, and the country-level results are especially negative for Vietnam and Thailand. In Chapter 4, the South Asian aggregate is statistically insignificant even though India and Pakistan exhibit large, opposite-signed, and statistically different relative responses. These results show that regional or global averages can conceal economically important differences across locations and exporters. They do not, by themselves, establish which specific institutional, policy, or market characteristics cause those differences.

A third lesson concerns measurement and identification. The economic interpretation of an empirical result depends on how the outcome is constructed and on the variation retained by the fixed-effects specification. In Chapter 2, the ERS state export allocation is a constructed cash-receipts-based allocation and contains no direct information on physical state export shipments. In Chapters 3 and 4, exporter-year fixed effects absorb exporter-wide annual conditions, including the main effect of flood exposure, so the preferred coefficients identify how the international margin changes relative to the domestic benchmark. The supplementary economic-significance exercises relax this fixed-effects structure to estimate the domestic and international margins separately and thereby provide scale, but they use different identifying variation and should not be interpreted as algebraic decompositions of the preferred relative estimates. These distinctions narrow the claims that can be made, but they also make the interpretation of the dissertation's findings more transparent and

internally consistent.

Finally, the results are relevant to agricultural and food-trade resilience because they show that weather exposure can be associated with both weaker production-value outcomes and heterogeneous relative trade responses in major producing and exporting regions. The evidence does not imply that every weather shock produces a particular trade adjustment or that the same mechanism operates across settings. Rather, it suggests that assessments of climate-related market risk should distinguish between production exposure, international-versus-domestic trade responses, and the institutional context in which those responses occur.

5.3 Policy implications

The policy implications of the dissertation should be interpreted as implications of the estimated risks rather than as evaluations of specific policy interventions. Chapter 2 provides evidence that extreme heat is associated with lower corn and soybean production value and that production-value risk may become more pronounced under the exploratory high-emission scenario. These findings support continued attention to heat resilience and agricultural risk management in major producing regions. Measures such as crop and technology adaptation, risk-management instruments, and inventory or marketing strategies may be relevant responses to production-side climate risk, but the Chapter 2 estimates do not evaluate the effectiveness or cost-effectiveness of any particular intervention.

For international staple markets, Chapters 3 and 4 suggest that climate-risk assessment should account for the concentration of export supply and for heterogeneous responses across major exporters. The Southeast Asian results show that the international margin can respond more negatively relative to the domestic benchmark during years with greater flood exposure, while the South Asian results show that the direction and magnitude of this relative response can differ sharply across exporters. For import-dependent countries and organizations concerned with food-market risk, diversification of sourcing and monitoring of

conditions in major exporting countries are therefore reasonable risk-management considerations. The dissertation does not quantify the gains from diversification or establish that a particular monitoring system would prevent supply disruptions.

The South Asian evidence also indicates that regional averages may be insufficient for policy analysis when major exporters operate under different market institutions and policy environments. India's history of rice export restrictions and Pakistan's strong export orientation provide plausible context for their contrasting estimates, but these factors are not separately identified in the empirical model. Policy analysis should therefore use institutional information to interpret exporter-specific risk while avoiding the assumption that a documented institutional feature necessarily caused a particular estimated response.

More broadly, the findings are consistent with a view of food-trade resilience in which both production exposure and the reliability of major exporters matter. Existing market systems can transmit or absorb shocks through prices, inventories, trade, and policy responses, but the present dissertation identifies only selected margins of that broader adjustment process. Policies designed to strengthen resilience should therefore be informed by evidence on these multiple margins rather than by assuming that production shocks translate mechanically into export outcomes.

5.4 Limitations and future research

Several limitations define priorities for future research. First, Chapter 2 studies production value rather than a complete physical supply-and-trade system. The ERS state export allocation does not measure physical state-level shipments, and its fixed-effects variation should not be used to infer state export behavior. Shipment-level information from rail, barge, truck, port, or firm-level sources, where consistently available, would make it possible to test directly whether weather-related changes in production outcomes are followed by changes in physical shipment patterns. Such data could also be combined with transportation

costs, local basis measures, and inventory information to study the links among production, storage, logistics, and trade without relying on a cash-receipts-based allocation measure.

Second, the Chapter 2 climate exercise is intentionally exploratory. It applies historical estimated weather–production relationships to future CMIP6 scenarios while holding relative prices, technology, and adaptation behavior fixed. Future work could incorporate endogenous adaptation, technological change, price adjustment, crop switching, and other behavioral responses when evaluating longer-run climate risk.

Third, the preferred rice-trade specifications identify differential international-versus-domestic responses rather than absolute changes in either margin. Chapters 3 and 4 now complement those estimates with separate-margin PPML regressions that provide economically interpretable associations for domestic and international flows, but these auxiliary specifications relax exporter-year fixed effects and therefore rely on different identifying variation. They should not be interpreted as the same estimand as the preferred gravity coefficients or as causal decompositions of those coefficients. In addition, the domestic benchmark is constructed from the available trade and production data and should not be interpreted as observed household consumption, internal shipments, or domestic food availability. Future work could combine the structural gravity framework with more direct measures of domestic trade, production, stocks, prices, and policy interventions to characterize absolute market adjustments alongside the relative trade response.

Fourth, the annual EM-DAT flood count is a broad measure of exposure. It does not capture the location of each event relative to rice-producing areas, the depth or duration of flooding, crop-calendar timing, infrastructure damage, or the share of production directly affected. Linking spatial flood measures with crop calendars, subnational production data, transportation networks, and market locations would improve measurement of the economic exposure associated with individual flood events.

Finally, the exporter heterogeneity documented in Chapters 3 and 4 motivates further research on the mechanisms behind differential trade responses. Export restrictions, procure-

ment systems, stock policies, market concentration, contractual arrangements, transportation constraints, and export orientation are plausible channels, but they are not separately identified in the present models. Future studies could combine trade data with explicit policy and institutional measures or exploit policy changes and other sources of quasi-experimental variation to test which mechanisms explain why international shipments respond more negatively or more favorably relative to domestic flows in different exporting countries. Extending the analysis across commodities and regions would also help establish how general these patterns are.

Overall, this dissertation provides evidence on complementary production and trade-response margins rather than on a single causal pathway from weather to production to international trade. Chapter 2 shows that extreme heat is associated with lower corn and soybean production value in the U.S. Midwest. Chapters 3 and 4 show that flood exposure is associated with differential international-versus-domestic rice-trade responses that vary substantially across regions and exporters, while supplementary separate-margin estimates provide additional evidence on the economic scale of selected country responses. Together, the essays demonstrate the importance of heterogeneity, careful measurement, and disciplined interpretation when evaluating extreme-weather risks in agricultural markets. These findings provide a basis for further work on how production, market institutions, and international trade jointly shape the resilience of agricultural and staple-food systems under changing weather risk.

Statement on the Use of Generative Artificial Intelligence

Generative artificial intelligence tools, including ChatGPT and Claude, were used during the preparation of this dissertation to assist with language editing, organization and clarity, LaTeX formatting, consistency checks, and revision of selected portions of text. All AI-assisted content was reviewed, revised, and verified by the author. The research questions, data preparation, empirical methods, statistical analyses, interpretation of results, conclusions, and final scholarly decisions were the responsibility of the author.

Appendix A

Chapter 2: Supporting Information Appendix

Weather Extremes, Production Value, and Export Allocations: Evidence from Corn and Soybeans in the U.S. Midwest

Atif Rao and Nelson Villoria

A.1 Data Appendix

A.1.1 Grid-Cell PRISM, NorESM2 and CESM2 Summary Statistics

The following table reports summary statistics for the raw daily PRISM grid-cell weather data, before aggregation to the state-year level. These statistics were previously shown in the main text; because the empirical analysis is conducted at the state-year level, we now report the state-year aggregates in main-text Table 1 and retain the grid-cell statistics here.

Future climate projections data obtained from two CMIP6 global climate models (GCM), NorESM2-MM and CESM2, under the SSP245 (intermediate-stabilization) and SSP585

Table A1.1a: *PRISM Daily Grid-Cell Weather Summary Statistics (2000–2022)*

Variable	Observations	Mean	Std. dev.	Min	Max
Minimum temperature (tmin)	1,056,234,698	2.86	11.40	-43.92	31.16
Maximum temperature (tmax)	1,056,234,698	15.29	12.52	-31.75	46.59
Precipitation (Prec)	1,056,234,698	2.15	5.37	0	230.64

Notes: The number of observations refers to grid-cell-by-day records pooled across the sample. Minimum daily temperatures are reported with their correct signs (for example, the tmin minimum of -43.92 °C reflects deep winter readings); an earlier version of this table omitted the negative signs, which is the inconsistency noted by Reviewer 2 (Comment 5) and is corrected here.

(high-emission) scenarios. The daily values for the weather variables from both models, including tmin, tmax and Prec are presented in appendix tables (A1.1b to A1.1e). We processed daily minimum and maximum temperatures and precipitation for 2023–2100 to construct the same variables (GDD, HDD, Prec, Fr) using identical methods as for the historical PRISM data.

Table A1.1b: *CMIP6 GCMs (NorESM2-MM SSP245) Weather Summary Statistic (2023–2100)*

Variable	Observations	Mean	Std. dev.	Min	Max
tmin	18,044,480	16.80215	9.782123	-33.96542	37.1454
tmax	18,044,480	27.72336	10.87398	-25.54804	53.3579
Prec	18,044,480	2.204837	5.265147	0	208.6724

Table A1.1c: *CMIP6 GCMs (NorESM2-MM SSP585) Weather Summary Statistic (2023–2100)*

Variable	Observations	Mean	Std. dev.	Min	Max
tmin	18,044,480	17.94314	10.08122	-30.78745	40.27093
tmax	18,044,480	28.8673	11.09826	-22.92049	54.69854
Prec	18,044,480	2.234672	5.377005	0	206.625

Table A1.1d: *CMIP6 GCMs (CESM2 SSP245) Weather Summary Statistic (2023–2100)*

Variable	Observations	Mean	Std. dev.	Min	Max
tmin	19,397,816	17.04045	9.574401	-29.22893	37.65063
tmax	19,397,816	27.37639	10.45811	-20.53652	53.22128
Prec	19,397,816	2.36462	5.703299	0	248.9889

Table A1.1e: *CMIP6 GCMs (CESM2 SSP585) Weather Summary Statistic (2023–2100)*

Variable	Observations	Mean	Std. dev.	Min	Max
tmin	19,397,816	18.55976	9.86929	-33.93147	42.71859
tmax	19,397,816	28.94291	10.69336	-21.16988	56.81399
Prec	19,397,816	2.256649	5.689609	0	266.8179

A.1.2 Descriptive Statistics of Key Variables Used in Empirical Analysis

Table A1.2: *Descriptive Statistics of Key Variables Used in the Empirical Analysis*

Variable	Mean	Std. dev.	Min	Max
GDD	3500.87	427.75	2721.87	4429.08
HDD	40.970	38.28	1.08	207.369
Prec	599.11	151.61	249.95	1117.72
Freezing	16.04178	9.162646	1.725329	47.17808
Corn Yield	151.9457	26.25	75	214
Corn ERS Allocation	661.2012	595.434	36.97404	3302.094
Corn Production	3.55e+09	3.13e+09	1.52e+08	1.64e+10
Soybean Yield	43.94384	8.868818	20	65
Soybean ERS Allocation	1141.917	909.2514	70.33143	5506.143
Soybean Production	2.42e+08	1.45e+08	4.68e+07	6.83e+08

A.1.3 Aggregation of Grid-Cell Weather to the State-Year Level

Weather exposure is constructed at the level of individual PRISM grid cells and then aggregated to the state-year level, adopting the within-cell exposure construction of Schlenker and Roberts (2009). For each 2.5 × 2.5 mile PRISM grid cell, we use a sinusoidal interpolation between the daily minimum and maximum temperatures to approximate the within-day temperature distribution. For each 1 °C threshold, this procedure calculates the fraction of the day above the threshold and the corresponding degree-day exposure. We then use differences in the time-above-threshold measures to construct exposure in each 1 °C temperature bin.

Computing these nonlinear degree-day quantities for each grid cell before spatial aggregation preserves within-state temperature heterogeneity that would be lost if temperatures were averaged before the nonlinear transformation. We aggregate the grid-cell daily measures to the state-day level by averaging across PRISM grid cells within each state. We then aggregate from the state-day level to the state-year growing-season level by summing precipitation, freezing exposure, degree days, and temperature-bin exposure over the growing season.

Because the empirical outcomes are observed at the state-year level, this aggregation is designed to summarize broad growing-season exposure within each state and to match the resolution of the USDA-NASS production data and the ERS export series. More spatially detailed weighting schemes could be explored in future work if comparable county-level production and export outcomes become available.

A.1.4 Annual Distribution of Weather Variables (2000–2022)

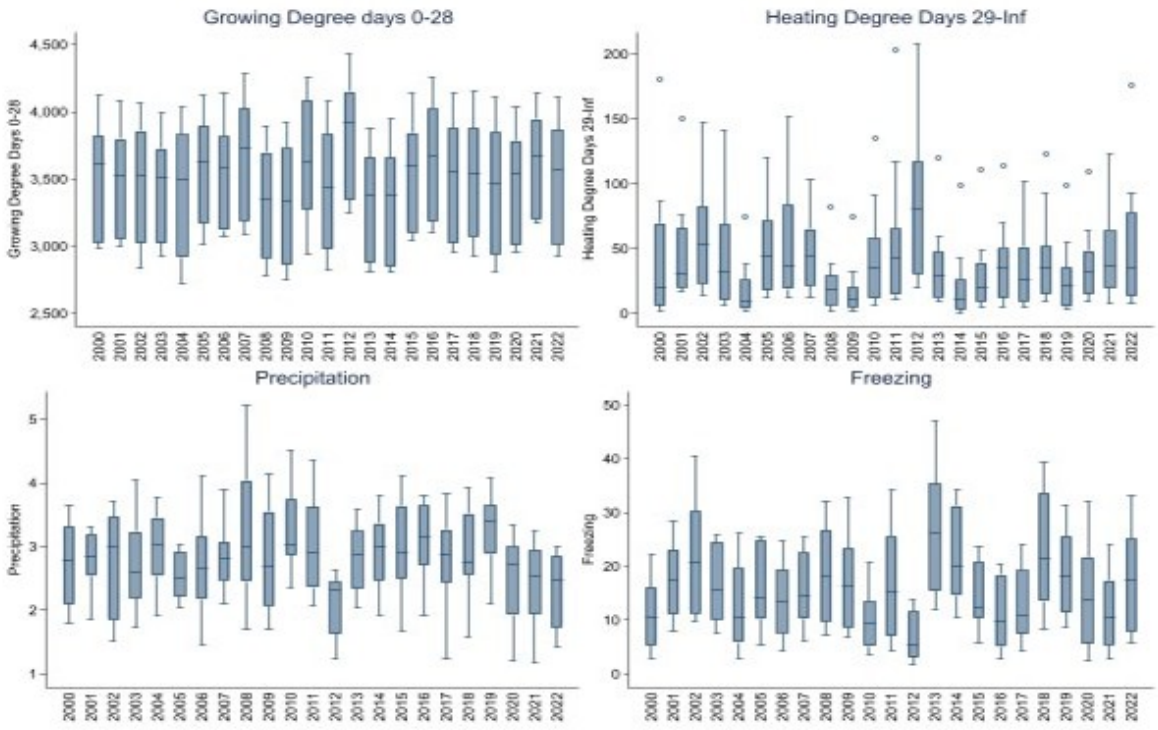


Figure A.1: *Annual Distribution of Growing Degree Days (0-28°C), Heating Degree Days (29°C-Inf), Precipitation, and Freezing Events in Midwestern U.S. States (2000-2022). Each box plot illustrates the median, interquartile range, and potential outliers for these key climatic variables over the study period.*

A.1.5 State-Level Trends in Corn ERS Export Allocation (2000–2022)

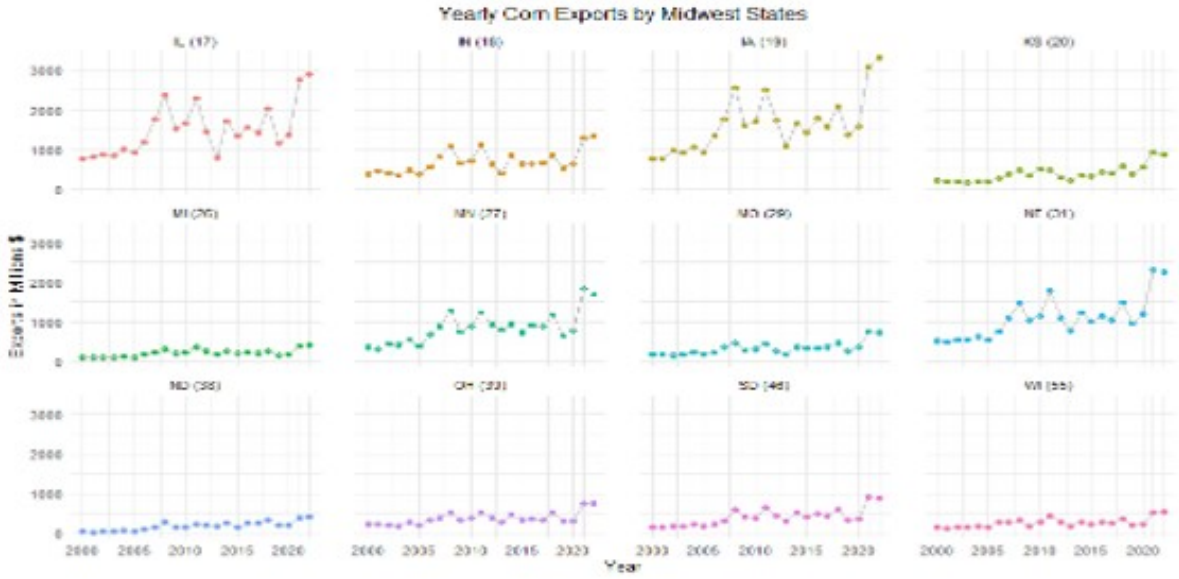


Figure A.2: *Yearly Corn ERS Export Allocation in Millions of Dollars by Individual Midwest States (2000-2022)*

A.1.6 State-Level Trends in Soybean ERS Export Allocation (2000–2022)

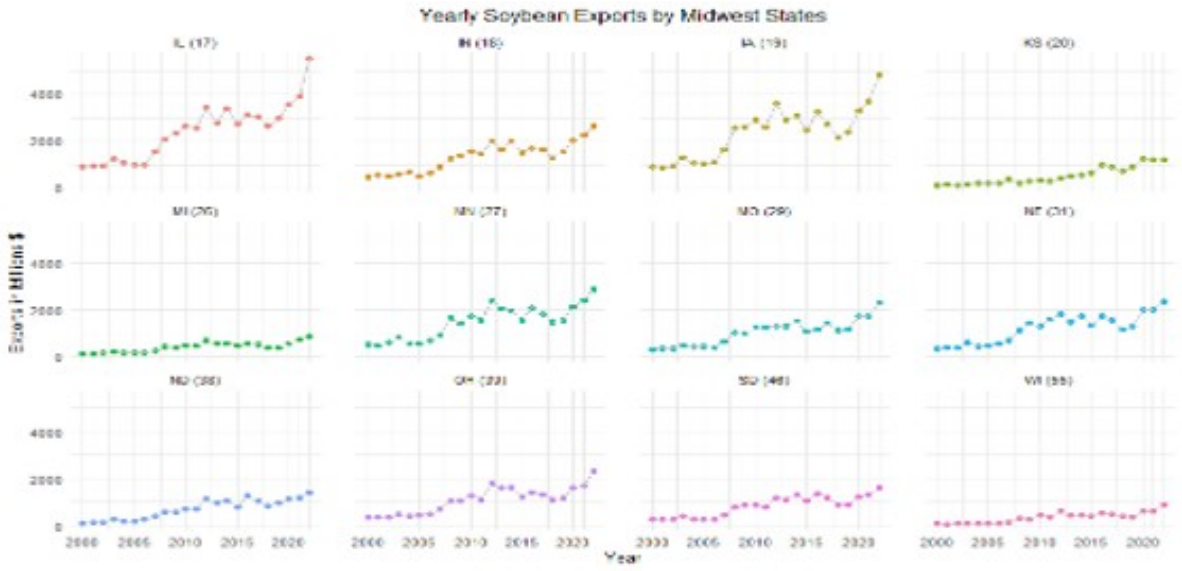


Figure A.3: *Yearly Soybean ERS Export Allocation in Millions of Dollars by Individual Midwest States (2000-2022)*

A.1.7 Data Strengths and Limitations of the ERS Export Allocation

This study uses the USDA's State Exports, Cash Receipts (CR) Estimates data. We state its central limitation first. The series is not a measure of exports: it allocates national export value to states in proportion to each state's share of national farm cash receipts (production value). Consequently, it contains no direct information on physical shipments, export timing, destination markets, port location, transportation costs, or state-specific export propensity. In regressions with year fixed effects, the national export-value component is absorbed by construction, so the remaining identifying variation is within-state variation in production-value (cash-receipts) shares, not independent variation in export behavior. The genuine strengths of the series are narrower: it provides consistent state-level coverage over the full sample period, and because it is denominated in value terms it is directly comparable to farm cash receipts, which supports the production-value analysis in this paper.

However, readers must note the following limitations. The cash receipts method does not measure physical shipments; instead, it estimates state exports by assuming they have the same share of national exports as they do of national production value. This approach has a significant drawback: it assumes all states have an equal propensity to export, regardless of location or access to transportation. As a result, it likely overestimates exports for inland states and underestimates them for those with access to ports. The method also does not capture the role of processing or value-added activities between farm production and export, which may bias export estimates for processed goods. Finally, the dataset does not include information on export destination markets or account for transportation costs included in export values. Therefore, readers should interpret all results on this series as reflecting production-value shares, not export behavior, export potential, or shipment volumes; questions about actual export behavior cannot be answered with these data.

