Bridging the Hemispheres: A Global Balancing Mechanism for Stabilizing Soybean Supply and Prices

Tetsuji Tanaka,[1,3] Jin Guo,[2] Laixiang Sun,[3,4] Xiao-Peng Song, [3]

[1]Department of Economics, Meiji Gakuin University, Tokyo, Japan

[2] Department of Economics, Setsunan University, Osaka, Japan

[3] Department of Geographical Sciences, University of Maryland, College Park, MD 20471, USA.

[4] School of Finance & Management, SOAS University of London, Russell Squre, London WC1H 0XG, UK.

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Abstract

Climate-induced yield variability and a global soybean import-to-production ratio exceeding 40% have rendered international food markets increasingly vulnerable to regional supply shocks. Here we evaluate a "global hedging mechanism" that leverages remote sensing (RS) technology to exploit the seasonal production asymmetries between the Northern and Southern Hemispheres. By integrating early-season forecasts from the Southern Hemisphere into the planting decisions of Northern Hemisphere farmers, this information-based coordination allows for ex ante production adjustments that stabilize global supply and prices. Using counterfactual simulations and risk-premium measures derived from expected utility and prospect theories, we demonstrate that the utilization of RS information reduces import price volatility across all eight sampled countries, with significant declines of 10.0% in Hungary and 9.3% in Iran. While conventional expected utility models estimate global annual welfare benefits up to USD 954 million , our behavioral analysis accounting for loss aversion

through prospect theory reveals that benefits could reach approximately USD 15.5 billion. These results underscore the disproportionate impact of price spikes on welfare in vulnerable, import-dependent economies. Our findings suggest that RS-based forecasting functions as a global public good, providing a cost-effective, market-compatible safety net. Investing in international RS infrastructure and integrating transparent information into food policy are essential steps for enhancing the resilience of the global agricultural value chain against future climatic crises.

1. Introduction

Climate change has increased the interannual variability of crop yields worldwide by altering temperature regimes, destabilizing water availability, and intensifying extreme weather events, with particularly strong effects observed for rain-fed summer crops (Lobell et al., 2011; Ray et al., 2015; Lesk et al., 2016; IPCC, 2022). As illustrated in Figure 1, the ratio of global imports to global production for soybeans has surged since the turn of the 21st century, recently surpassing the 40% mark. This indicates that nearly half of global soybean production is now traded on international markets; consequently, the impact of supply shocks in specific producing regions on global food security has reached unprecedented levels.