A.2 Regression Results, Diagnostics, and Robustness Checks

A.2.1 Baseline Regression Results - Corn Yield, Production, and ERS Export Allocation (2000–2022)

Table A2.1: *Aggregate Regression Results – Corn Yield, Production, and ERS Export Allocation (2000–22)*

Independent Variables	**Yield**	**Production**	**ERS Allocation**
GDD	0.000074	-0.000087	-0.000141
	(0.00009)	(0.00037)	(0.00022)
HDD	-0.003882***	-0.006087***	-0.003753***
	(0.00087)	(0.00122)	(0.00091)
Prec	-0.000312	-0.002045	-0.002221***
	(0.000539)	(0.001025)	(0.000600)
Freezing	-0.004781	-0.004528	0.007862
	(0.003843)	(0.007837)	(0.004231)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	276	276	276
R-squared	0.845756	0.976271	0.974079
Adjusted R^2	0.821024	0.972466	0.969923

*Standard errors in parentheses clustered by year * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01*

A.2.2 Baseline Regression Results - Soybean Yield, Production, and ERS Export Allocation (2000–2022)

Table A2.2: *Aggregate Regression Results – Soybean Yield, Production, and ERS Export Allocation (2000–22)*

Independent Variables	**Yield**	**Production**	**ERS Allocation**
GDD	0.000428**	0.000212	0.000161
	(0.000161)	(0.000188)	(0.000284)
HDD	-0.004547***	-0.005728***	-0.004273***
	(0.000710)	(0.001158)	(0.001448)
Prec	0.000894**	-0.000831	-0.001094
	(0.000345)	(0.000753)	(0.000641)
Freezing	-0.002067	-0.003354	-0.002623
	(0.003539)	(0.004099)	(0.005366)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	276	276	276
R-squared	0.904721	0.978649	0.971341
Adjusted Rˆ2	0.889444	0.975226	0.966746

*Standard errors in parentheses clustered by year * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01*

A.2.3 State Distribution of One Standard Deviation of HDD (2000–2022)

Table A2.3: *Study States and their Distribution of One Standard Deviation of HDD (2000–22)*

Fips	State	State code	PRISM SD_HDD
17	Illinois	IL	21.05487
18	Indiana	IN	18.74836
19	Iowa	IA	14.97537
20	Kansas	KS	37.34651
26	Michigan	MI	6.147604
27	Minnesota	MN	5.86105
29	Missouri	MO	28.21003
31	Nebraska	NE	25.13691
38	North Dakota	ND	10.59377
39	Ohio	OH	13.25308
46	South Dakota	SD	22.65115
55	Wisconsin	WI	7.067014

This is the One Standard Deviation of Heating Degree Days for each state in Midwest according to PRISM weather dataset

A.2.4 State-Level Impact of HDD on Corn Production and ERS Export Allocation (2000–2022)

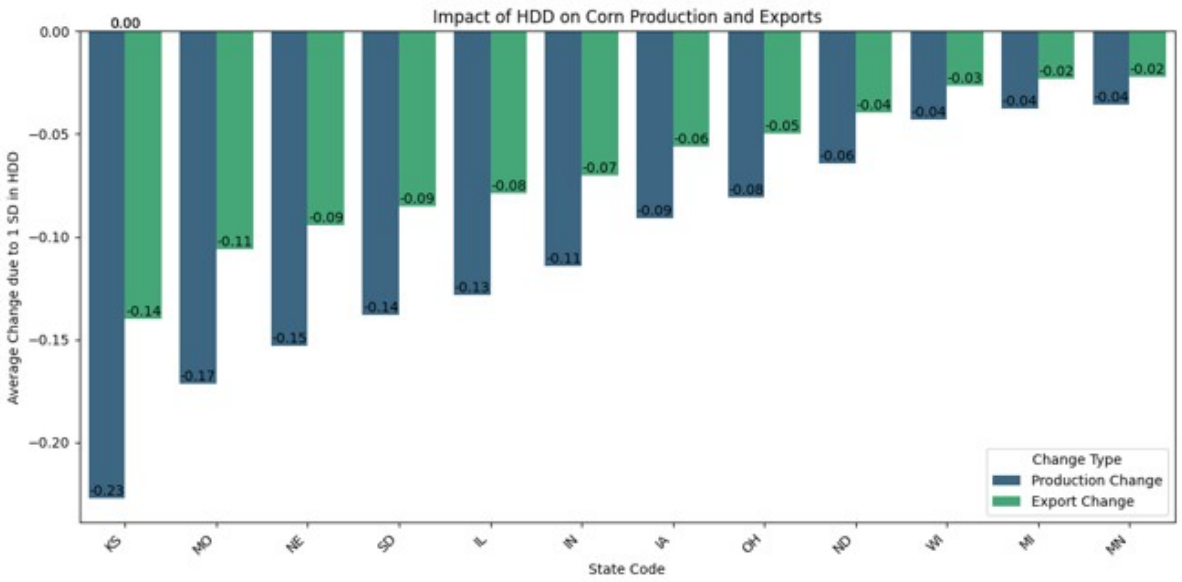


Figure A.4: *Average Change in Corn Production Value and the ERS Export Allocation Due to a One Standard Deviation Increase in Heating Degree Days (HDD), by State. This bar chart quantifies the heterogeneous impact of heat stress on corn, showing that a positive shock to HDD is associated with a significant negative adjustment in both production value (Prod) and the ERS cash-receipts-based export allocation (Exp), with the magnitude of these contractions varying considerably across U.S. Midwest states.*

A.2.5 State-Level Impact of HDD on Soybean Production and ERS Export Allocation (2000–2022)

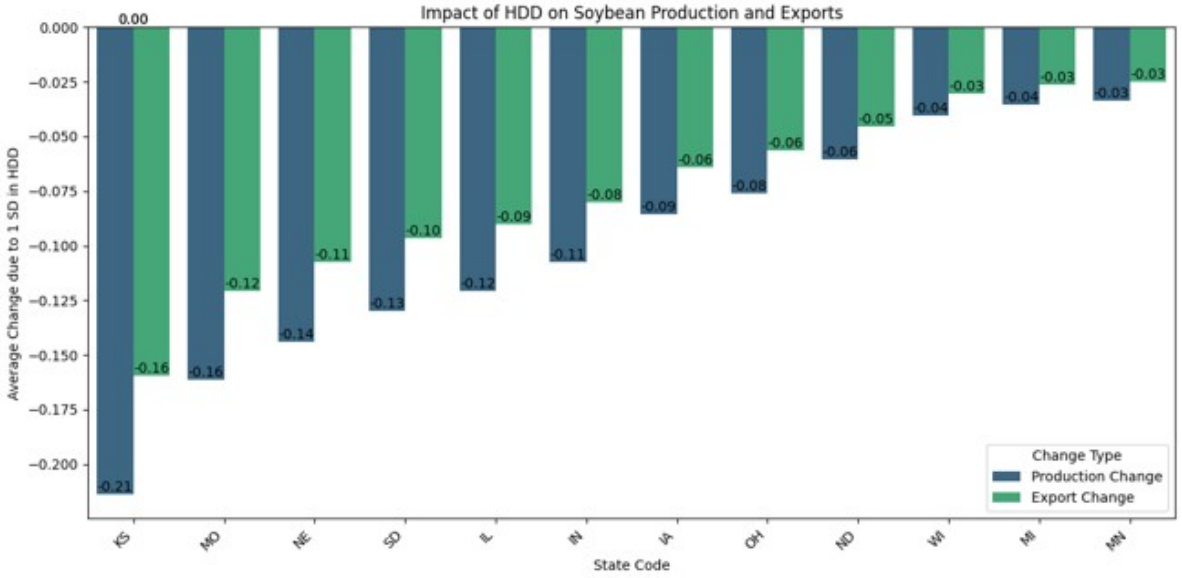


Figure A.5: *Average Change in Soybean Production Value and the ERS Export Allocation Due to a One Standard Deviation Increase in Heating Degree Days (HDD), by State. This bar chart illustrates the heterogeneous response of soybean production value (Prod) and the ERS cash-receipts-based export allocation (Exp) to increased heat stress, showing a significant negative adjustment in both outcomes, with the magnitude of these contractions varying considerably across U.S. Midwest states.*

A.2.6 Within-State Variation of the ERS Export Allocation

Because the ERS state export allocation is derived from production-value shares, a natural question is whether it retains enough independent variation to identify the weather response once national movements are absorbed by year fixed effects. Table A2.6 reports two diagnostics. Panel A reports the standard panel variance decomposition of the log ERS export allocation. Panel B reports the correlation between logged production value and the logged ERS export allocation before and after removing state and year fixed effects.

Panel A shows that the ERS export allocation contains meaningful variation within states over time. For corn, the overall standard deviation is 0.868 log points, the between-state standard deviation is 0.764, and the within-state standard deviation is 0.466. For soybeans, the corresponding values are 0.899, 0.664, and 0.635. Thus, although persistent differences across states explain an important part of the variation, the ERS export allocation also changes substantially within the same state over time.

Panel B shows that production value and the ERS export allocation are highly correlated in levels, as expected given the production-share-based construction of the ERS series. The raw correlations are 0.956 for corn and 0.972 for soybeans. After removing state and year fixed effects, however, the correlations fall to 0.756 for corn and 0.600 for soybeans. This decline indicates that the identifying variation used in the fixed-effects regressions is not simply the raw cross-sectional comovement between production and the ERS export allocation. These diagnostics characterize the variation that identifies the allocation estimates: within-state movements in relative cash-receipt shares. They do not, and cannot, restore the export information removed by the year fixed effects, and we do not present them as evidence that the series contains export behavior.

Table A2.6 reports descriptive diagnostics in Panels A and B and the formal coefficient-equality analysis in Panels C–F.

Table A2.6: *Variation in production value and the ERS export allocation, and test of equality of the HDD coefficient across outcomes (state-year panel, 2000–2022).*

Panel A. Variance decomposition, variables in logs.

Series	Overall SD	Between-state SD	Within-state SD
Corn production value	0.894	0.740	0.543
Corn ERS export allocation	0.868	0.764	0.466
Soybean production value	0.780	0.626	0.497
Soybean ERS export allocation	0.899	0.664	0.635

Notes: This panel reports the overall, between-state, and within-state standard deviations of log production value and the log ERS export allocation. The within-state standard deviation captures variation within the same state over time, while the between-state standard deviation captures persistent differences across states. Production-value rows are reported alongside the ERS allocation to facilitate direct comparison of the variation in the two series.

Panel B. Correlation and residual dispersion, production value and the ERS export allocation, variables in logs.

Crop	Raw correlation	After state & year FE	SD of FE residual, production value	SD of FE residual, allocation
Corn	0.956	0.756	0.153	0.148
Soybean	0.972	0.600	0.130	0.159

Notes: This panel reports the correlation between logged production value and the logged ERS export allocation before and after removing state and year fixed effects, together with the standard deviations of the corresponding fixed effects residuals. The decline in the correlation after fixed effects shows that the regressions are not identified solely by the raw comovement between the two series. Under the assumption that the residual variation in the ERS allocation can be represented as a scaled version of residual production value plus an unrelated error component, the residual correlations and dispersions imply an attenuation factor of approximately 0.73 for both corn and soybeans. These implied values are compared with the estimated allocation-to-production coefficient ratios in Panel E.

Panels C–F. Test of equality of the HDD coefficient across outcomes.

	Corn	Soybeans
Panel C. HDD coefficients		
Log production value (β_P)	-0.00609 (0.00180)	-0.00573 (0.00067)
Log ERS export allocation (β_A)	-0.00375 (0.00134)	-0.00427 (0.00090)
Panel D. Test of equality ($\beta_A = \beta_P$)		
Difference ($\beta_A - \beta_P$)	0.00233 (0.00067)	0.00145 (0.00056)
F(1, 11)	12.25	6.77
p-value (cluster-robust)	0.005	0.025
p-value (wild cluster bootstrap)	0.004	0.014
Panel E. Implied attenuation		
Estimated ratio β_A/β_P [95% CI]	0.62 [0.47, 0.76]	0.75 [0.54, 0.95]
Ratio implied by Panel B	0.73	0.73
Panel F. Specification		
Observations (stacked)	552	552
State-year cells	276	276
Clusters (states)	12	12
Fixed effects	State × outcome, Year × outcome	State × outcome, Year × outcome
Controls	GDD, precipitation, freezing days, t, t squared (outcome-specific)	GDD, precipitation, freezing days, t, t squared (outcome-specific)

Notes: Panels C–F report a stacked estimation of the production-value and ERS-allocation equations using the same state-year sample. Each state-year contributes two observations, one for each outcome. All weather covariates and fixed effects are interacted with the outcome indicator, allowing the two equations to have separate coefficients and fixed effects. The reported difference is the coefficient on the interaction between HDD and the ERS-allocation indicator. Standard errors in parentheses are clustered by state. The stacked equality test clusters by state to allow arbitrary within state dependence over time in the cross outcome comparison. This differs from the baseline year clustering, which addresses spatial correlation in weather shocks across states. Given the small number of state clusters, we also report wild cluster bootstrap p values using Webb weights. Wild cluster bootstrap p-values are based on Webb weights with 9,999 replications to account for the small number of state clusters. Panel E reports the estimated ratio of the ERS-allocation HDD coefficient to the production-value HDD coefficient and compares it with the benchmark implied by the residual correlation and residual dispersion reported in Panel B. The Panel B value is based on residualization using state and year fixed effects and is therefore treated as a benchmark rather than a point prediction. For both crops, the confidence interval for the estimated coefficient ratio contains the corresponding benchmark value of 0.73. The equality tests indicate that the HDD coefficients differ across the two outcomes. Together with the residual diagnostics, this difference is consistent with the measurement wedge between ERS cash receipts and NASS production value and should not be interpreted as evidence of export behavior or buffering.

A.2.7 Grain-Stocks Diagnostics (Storage Channel)

This section reports commodity-balance diagnostics using grain-stocks data. These tests cannot establish export buffering, because the dependent variable in the allocation equation is a cash-receipts-based allocation that contains no shipment information; they characterize the inventory response to heat and descriptive heterogeneity of the allocation series. We merge USDA quarterly state grain-stocks data onto the state-year panel and define carry-in stocks as the March 1 level, which is predetermined relative to the March–September growing-season heat exposure. We define ending stocks as the December 1 post-harvest level. Stocks enter in logs, and the carry-in term is centered at its mean so that the HDD main effect can be interpreted at average carry-in stocks. All specifications use the same controls as the main model: state and year fixed effects, precipitation, and the remaining weather controls, with standard errors clustered by year.

Taken together, the pass-through results document a production-side inventory response to heat for both crops. The interaction results show that the allocation's response to heat varies with carry-in stocks for soybeans but not for corn. Because the allocation contains no shipment information, these patterns describe heterogeneity of the constructed series and cannot establish whether physical exports are buffered by storage; we do not draw any

Table A2.7a: *HDD effect on ending stocks (pass-through).*

Variable	Soybean ending stocks	Corn ending stocks
HDD (¿29 °C)	-0.0049*** (0.0008)	-0.0056*** (0.0010)
GDD (0-28 °C)	0.0002 (0.0002)	-0.0001 (0.0003)
Freezing days	-0.0055 (0.0032)	-0.0070 (0.0068)
Observations	275	276
R-squared	0.976	0.971

*Notes: Dependent variable is log December 1 stocks, measured in bushels. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. The negative HDD coefficients indicate that higher growing-season heat is associated with lower end-of-season stocks for both crops, consistent with inventories being drawn down following heat shocks.*

Table A2.7b: *Allocation equation with HDD × carry-in interaction.*

Variable	Soybean ERS export allocation	Corn ERS export allocation
HDD (¿29 °C)	-0.0025* (0.0013)	-0.0022** (0.0009)
Carry-in stocks (centered)	0.3696*** (0.0784)	0.6324*** (0.0529)
HDD × carry-in	0.0020*** (0.0007)	0.0001 (0.0005)
GDD (0-28 °C)	0.0001 (0.0003)	0.0001 (0.0002)
Observations	274	276
R-squared	0.979	0.989

*Notes: Dependent variable is the log ERS export allocation. Carry-in stocks are measured using the March 1 reading and are centered at their sample mean. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. The positive and statistically significant interaction for soybeans indicates that higher carry-in stocks reduce the negative association between HDD and the ERS export allocation. For corn, the interaction is close to zero and statistically insignificant.*

Table A2.7c: *Marginal effect of HDD on the ERS export allocation across the carry-in distribution (centered log carry-in).*

Carry-in level	Soybean dln(exp)/dHDD	Corn dln(exp)/dHDD
Low (-1)	-0.0045*** (0.0014)	-0.0023* (0.0011)
Mean (0)	-0.0025* (0.0013)	-0.0022** (0.0009)
High (+1)	-0.0005 (0.0016)	-0.0021** (0.0010)

*Notes: Carry-in is measured as centered log carry-in stocks. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. For soybeans, the marginal effect of HDD moves toward zero as carry-in stocks rise; for corn, the marginal effect is nearly unchanged across the carry-in distribution. These patterns describe heterogeneity of the allocation series across stock conditions; because the allocation contains no shipment information, they cannot establish export buffering.*

trade-mechanism conclusion from them.

A.2.8 Lagged-Weather Specification

To examine the timing of the ERS export-allocation response relative to growing-season heat, we re-estimate the ERS export-allocation equation with HDD entering contemporaneously, with a one-year lag, and with both terms included together. The lagged specification allows the current ERS export allocation to be associated with heat exposure from the previous growing season, which we treat as descriptive dynamics of the constructed series; because the allocation contains no shipment information, these specifications cannot identify marketing or shipment-timing behavior. The specification is otherwise identical to the baseline ERSexport-measure equation, with state and year fixed effects, the same weather controls, and standard errors clustered by year.

For corn, both contemporaneous and lagged heat remain negative and statistically significant when entered together, indicating that the allocation series contains both current-year and lagged components. We do not interpret these dynamics as evidence on marketing or shipment timing, because the allocation contains no shipment information and cannot distinguish shipment behavior from persistence in cash-receipt shares. For soybeans, the

Table A2.8: *Lagged-weather ERS allocation specifications. Coefficients on heating degree days*

Specification	Corn: HDD(t)	Corn: HDD (t-1)	Soy: HDD(t)	Soy: HDD(t-1)
Contemporaneous	-0.0038*** (0.0013)	–	-0.0043*** (0.0014)	–
One-year lag only	–	-0.0040*** (0.0011)	–	-0.0026* (0.0013)
Contemporaneous + lag	-0.0029** (0.0012)	-0.0033** (0.0013)	-0.0031** (0.0014)	-0.0018 (0.0012)

*Notes: Dependent variable is the log ERS export allocation. The contemporaneous specifications use 276 state-year observations; the lagged specifications use 264 observations, losing the first year for each state. Each specification includes state and year fixed effects and the same weather controls as the baseline model. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01.*

contemporaneous response dominates; the lagged coefficient is negative but not statistically significant once contemporaneous heat is included.

A.2.9 Robustness to Time Trends

This section reports the sensitivity of the HDD estimates to alternative time-trend specifications. The baseline specification includes state and year fixed effects. Although a global quadratic time trend was originally specified, it is collinear with the year fixed effects because year fixed effects absorb common time variation. The global quadratic trend is therefore dropped from the regression, and removing it leaves the estimates unchanged. We therefore report the baseline once and focus the robustness check on specifications with state-specific linear and quadratic time trends.

The production responses remain negative and statistically significant across all specifications. The soybean ERS export-allocation response also remains negative and statistically significant throughout. The corn ERS export-allocation response is more sensitive to flexible state-specific trends: it weakens to marginal significance under state-specific linear trends, although it remains negative and is statistically significant in the baseline and under state-specific quadratic trends. This pattern suggests that the negative heat relationship is generally preserved, but the corn export-measure estimate is more sensitive to flexible trend

controls than the production estimates and the soybean export-measure estimate.

Table A2.9: *HDD coefficient under alternative time-trend specifications.*

Outcome (HDD coef.)	Baseline	+ State linear trends	+ State-specific quad. trends
Corn ERS export allocation	-0.0038*** (0.0013)	-0.0019 * (0.0014)	-0.0023** (0.0010)
Soybean ERS export allocation	-0.0043*** (0.0014)	-0.0032** (0.0013)	-0.0039*** (0.0009)
Corn production	-0.0061*** (0.0012)	-0.0043*** (0.0014)	-0.0047*** (0.0010)
Soybean production	-0.0057*** (0.0012)	-0.0046*** (0.0008)	-0.0042*** (0.0007)

*Notes: Each cell reports the HDD coefficient from a separate regression of the row outcome on the weather variables, with state and year fixed effects. The "state linear trends" specification adds a separate linear time trend for each state. The "state quadratic trends" specification adds state-specific linear and quadratic time trends. All specifications use 276 state-year observations. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01.*

A.2.10 Price-Offset Check: Production in Value versus Quantity

This section examines whether the smaller estimated response of the ERS export allocation could be explained mechanically by using value-based outcomes. In the baseline regressions, both production and the ERS export allocation are measured in value terms, in log dollars. The physical production series, measured in bushels, is not used in the baseline. Because both baseline outcomes are value measures, a heat-induced price increase would affect production value and allocated export value in the same general direction. This makes a pure units mismatch unlikely to explain the smaller estimated HDD response for the ERS export allocation.

To assess the potential role of price movements directly, we re-estimate the production equation with output measured in bushels rather than dollars. Since the difference between production value and production quantity reflects the output price component, the gap between the value-based and quantity-based HDD coefficients provides an implied measure of the state-level price response to own-state heat.

Table A2.10: *HDD response of production measured in value and in quantity.*

Production outcome (HDD coef.)	In value ($)	In quantity (bushels)	Implied price component
Corn production	-0.0061*** (0.0012)	-0.0066*** (0.0012)	+0.0005 (8%)
Soybean production	-0.0057*** (0.0012)	-0.0061*** (0.0012)	+0.0004 (7%)

*Notes: All specifications use 276 state-year observations with state and year fixed effects and the same weather controls as the baseline model. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. The implied price component is the difference between the value-based and quantity-based HDD coefficients, expressed both in log points and as a share of the quantity coefficient. The implied price component is small, approximately 7 to 8 percent of the quantity response, which supports interpreting the production-value estimates as predominantly quantity-driven. This check speaks only to the measurement of the production outcome; the smaller response of the ERS allocation relative to production is interpreted as reflecting the measurement wedge between ERS cash receipts and NASS production value, as discussed in the main text. A comparable state-level export quantity series is not available.*

A.2.11 Robustness to Alternative Heat Thresholds

Our baseline heat measure defines HDD using exposure above 29°C. This threshold matches the corn critical temperature in Schlenker and Roberts (2009) and is one degree below their soybean threshold of approximately 30°C. To confirm that the results do not depend on this cutoff, we re-estimate the main outcome equations using alternative heat thresholds of 28°C, 29°C, and 30°C. The 29°C column corresponds to the baseline specification used throughout the paper.

Table A2.11: *HDD coefficient under alternative heat thresholds.*

Outcome (HDD coef.)	HDD > 28°C	HDD > 29°C (baseline)	HDD > 30°C
Corn ERS export allocation	-0.0034*** (0.0011)	-0.0038*** (0.0013)	-0.0043*** (0.0015)
Soybean ERS export allocation	-0.0037*** (0.0013)	-0.0043*** (0.0014)	-0.0051*** (0.0017)
Corn production	-0.0055*** (0.0011)	-0.0061*** (0.0012)	-0.0069*** (0.0014)
Soybean production	-0.0050*** (0.0010)	-0.0057*** (0.0012)	-0.0067*** (0.0014)

*Notes: Each cell reports the HDD coefficient from a separate regression of the row outcome on the weather variables, with state and year fixed effects and the same controls as the baseline model. All specifications use 276 state-year observations. Standard errors clustered by year are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. The heat coefficient is negative and statistically significant at the 1 percent level for all four outcomes across all three thresholds. The magnitude increases slightly as the threshold rises, which is expected because higher cutoffs isolate more extreme heat exposure. The sign, significance, and ordering of the coefficients are unchanged: the ERS export allocation responds less than production across all thresholds.*

A.2.12 Robustness to Alternative Standard Error Clustering

Our baseline standard errors are clustered by year, which allows for arbitrary spatial correlation of weather shocks across states within a given year. To assess the sensitivity of inference to this choice, we also report standard errors clustered by state, which allows serial correlation within a state over time, and two-way clustered standard errors by state and year. The estimated HDD coefficient is identical across columns by construction; only the standard error changes.

Table A2.12: *HDD coefficient under alternative clustering of standard errors.*

Outcome (HDD coef.)	**Cluster by year (baseline)**	**Cluster by state**	**Two-way (state, year)**
Corn ERS export allocations	-0.0038*** (0.0013)	-0.0038*** (0.0013)	-0.0038* (0.0020)
Soybean ERS export allocation	-0.0043*** (0.0014)	-0.0043*** (0.0009)	-0.0043*** (0.0013)
Corn production	-0.0061*** (0.0012)	-0.0061*** (0.0018)	-0.0061* (0.0033)
Soybean production	-0.0057*** (0.0012)	-0.0057*** (0.0007)	-0.0057*** (0.0012)

*Notes: Each cell reports the HDD coefficient from the baseline specification using 276 state-year observations with state and year fixed effects and the same weather controls as the main model. The estimated coefficient is unchanged across columns; only the clustering method used to compute the standard error changes. Standard errors are reported in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01.*

The HDD coefficient remains negative under all three clustering schemes. Under clustering by year and clustering by state, all four outcomes remain statistically significant at the 1 percent level. Under two-way clustering by state and year, the soybean production and soybean ERS export-allocation responses remain significant at the 1 percent level, while the corn production and corn ERS export-allocation responses weaken to the 10 percent level. Because the panel contains only twelve state clusters, the two-way clustered standard errors should be interpreted cautiously. We therefore retain year clustering as the baseline because it directly addresses the within-year spatial correlation of weather shocks across states. At the same time, we report the alternative clustering results transparently: the sign of the HDD coefficient and the ordering in which the ERS export allocation responds less than production are preserved across all three clustering schemes.

A.3 State-wise Future Projections and Volatility (2023–2100)

A.3.1 State-wise Corn Production Projections and Volatility (2023–2100)

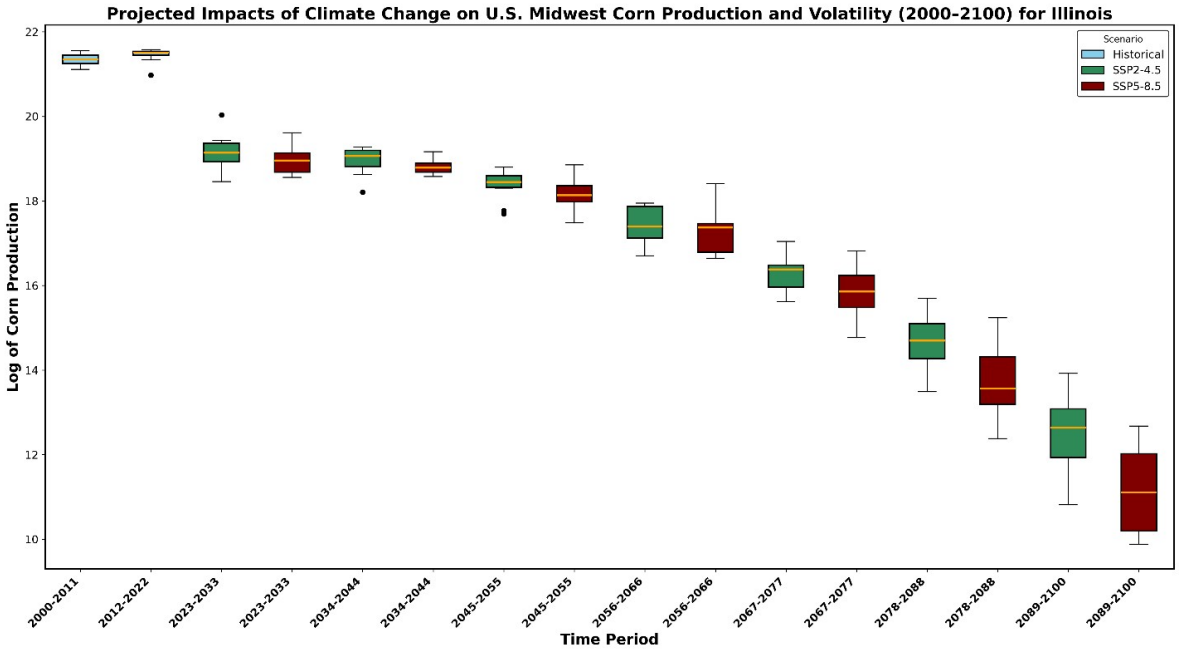


Figure A.6: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 (green) and SSPs585 (maroon) in Illinois. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

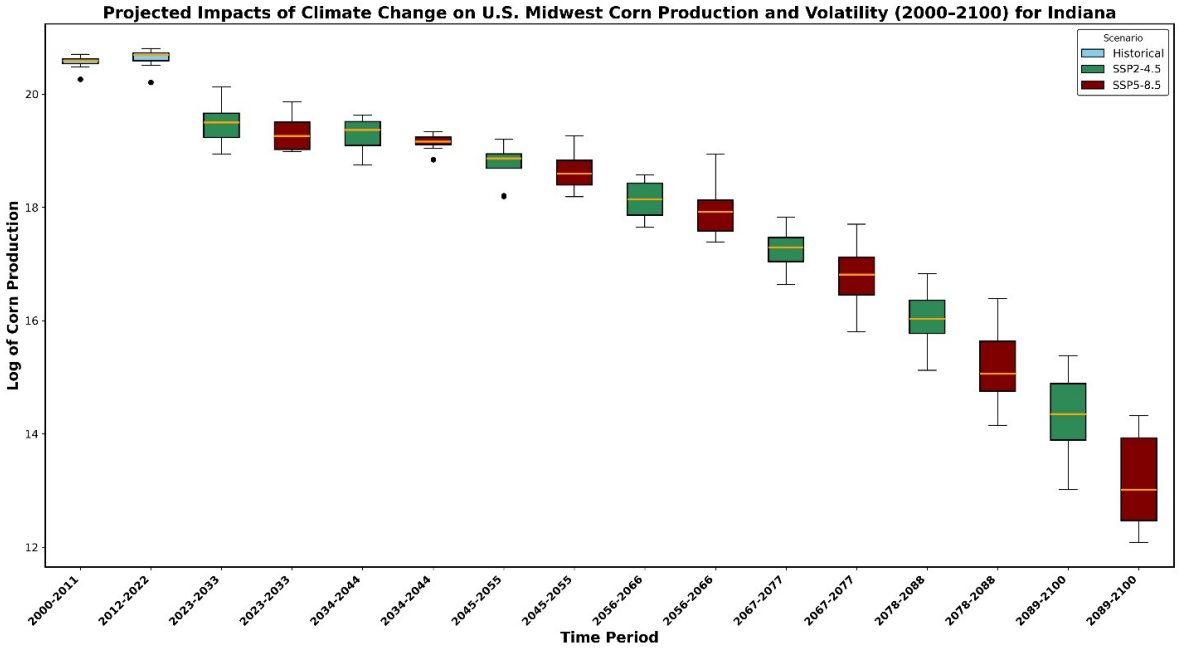


Figure A.7: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Indiana. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

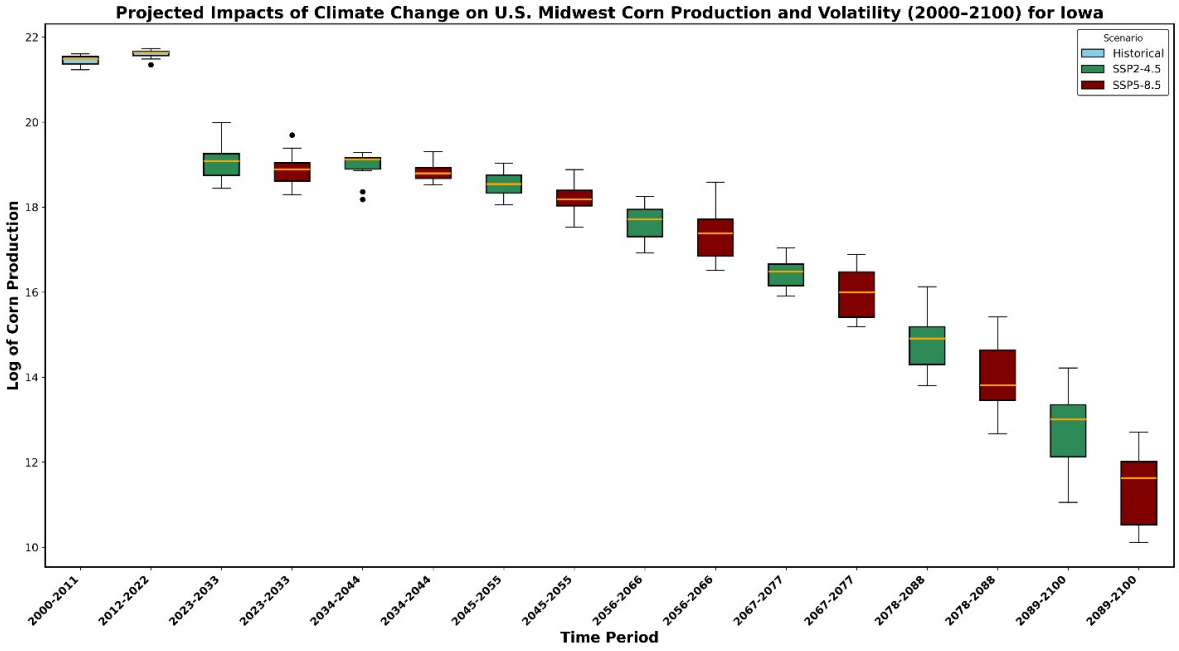


Figure A.8: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Iowa. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

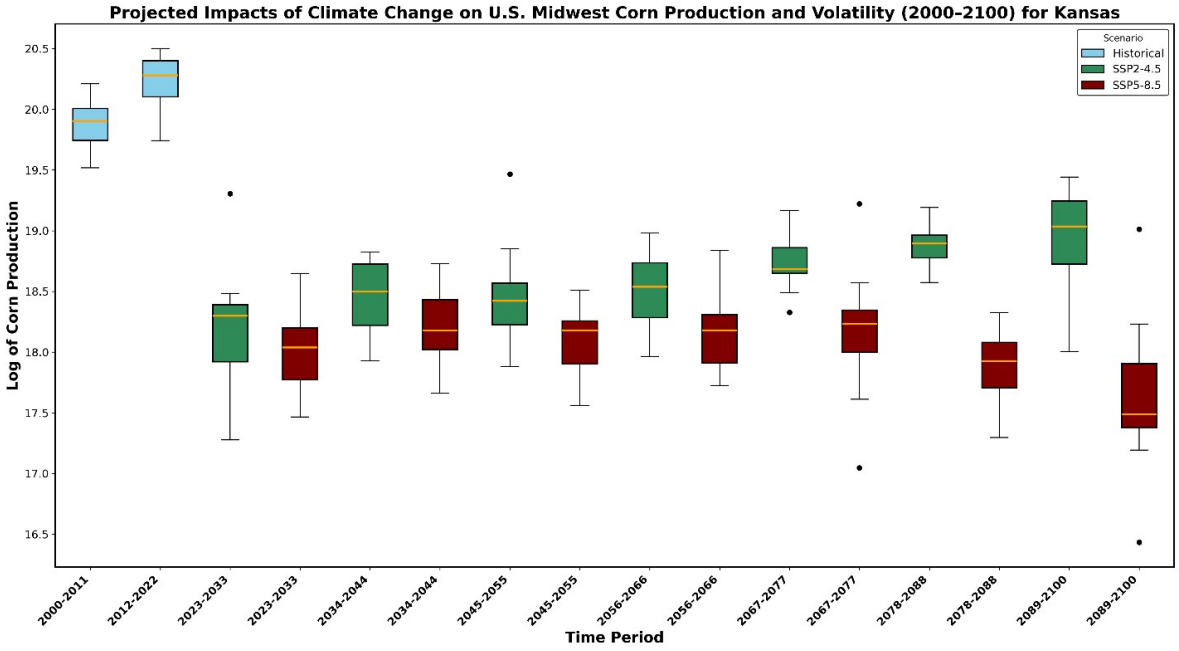


Figure A.9: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Kansas. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

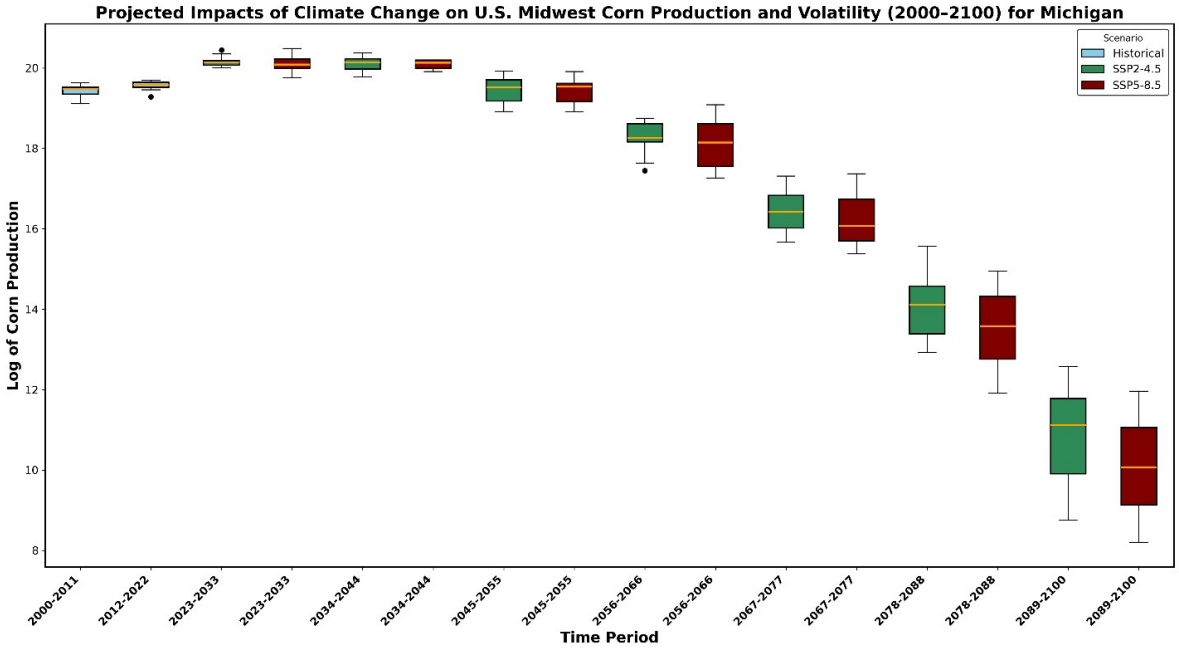


Figure A.10: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Michigan. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

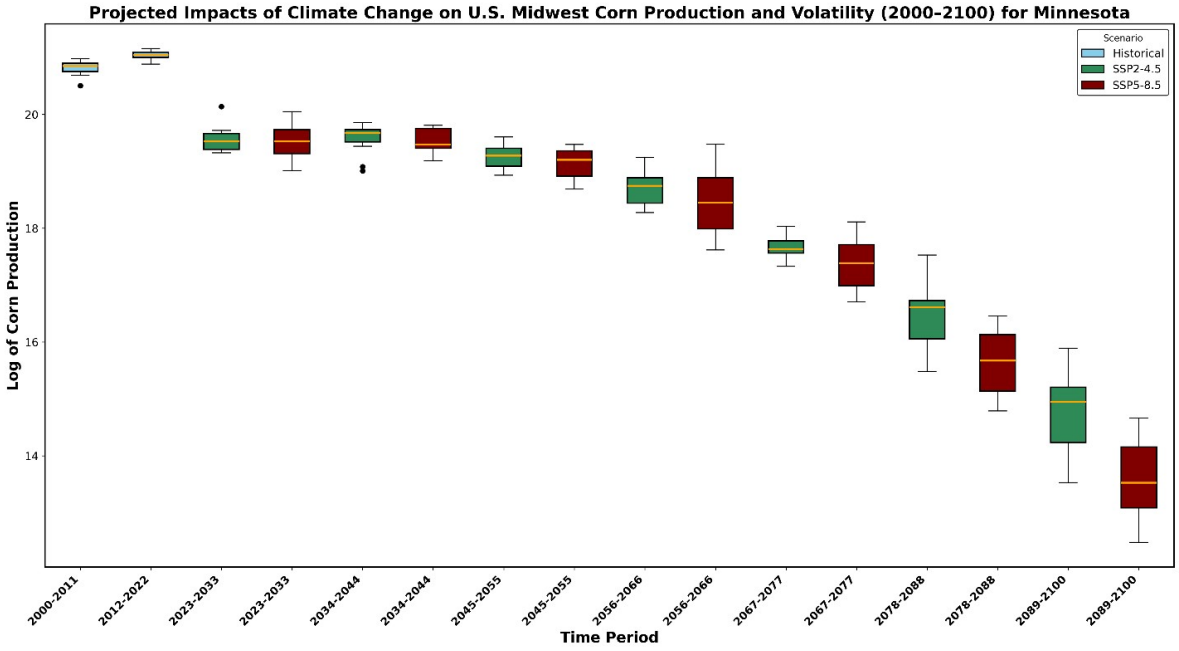


Figure A.11: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Minnesota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

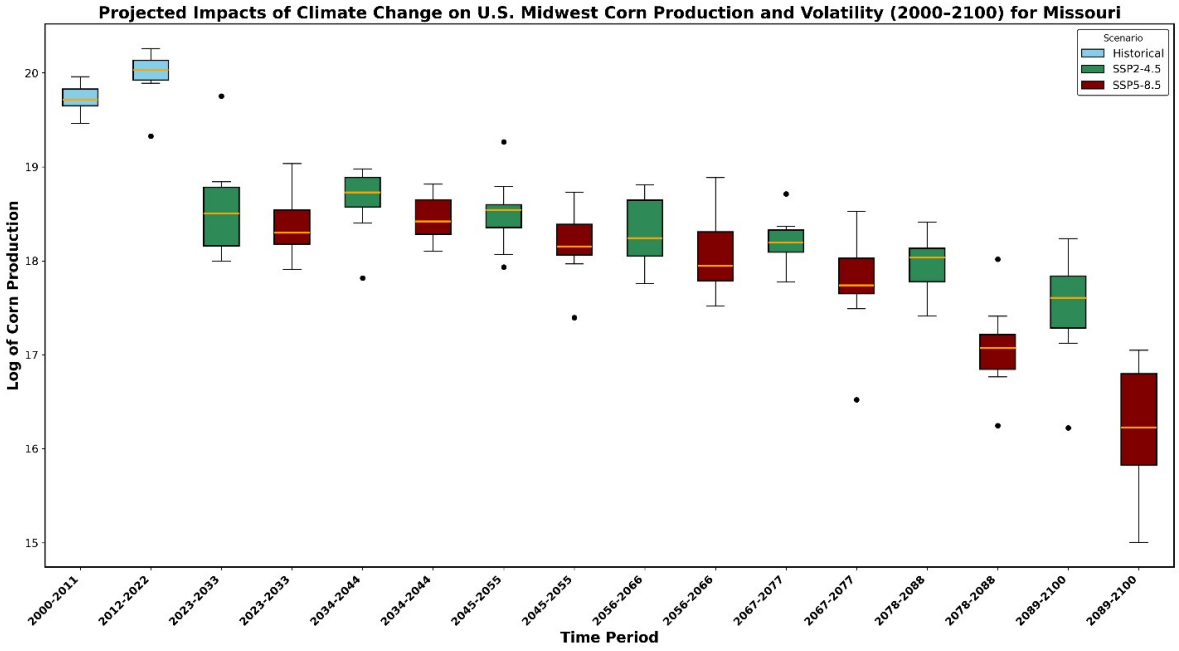


Figure A.12: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Missouri. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

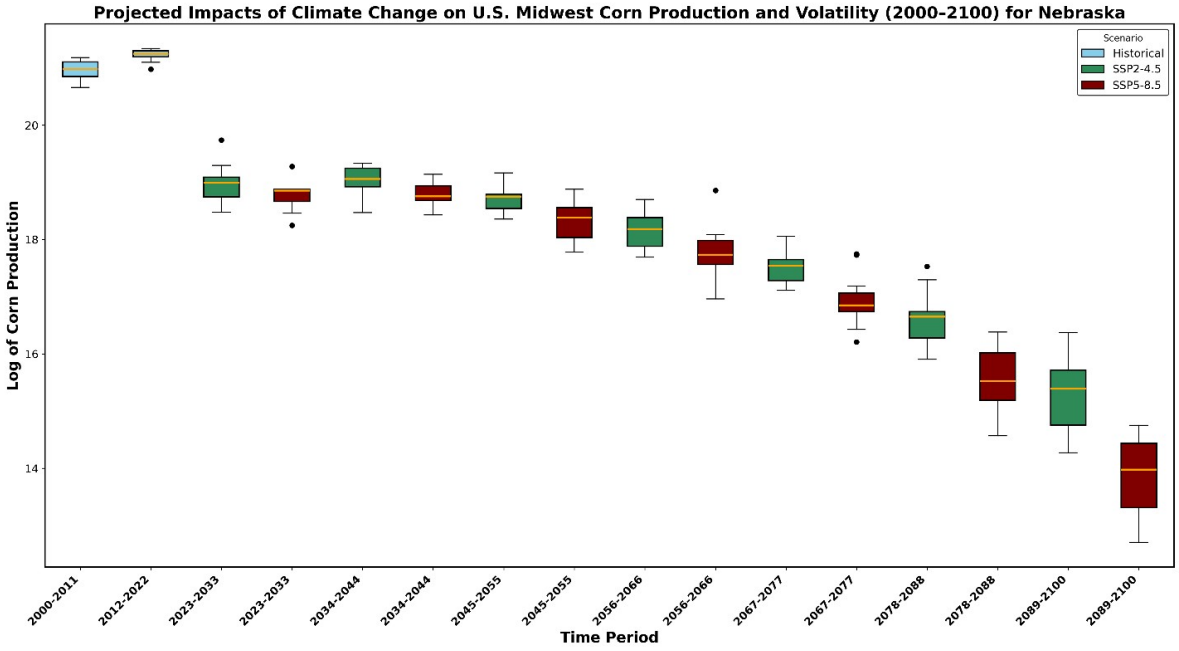


Figure A.13: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Nebraska. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

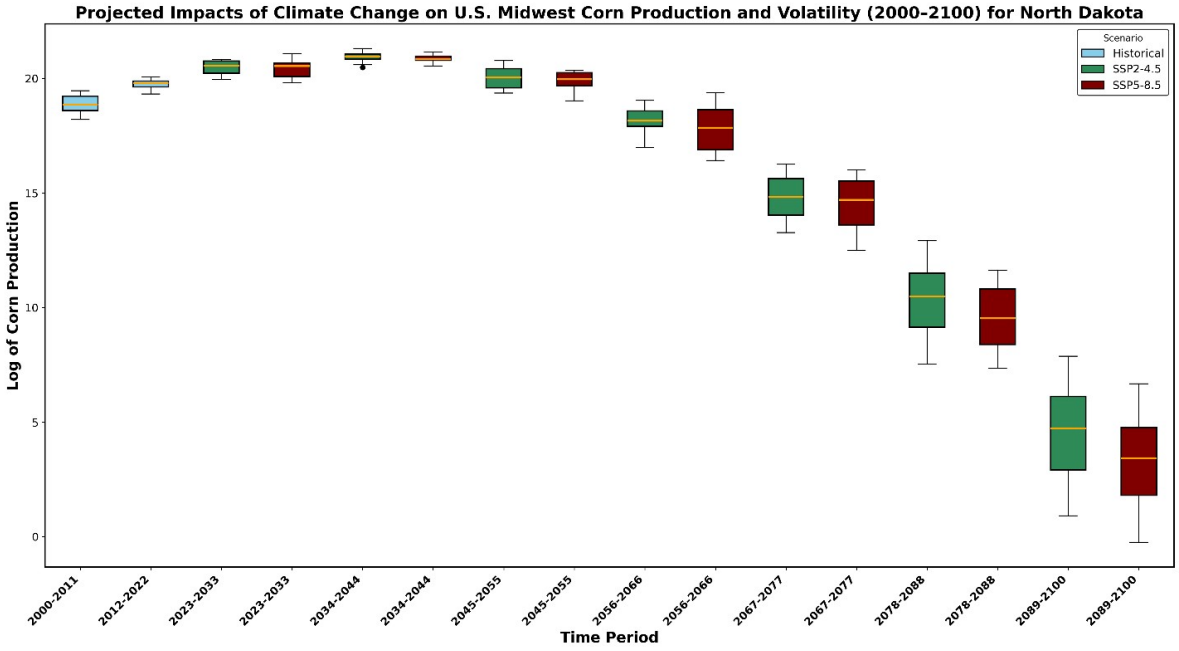


Figure A.14: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in North Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

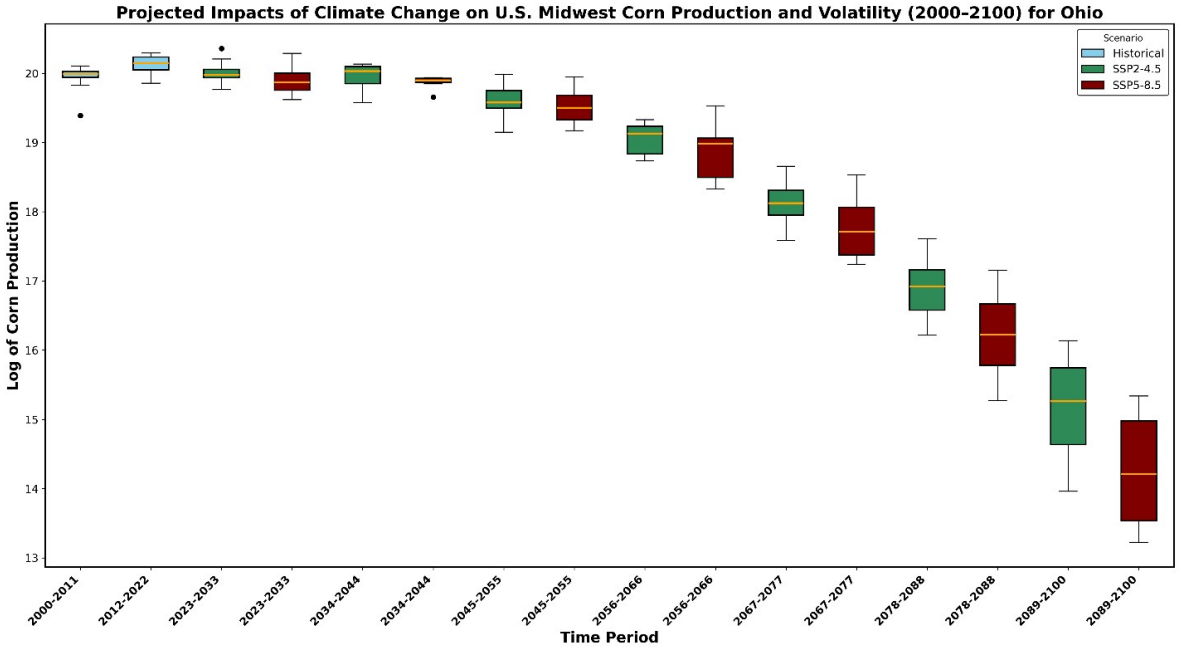


Figure A.15: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Ohio. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

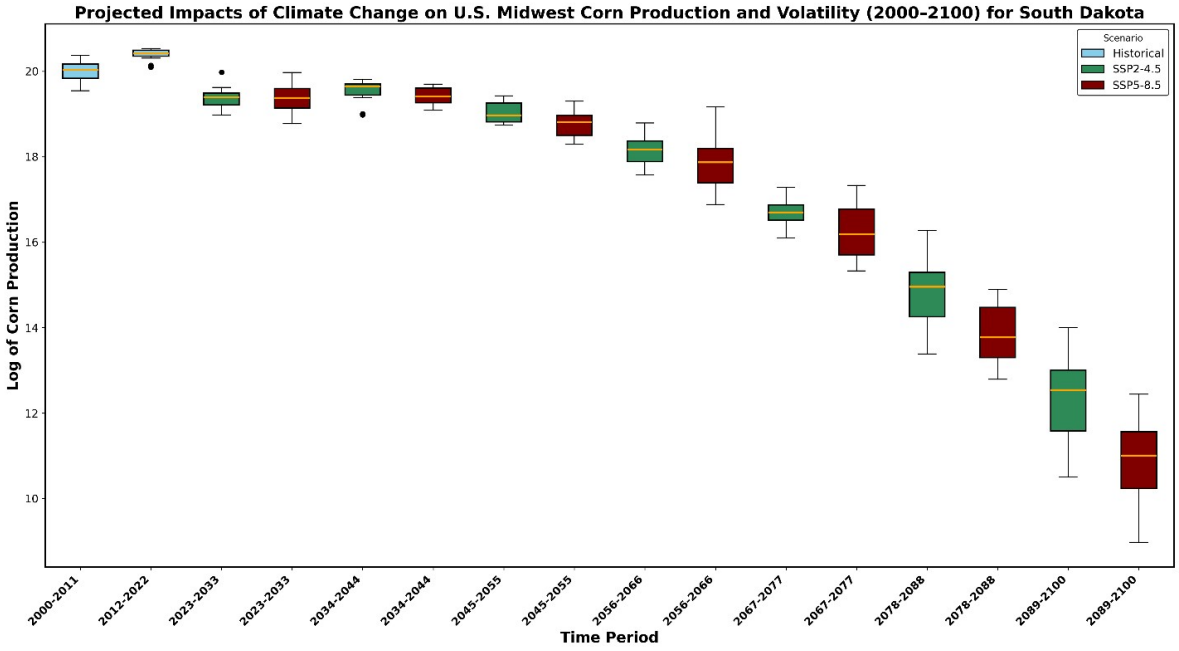


Figure A.16: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in South Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

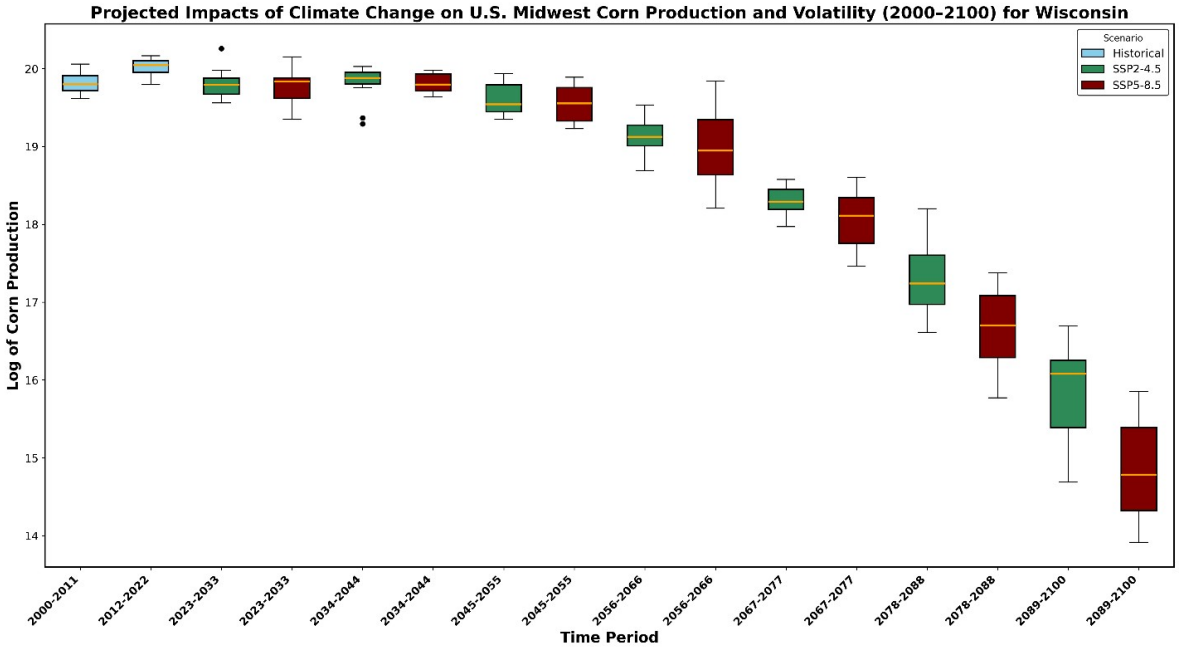


Figure A.17: *This box plot visualizes the distribution of log corn production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Wisconsin. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of corn production over time.*

A.3.2 State-wise Corn ERS Allocation Projections and Volatility (2023–2100)

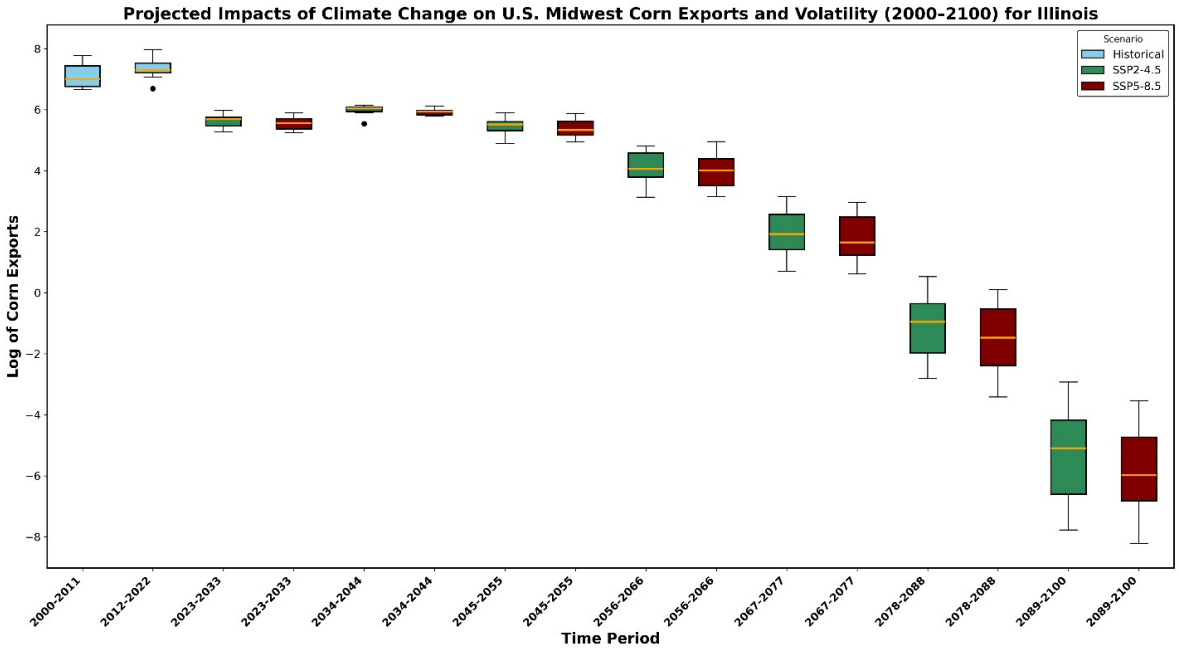


Figure A.18: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Illinois. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

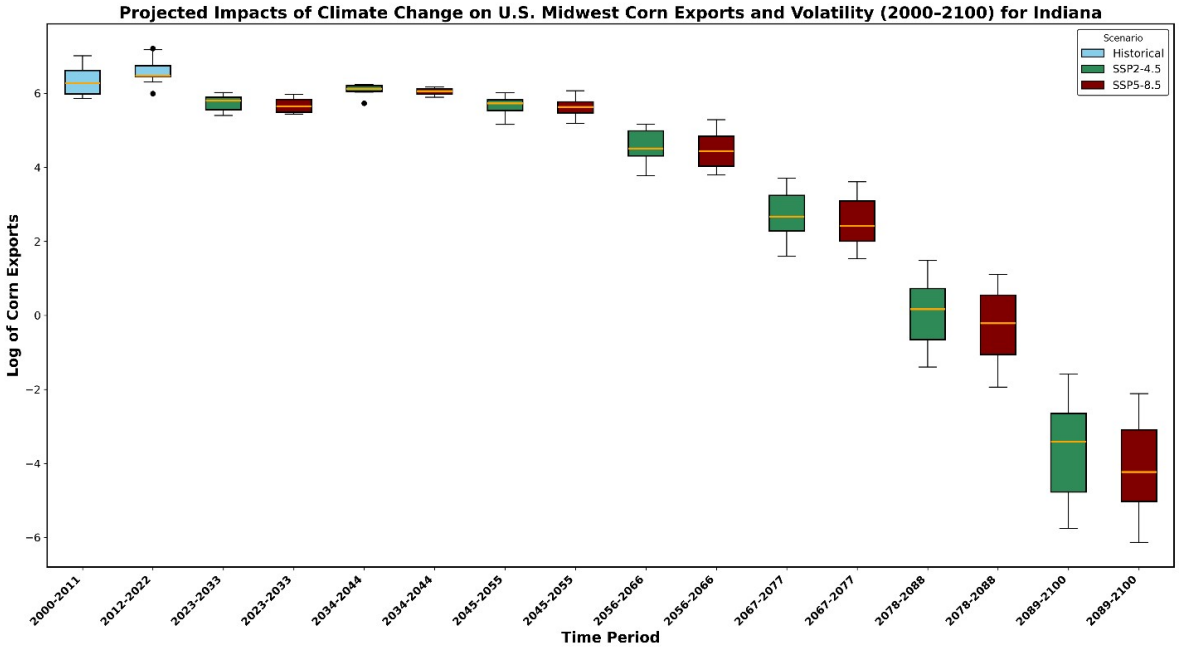


Figure A.19: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Indiana. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

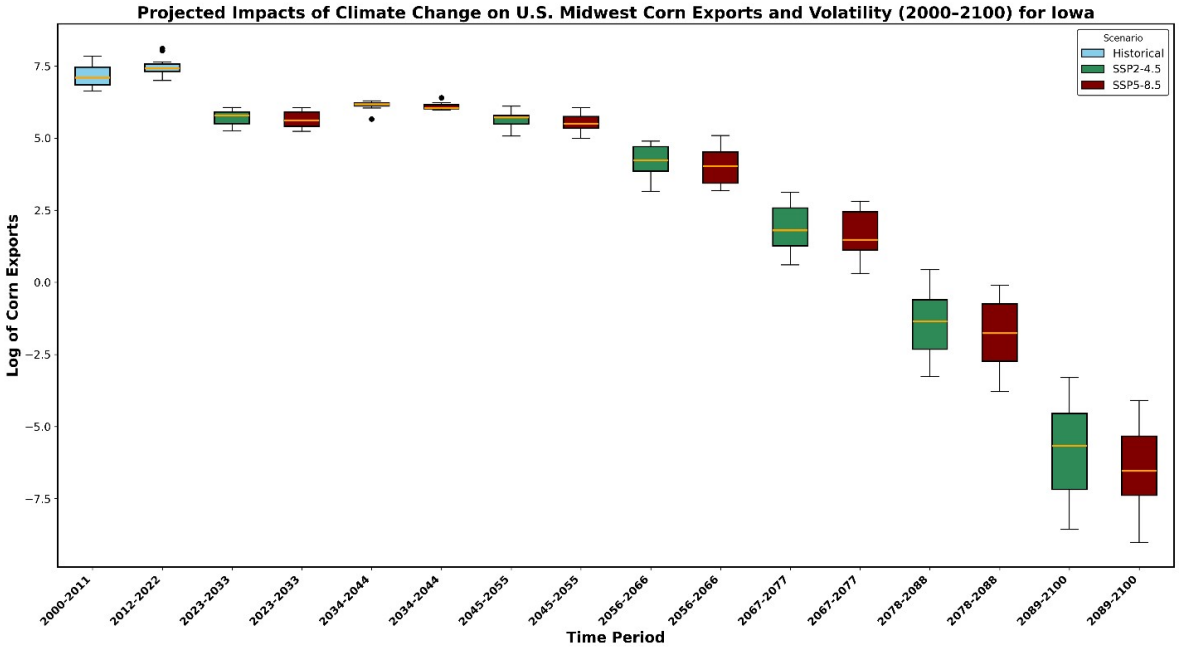


Figure A.20: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Iowa. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

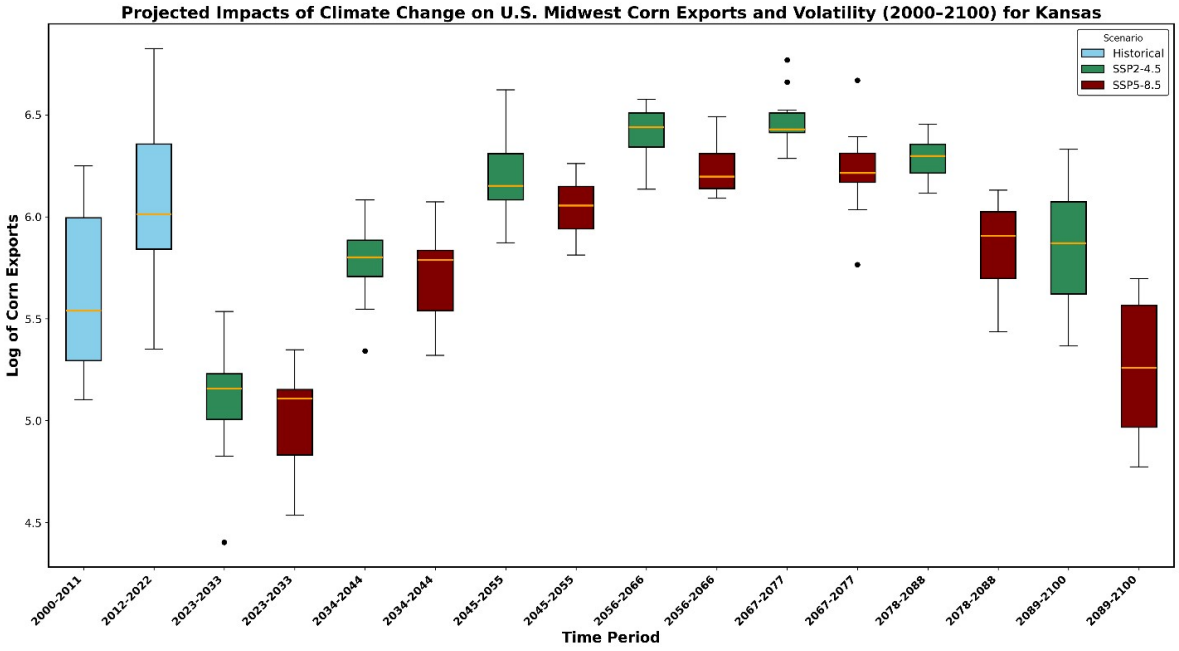


Figure A.21: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Kansas. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

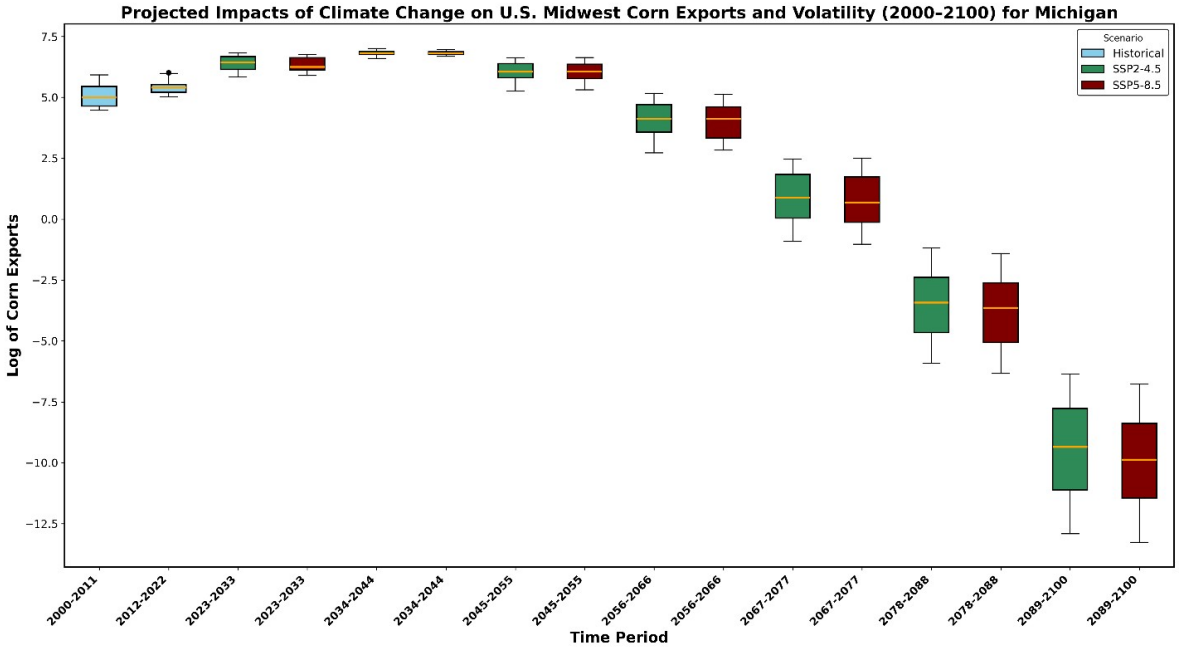


Figure A.22: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Michigan. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

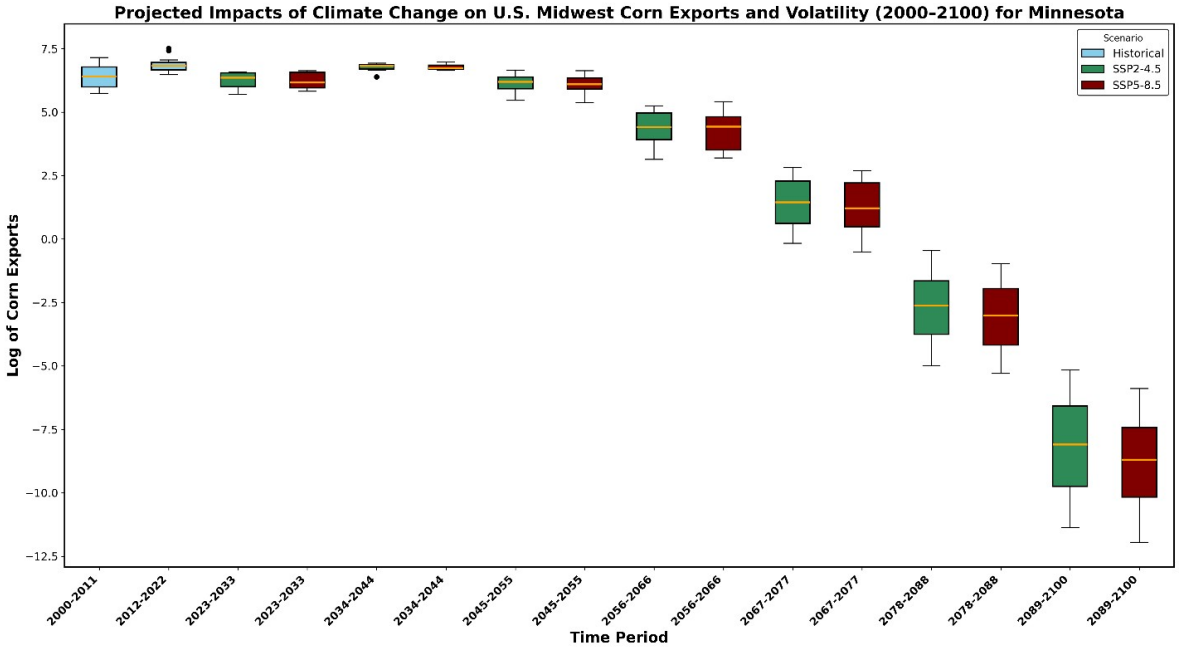


Figure A.23: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Minnesota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

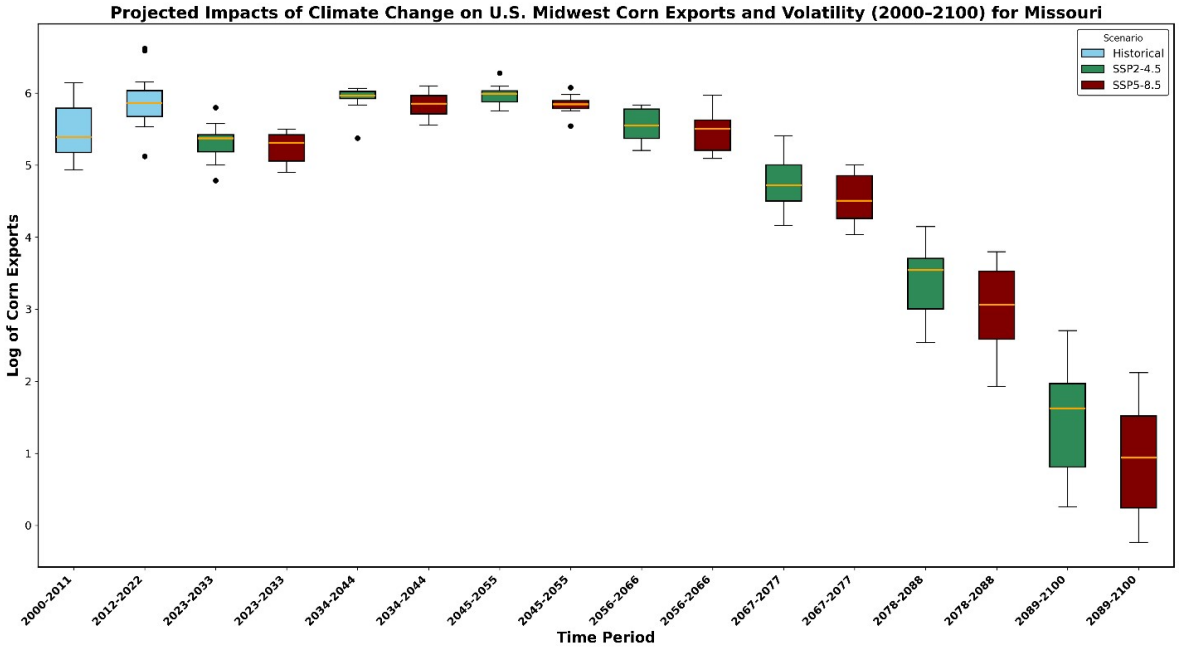


Figure A.24: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Missouri. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

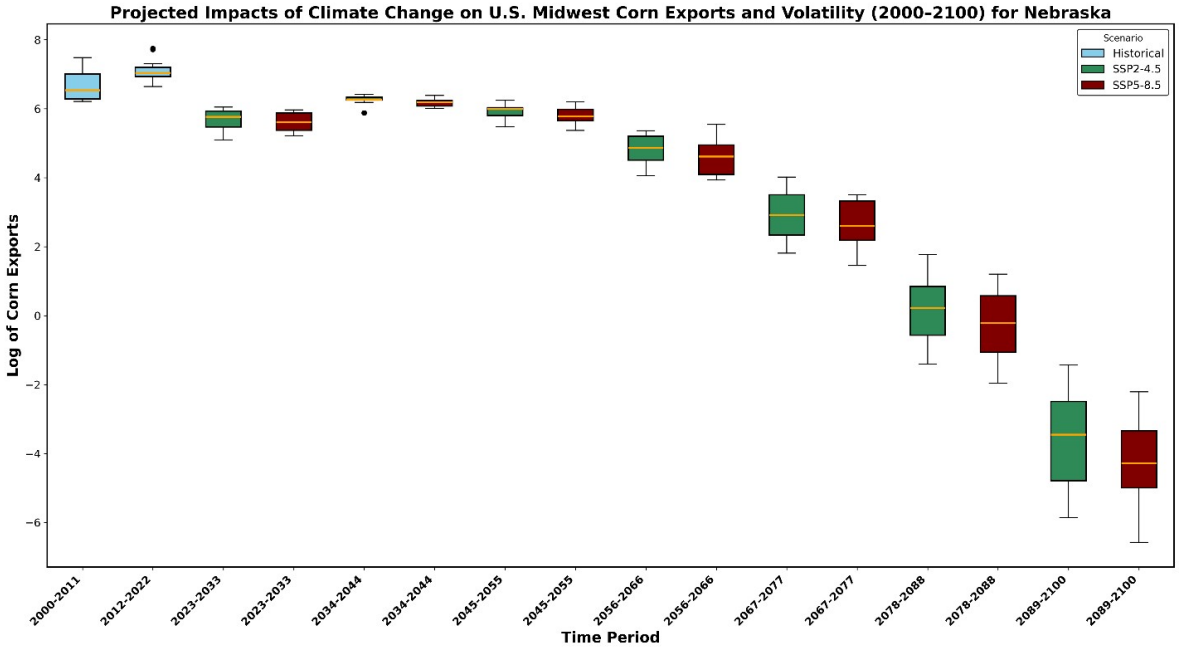


Figure A.25: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Nebraska. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

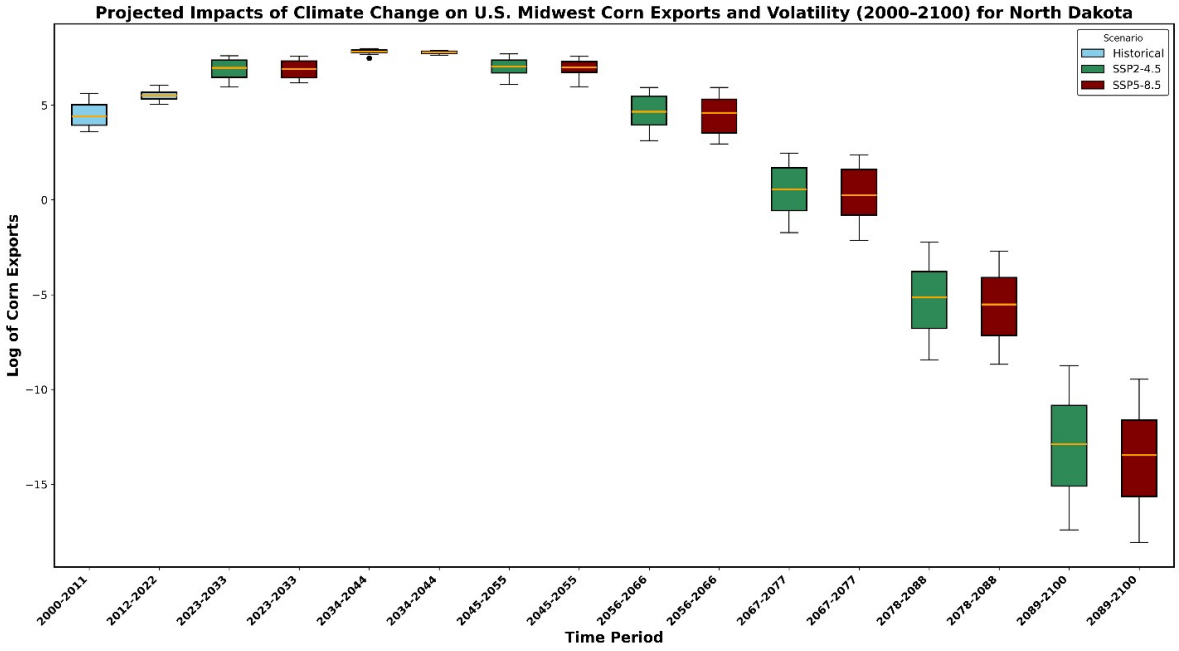


Figure A.26: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in North Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

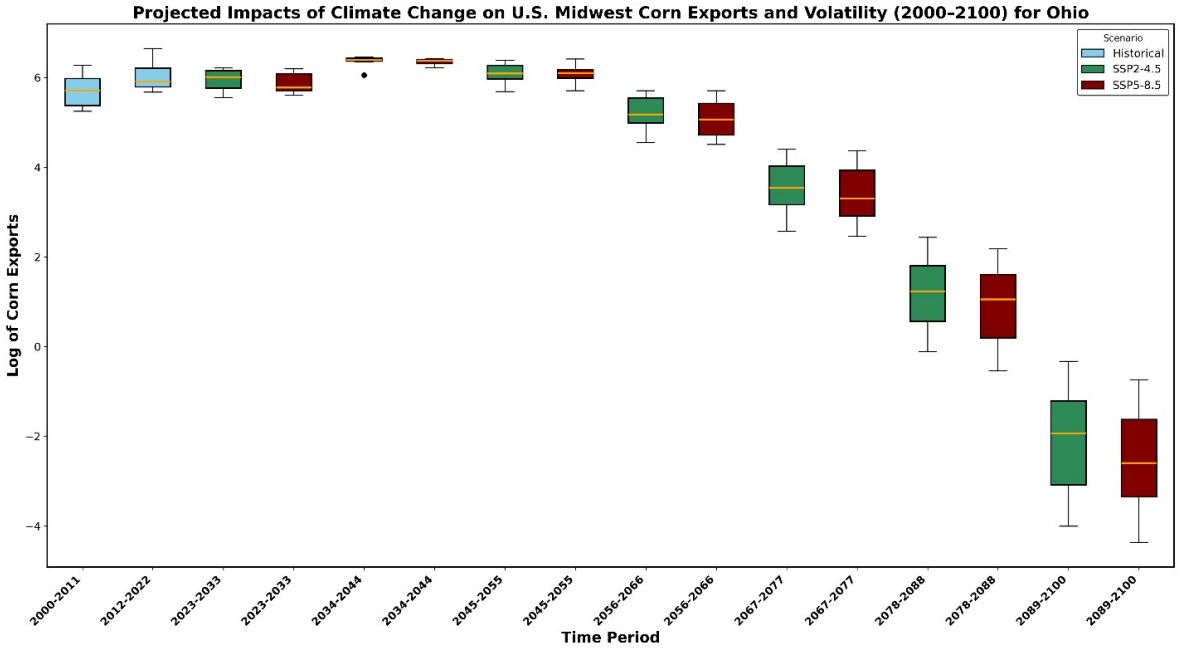


Figure A.27: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Ohio. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

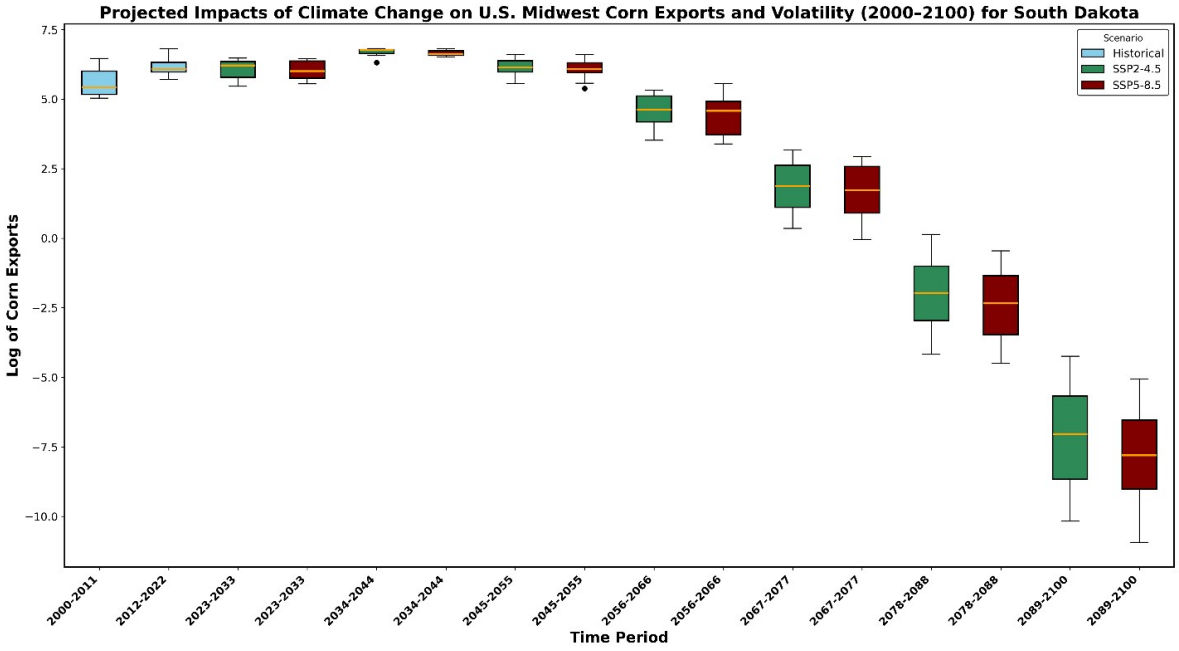


Figure A.28: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in South Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

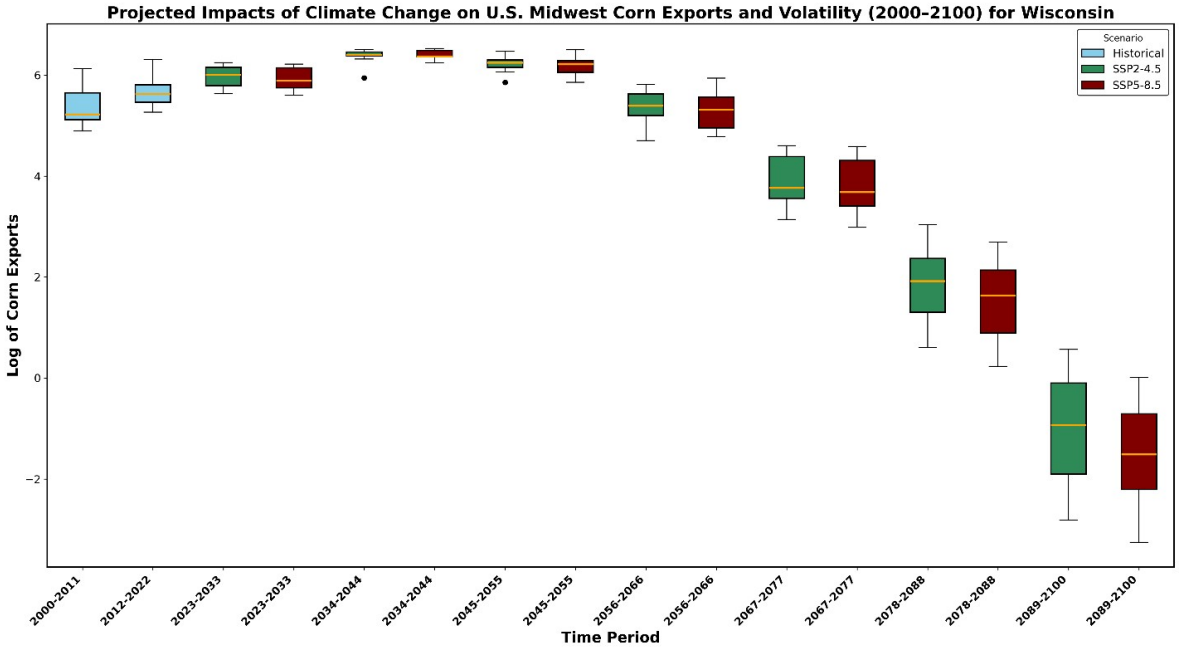


Figure A.29: *This box plot visualizes the distribution of log corn ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Wisconsin. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the corn ERS export allocation over time.*

A.3.3 State-wise Soybean Production Projections and Volatility (2023–2100)

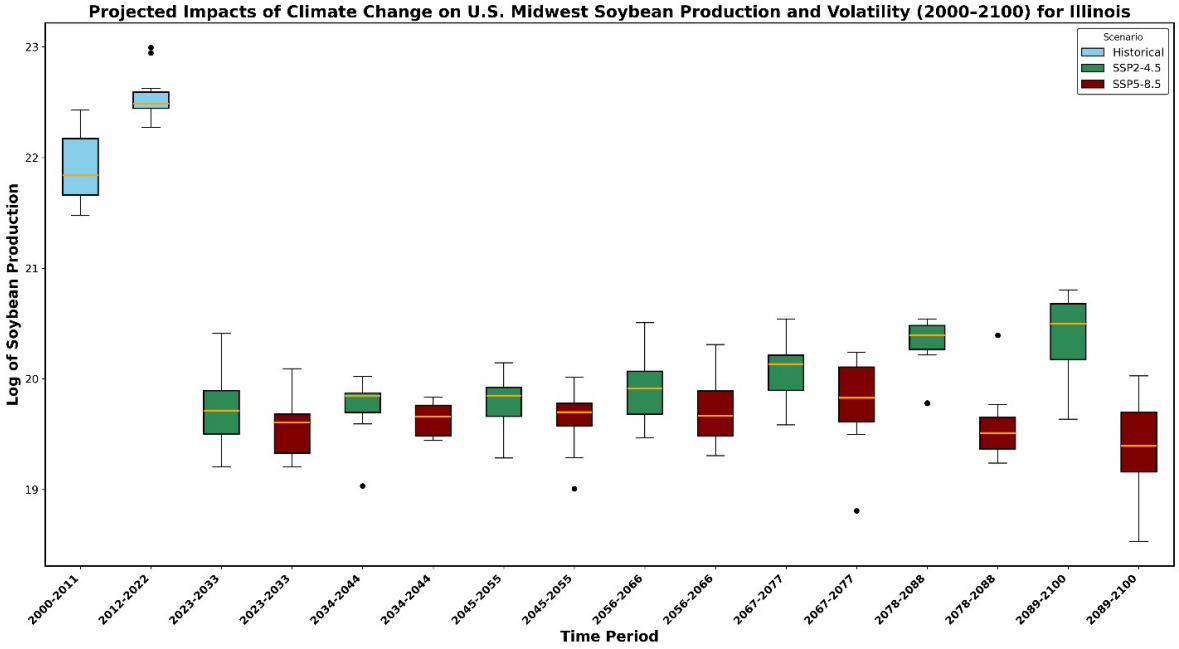


Figure A.30: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Illinois. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

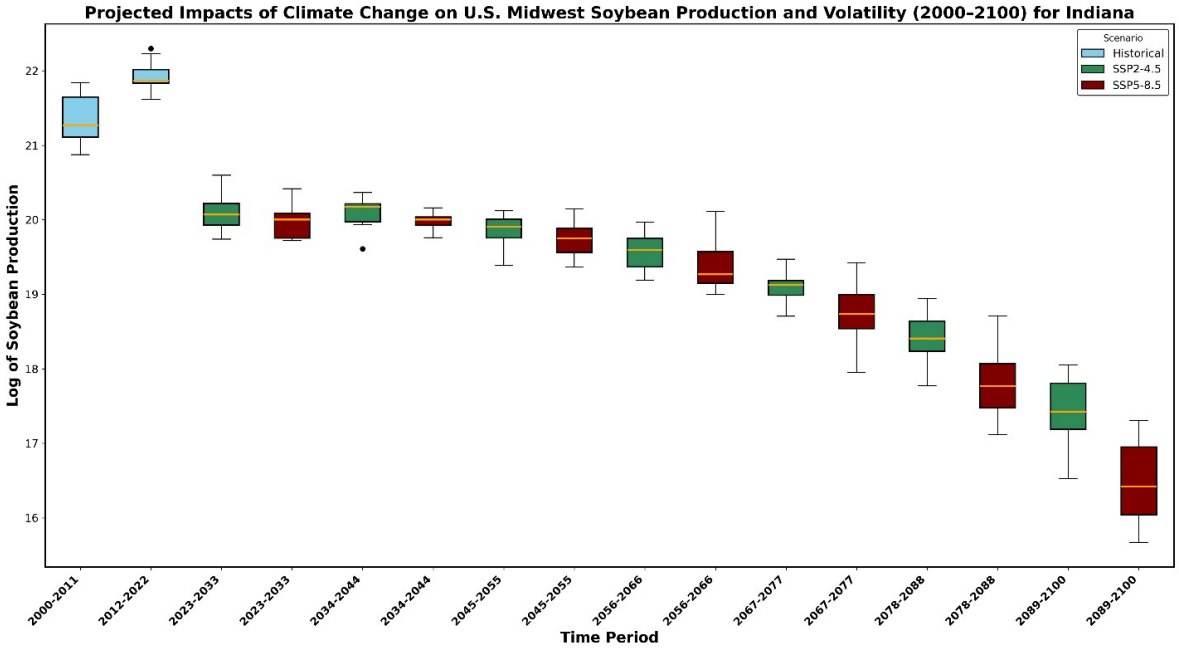


Figure A.31: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Indiana. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

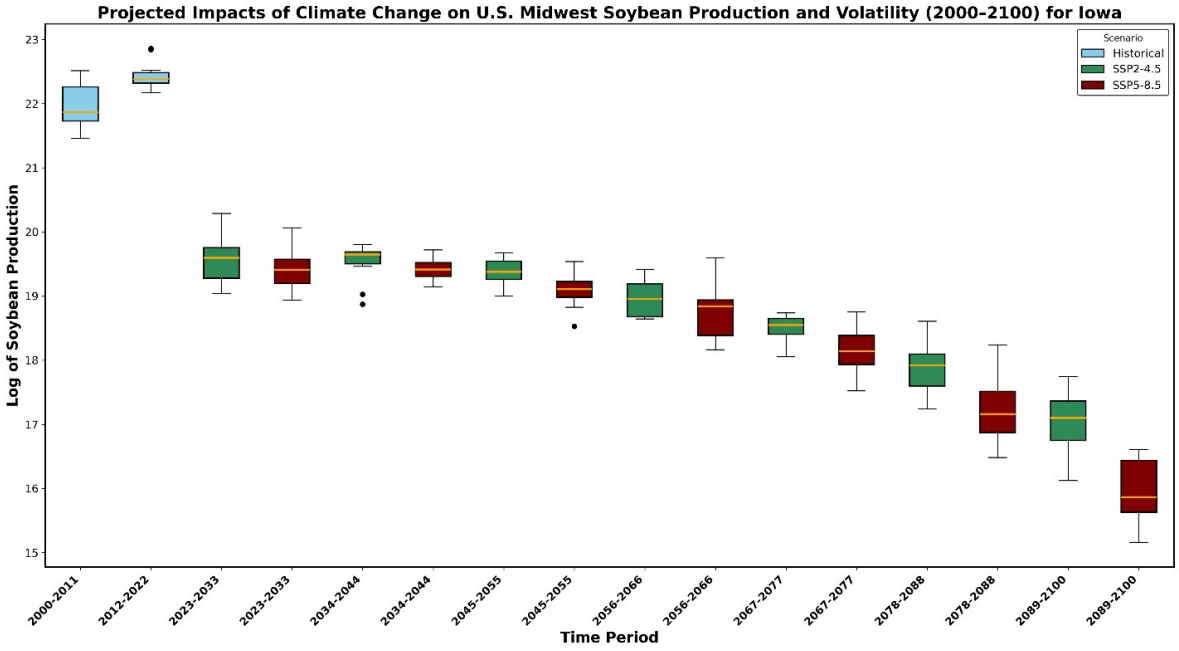


Figure A.32: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Iowa. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

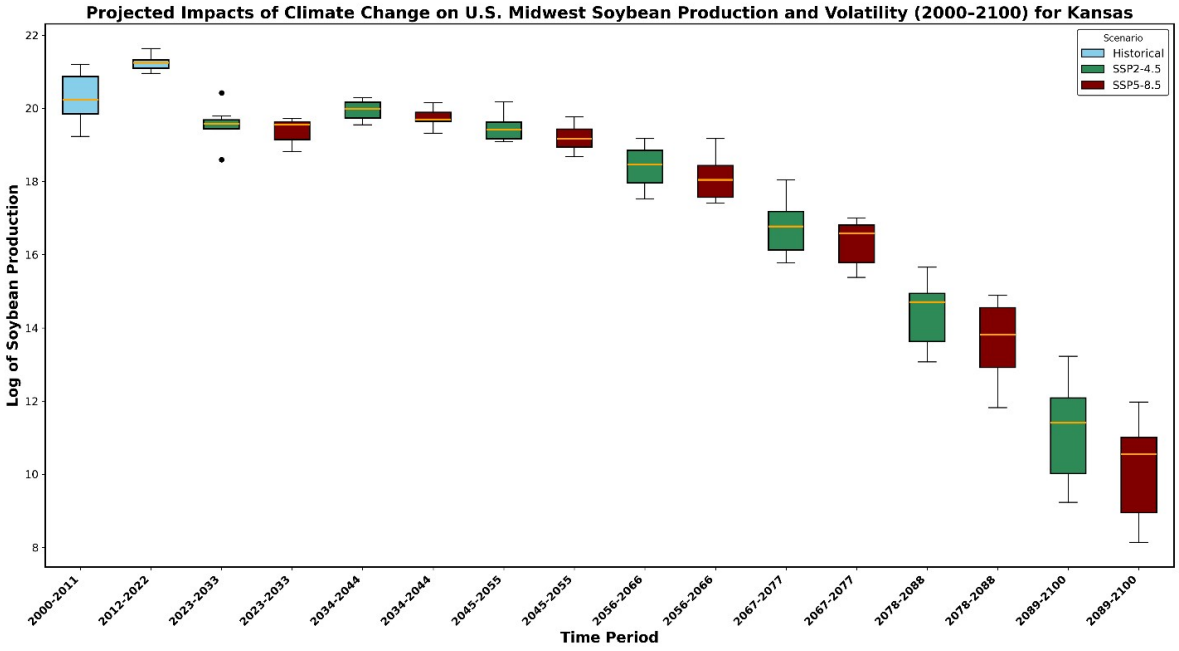


Figure A.33: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Kansas. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

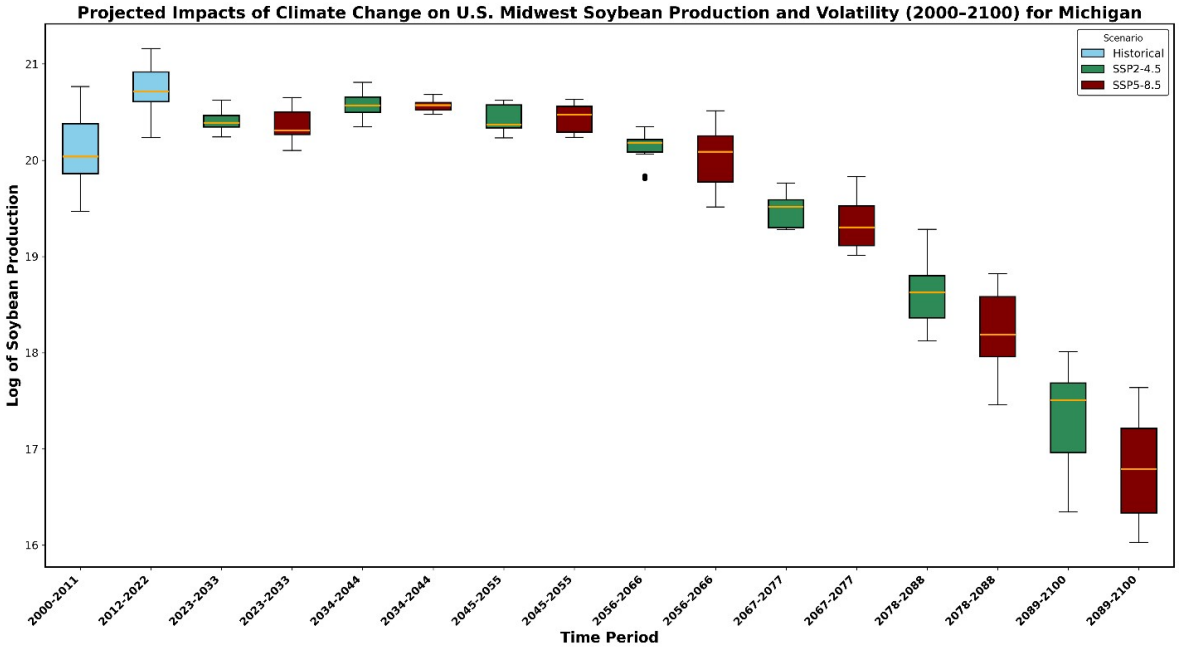


Figure A.34: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Michigan. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

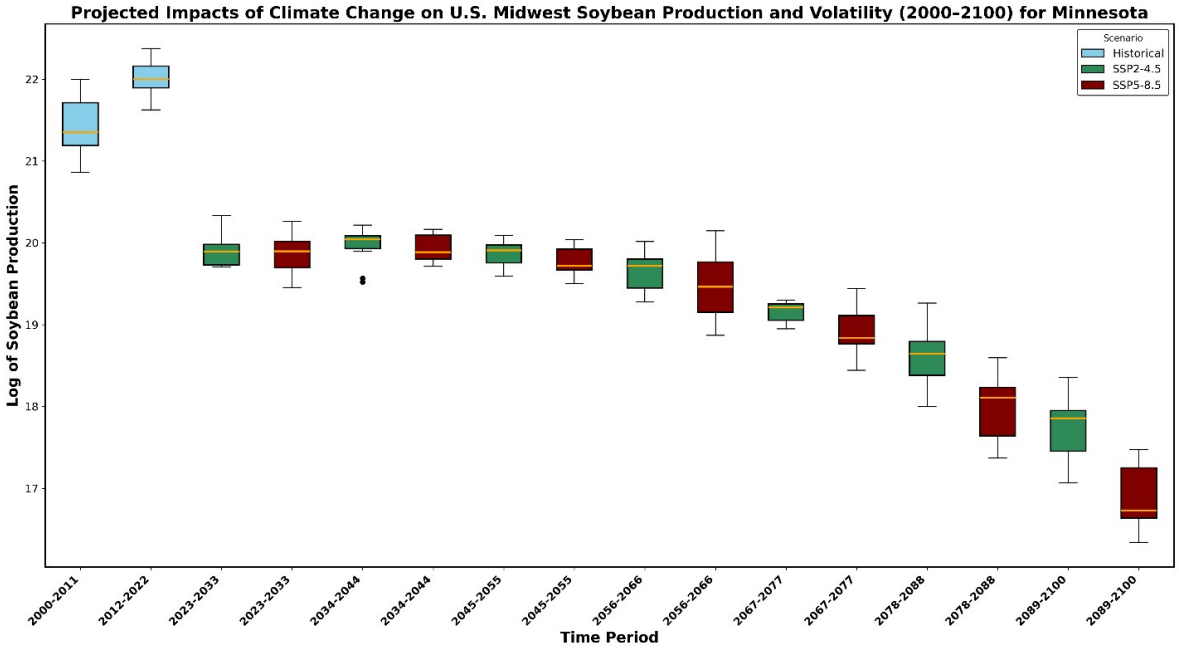


Figure A.35: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Minnesota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

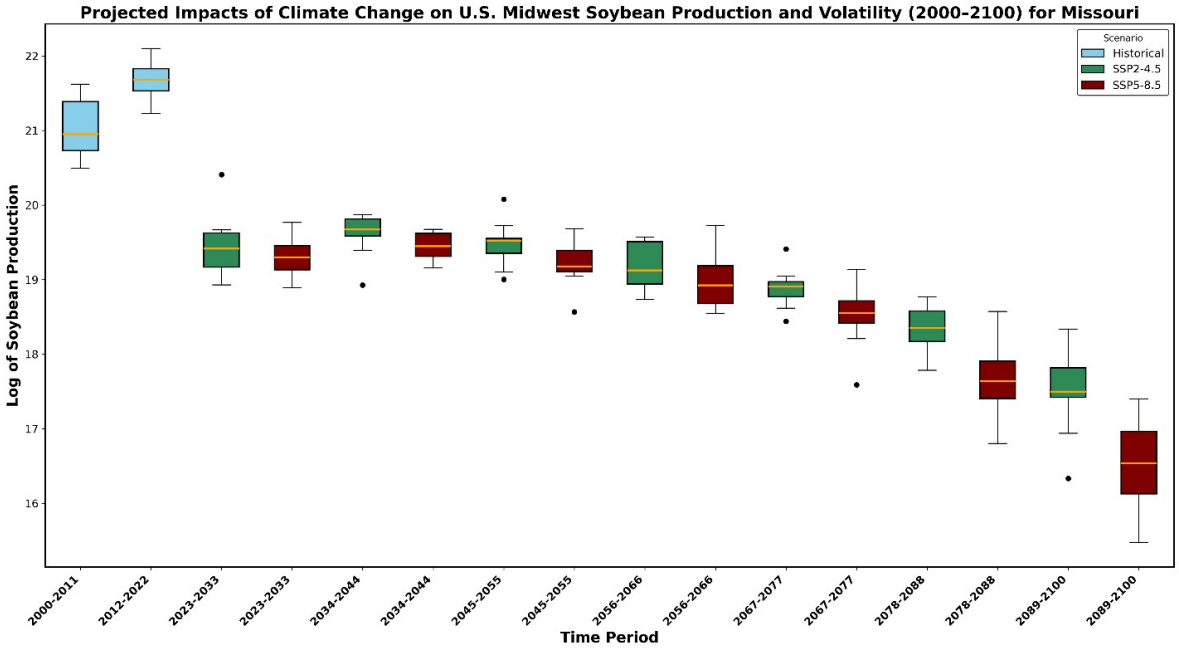


Figure A.36: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Missouri. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

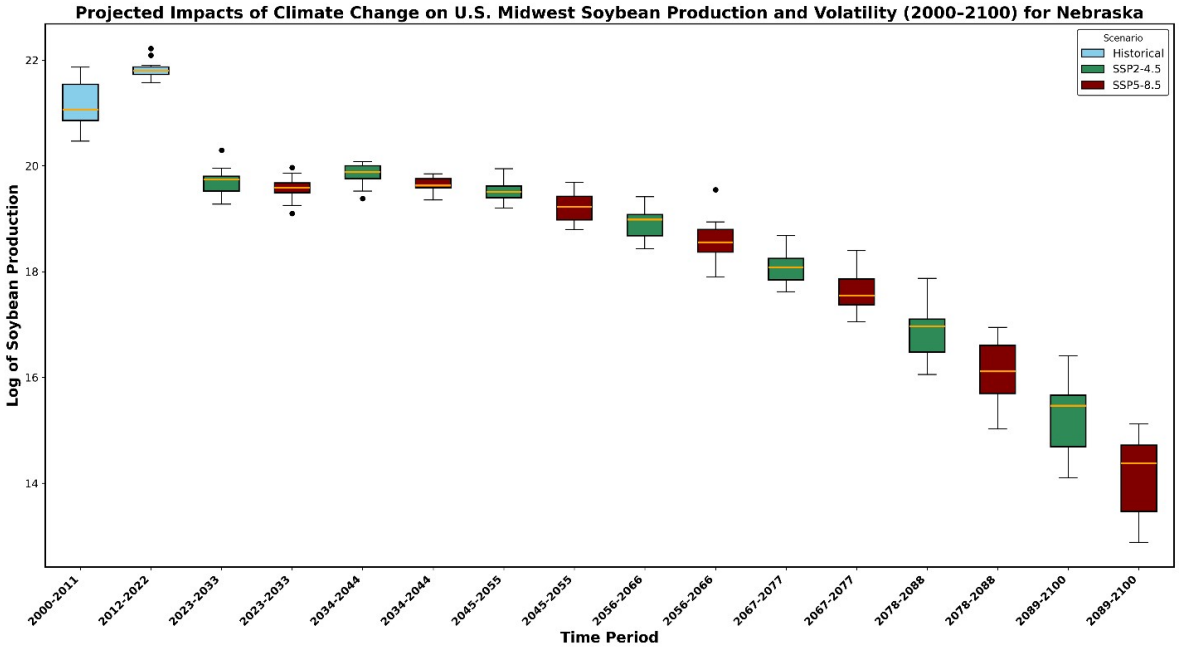


Figure A.37: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Nebraska. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

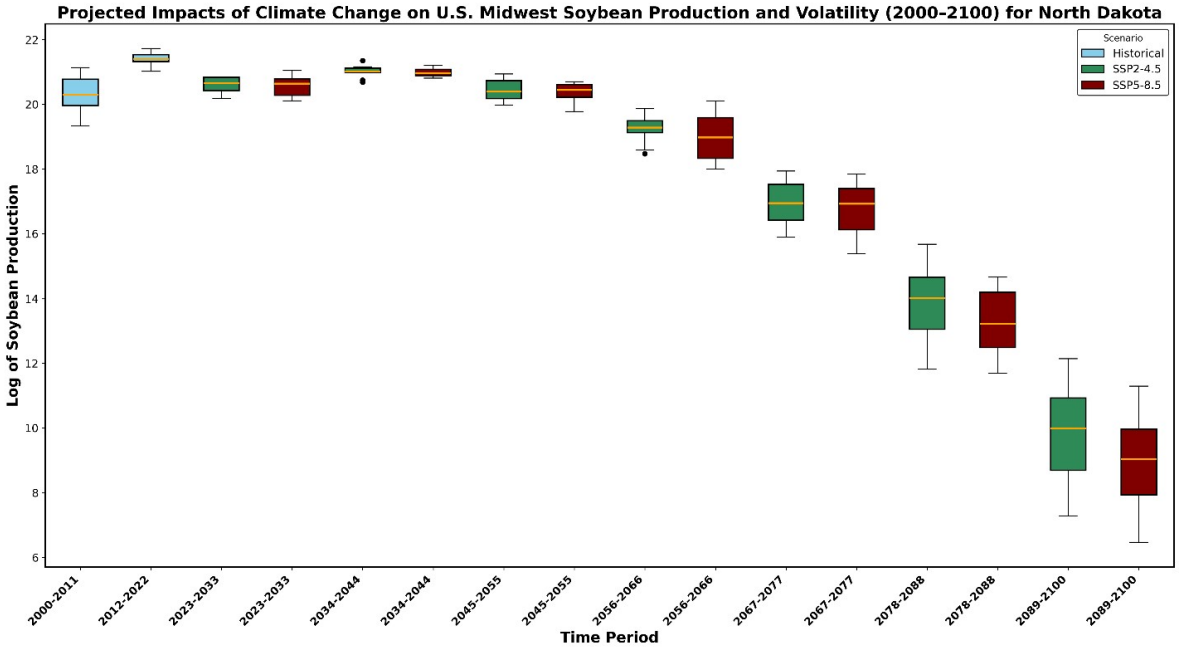


Figure A.38: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in North Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

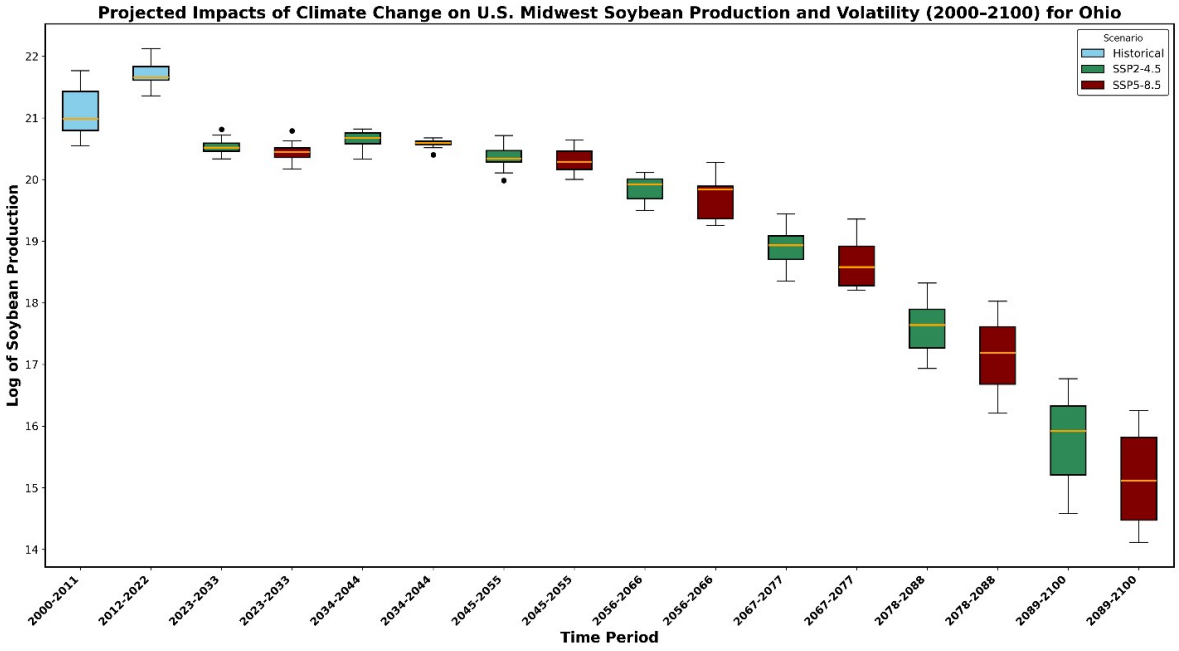


Figure A.39: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Ohio. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

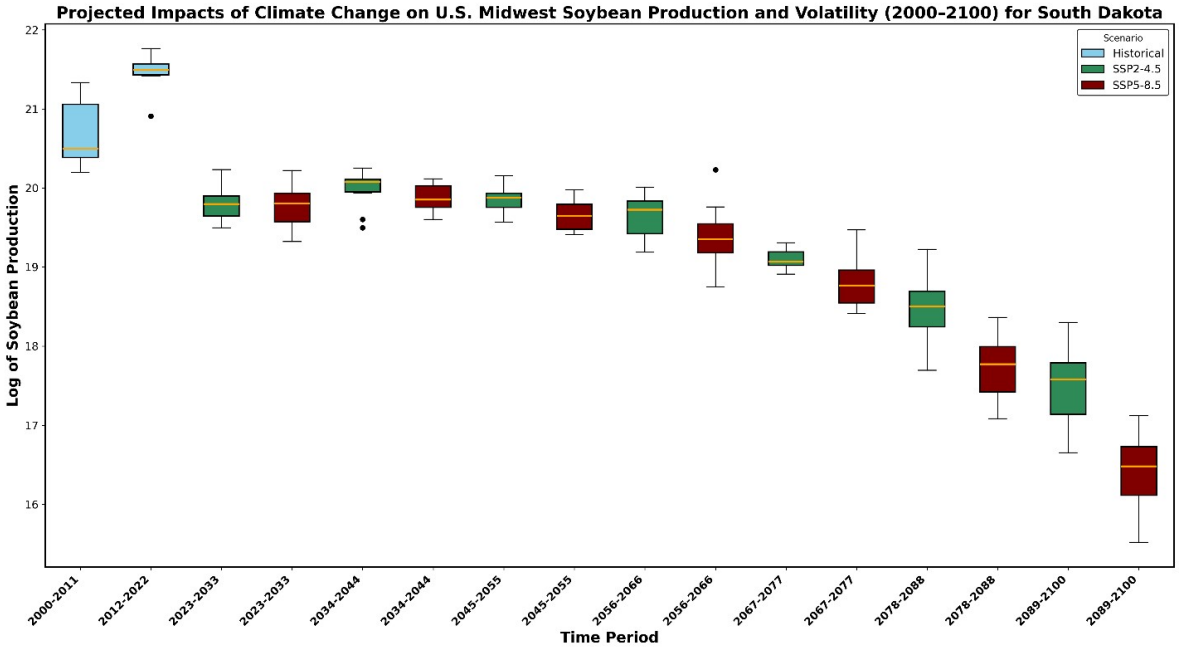


Figure A.40: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in South Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

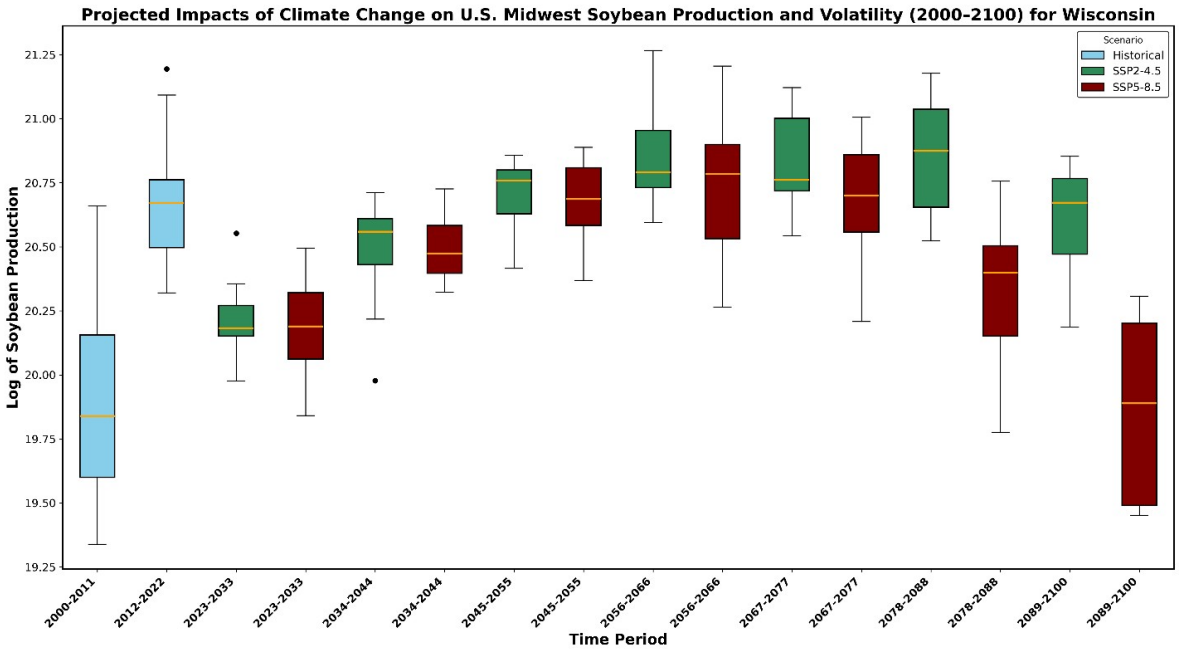


Figure A.41: *This box plot visualizes the distribution of log soybean production for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Wisconsin. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of soybean productions over time.*

A.3.4 State-wise Soybean ERS Allocation Projections and Volatility (2023–2100)

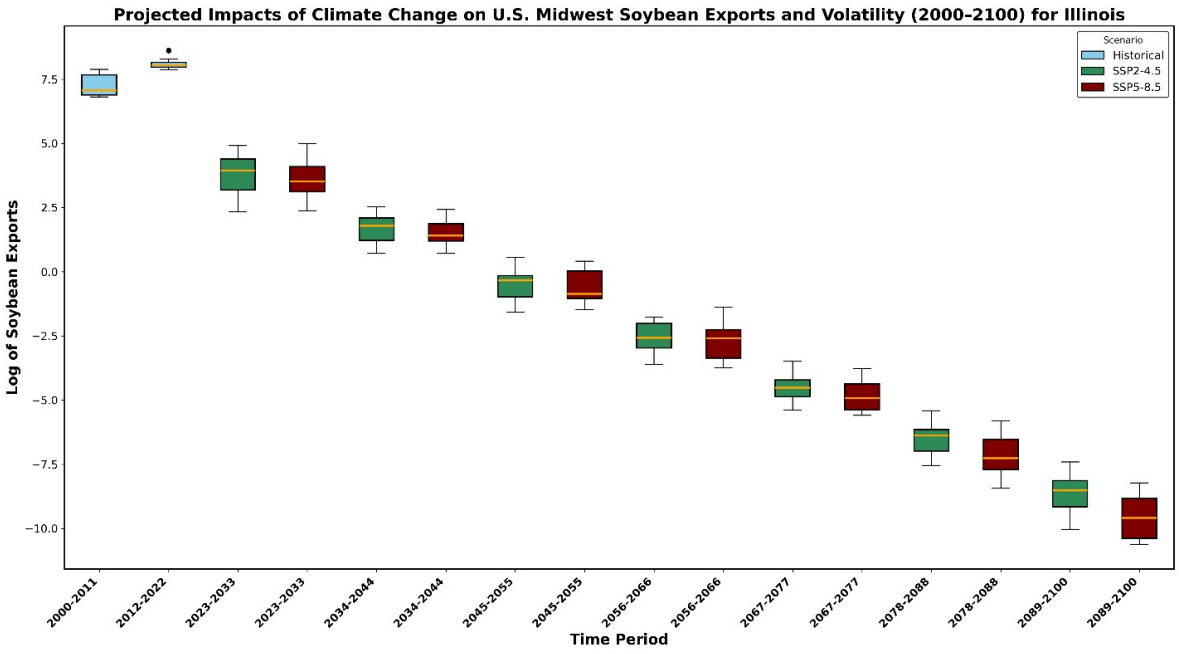


Figure A.42: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Illinois. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

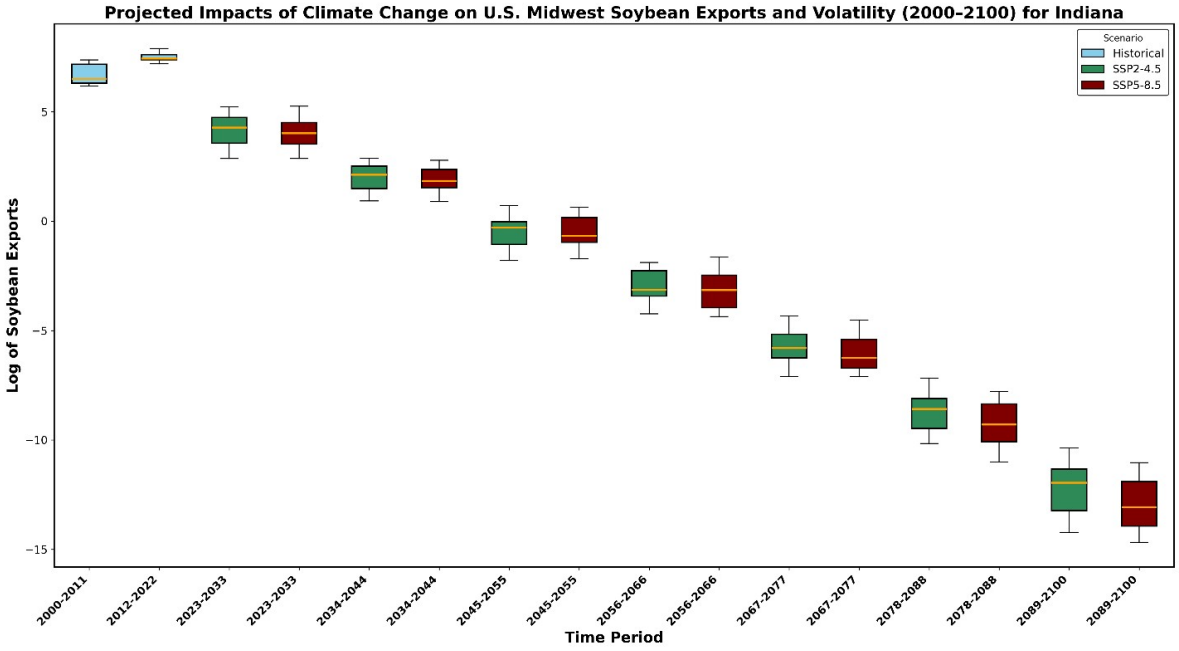


Figure A.43: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Indiana. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

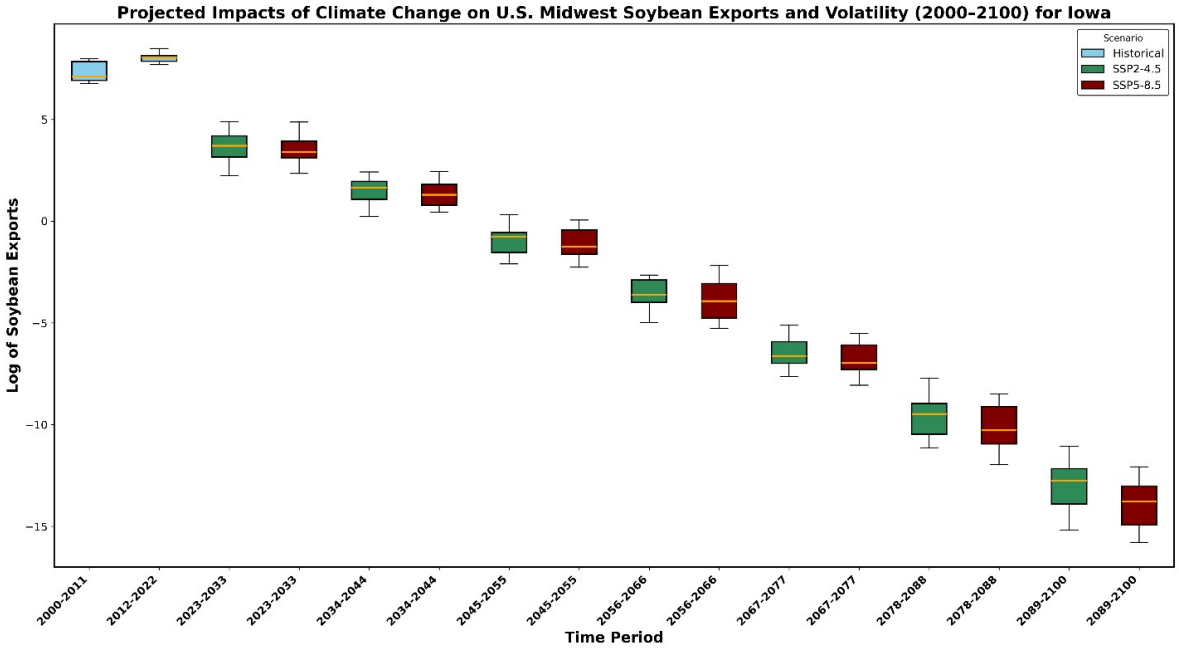


Figure A.44: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Iowa. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

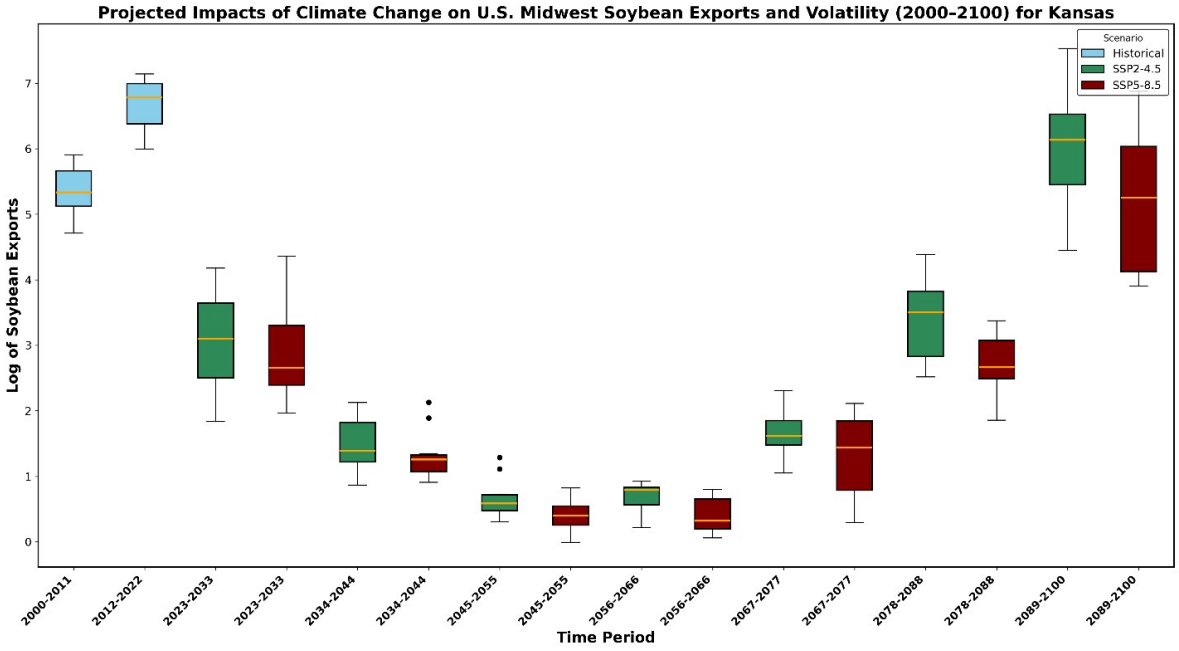


Figure A.45: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Kansas. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

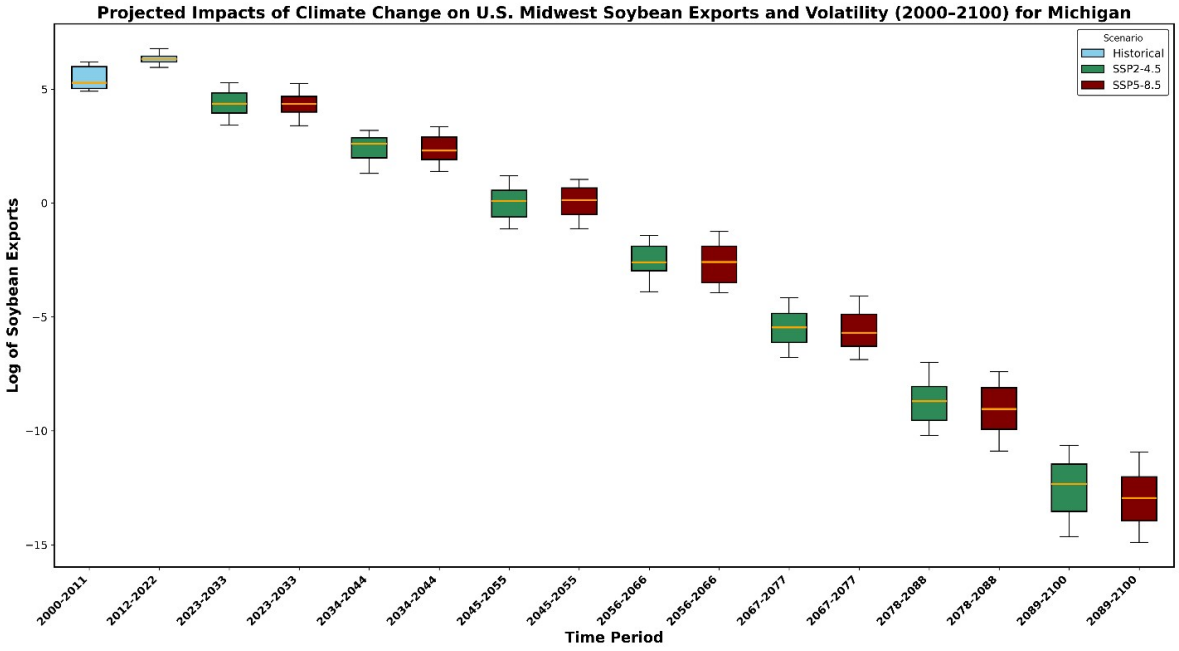


Figure A.46: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Michigan. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

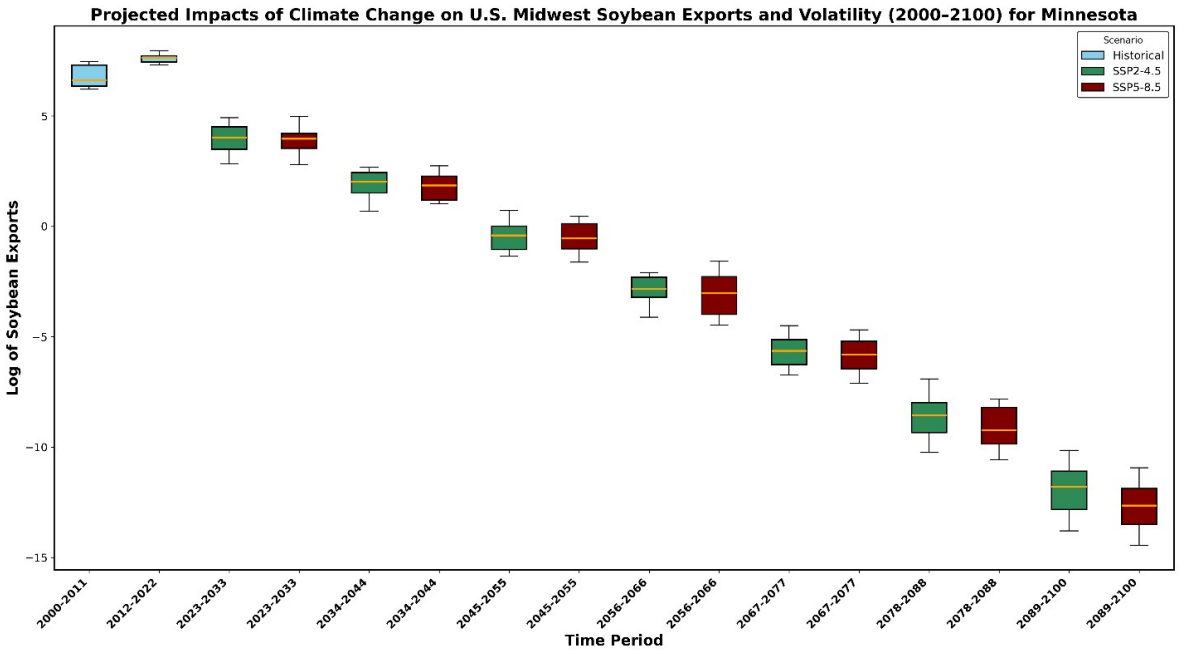


Figure A.47: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Minnesota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

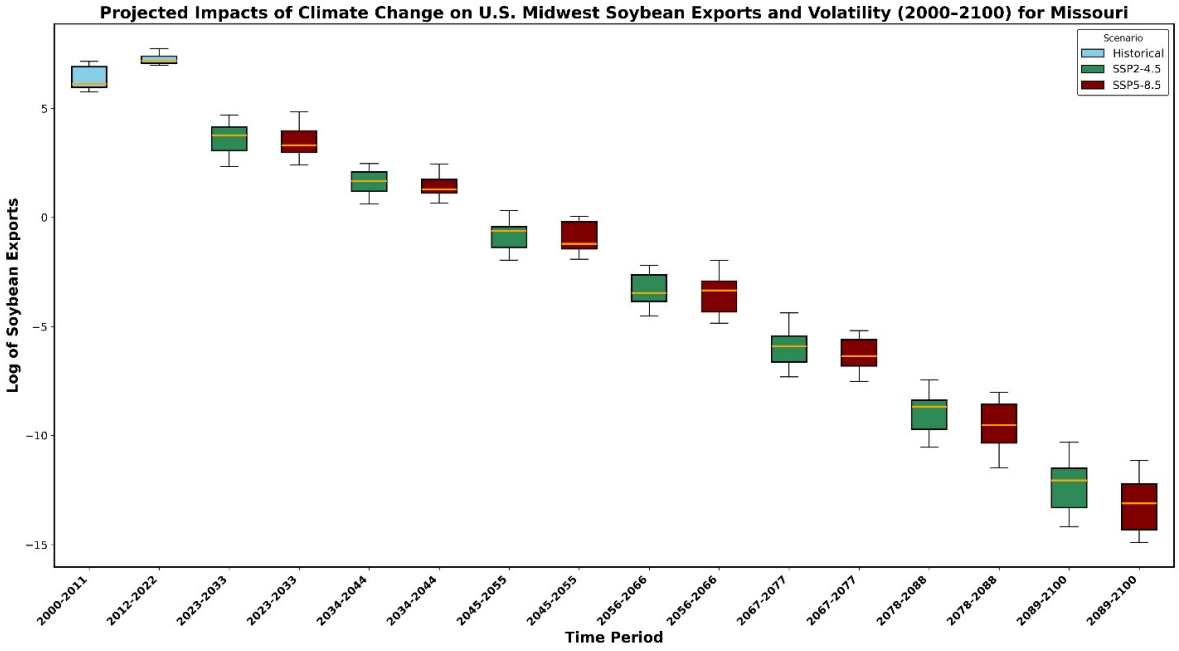


Figure A.48: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Missouri. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

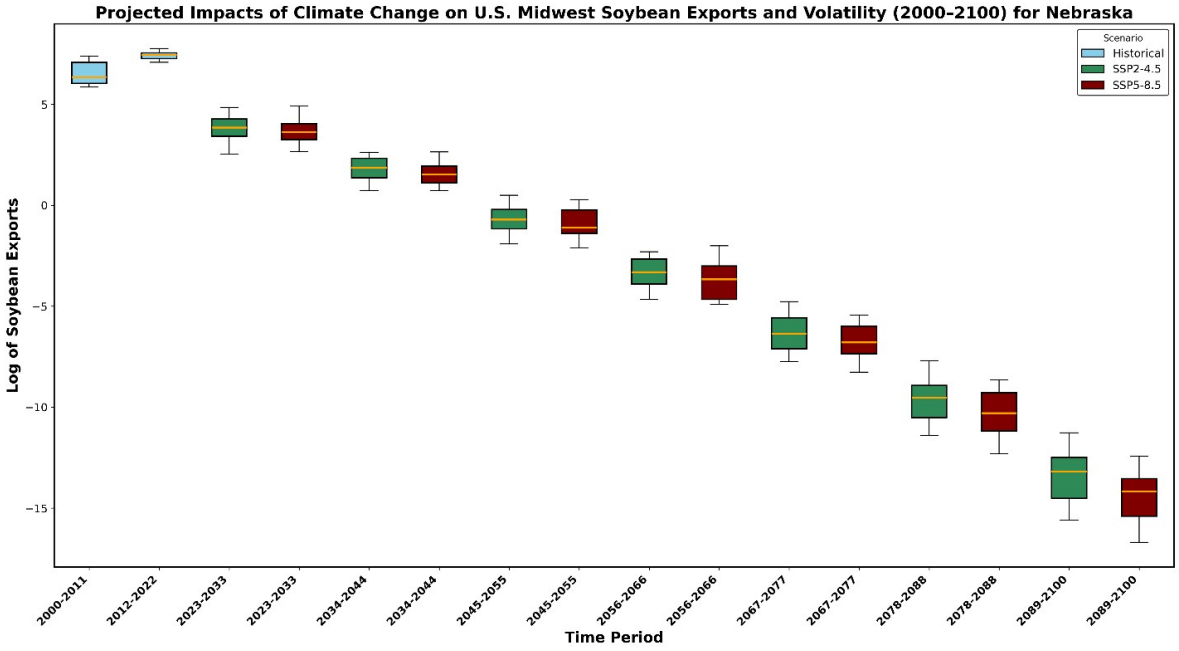


Figure A.49: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Nebraska. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

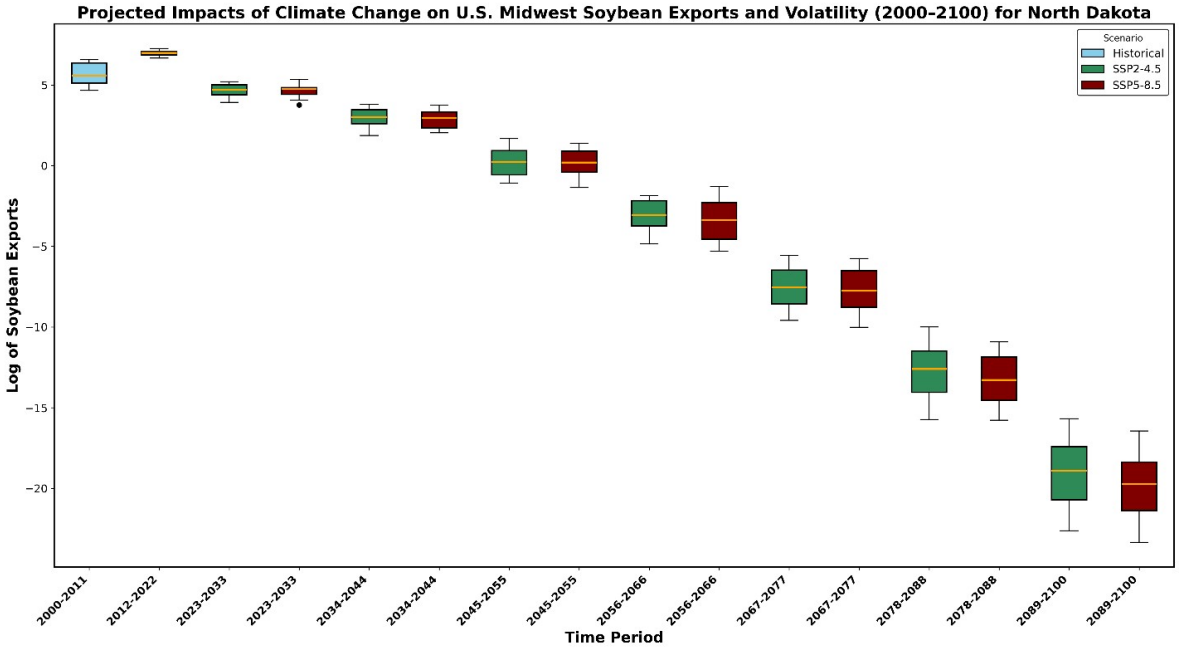


Figure A.50: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in North Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

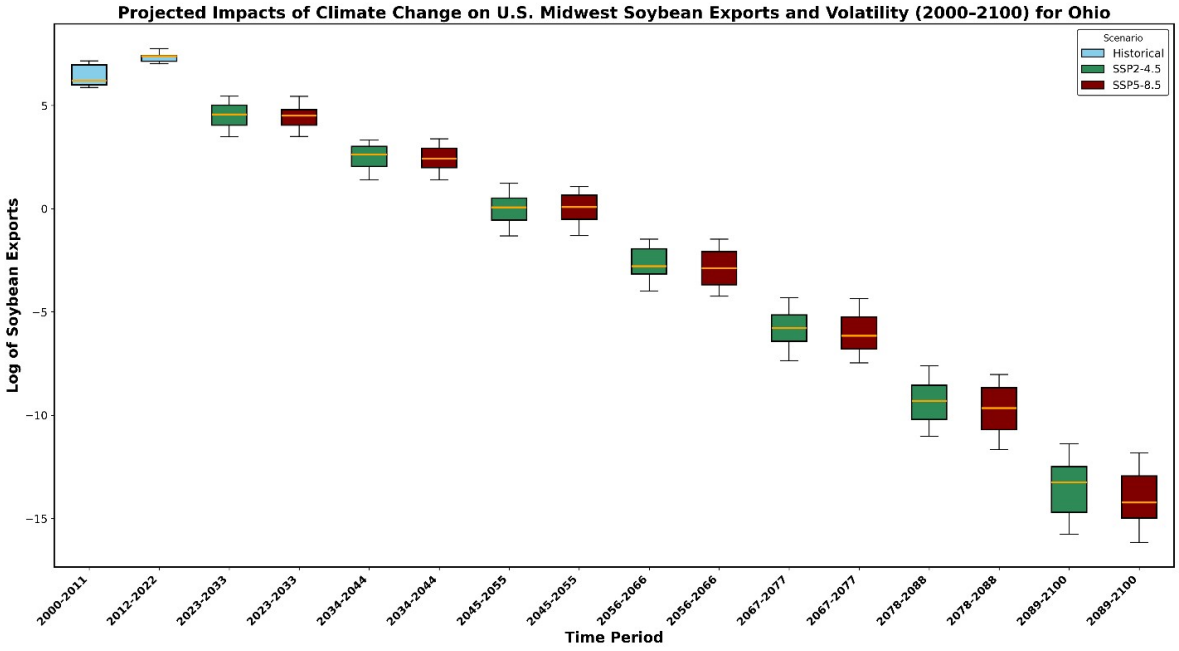


Figure A.51: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Ohio. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

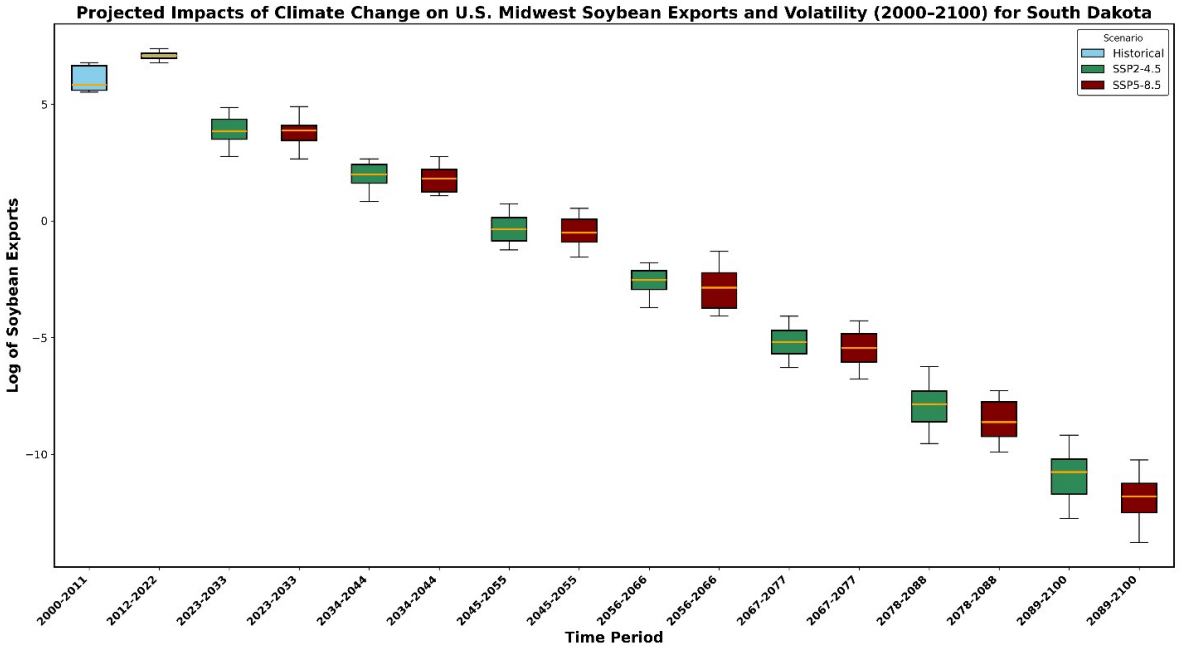


Figure A.52: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in South Dakota. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

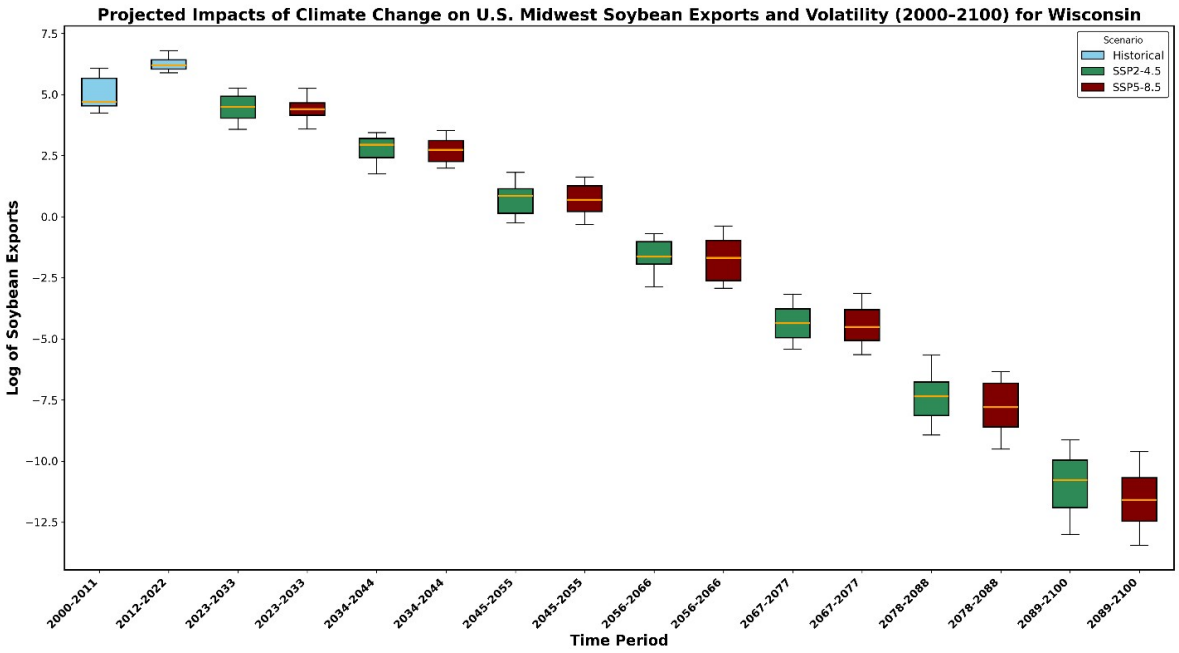


Figure A.53: *This box plot visualizes the distribution of log soybean ERS export allocation for the historical period (blue) and future climate scenarios SSPs245 and SSPs585 in Wisconsin. The height of each box and its whiskers represent volatility, while the median line shows the scenario median. The figure demonstrates how future climate pathways are projected to impact both the level and variability of the soybean ERS export allocation over time.*

A.4 CESM2 Model Projections under SSP245 and SSP585

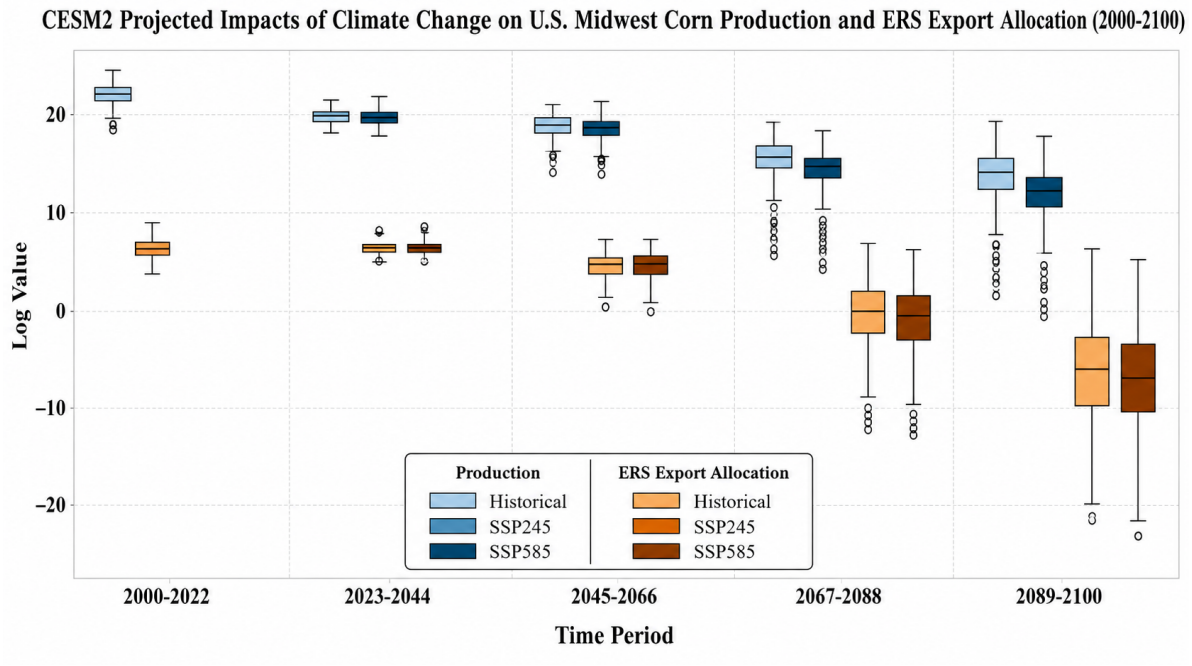


Figure A.54: *Projected distribution of U.S. Midwest corn production value and ERS state export allocation, 2000–2100. The blue boxes represent corn production value, and the orange boxes represent the ERS state export allocation. Historical values are based on PRISM weather data for 2000–2022, while future scenario values are based on CESM2 projections under SSP245 and SSP585. The horizontal line within each box indicates the median, the box shows the interquartile range, the whiskers show the range excluding outliers, and the circles indicate outliers. The figure shows that corn production value shifts downward and becomes more dispersed over time, especially under SSP585. The ERS allocation paths are reported as secondary mechanical scenario illustrations of the constructed cash-receipts-based allocation series and should not be interpreted as forecasts of future exports or physical shipments.*

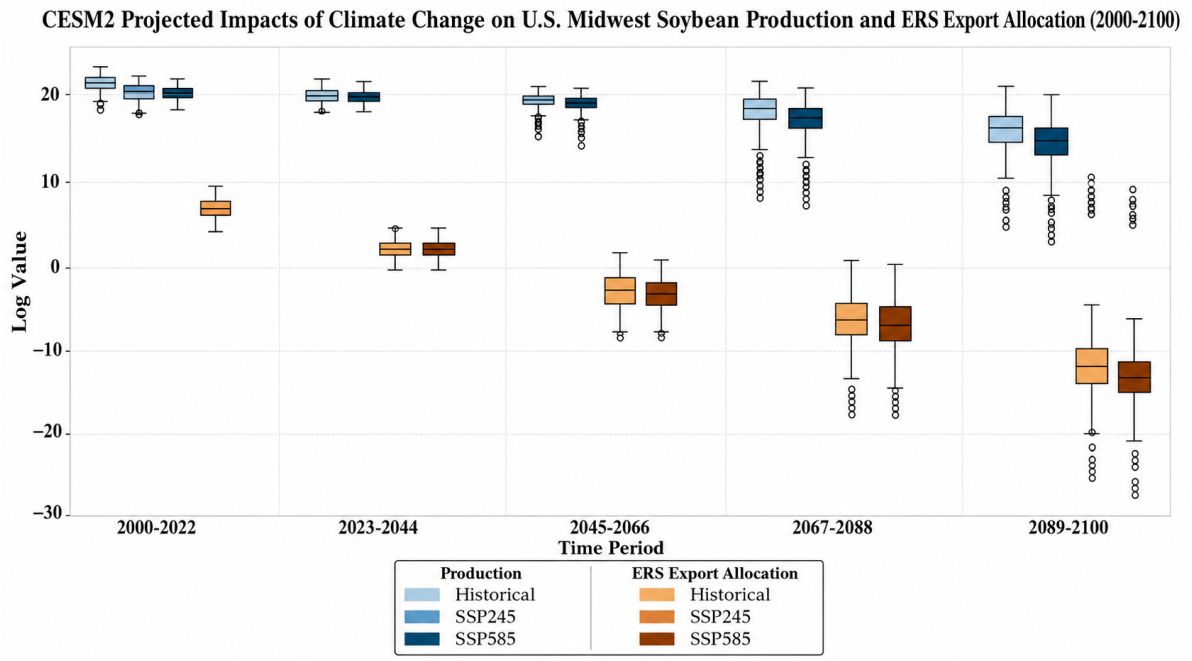


Figure A.55: *Projected distribution of U.S. Midwest soybean production value and ERS state export allocation, 2000–2100. The blue boxes represent soybean production value, and the orange boxes represent the ERS state export allocation. Historical values are based on PRISM weather data for 2000–2022, while future scenario values are based on CESM2 projections under SSP245 and SSP585. The horizontal line within each box indicates the median, the box shows the interquartile range, the whiskers show the range excluding outliers, and the circles indicate outliers. The figure shows that soybean production value shifts downward and becomes more dispersed over time, especially under SSP585. The ERS allocation paths are reported as secondary mechanical scenario illustrations of the constructed cash-receipts-based allocation series and should not be interpreted as forecasts of future exports or physical shipments.*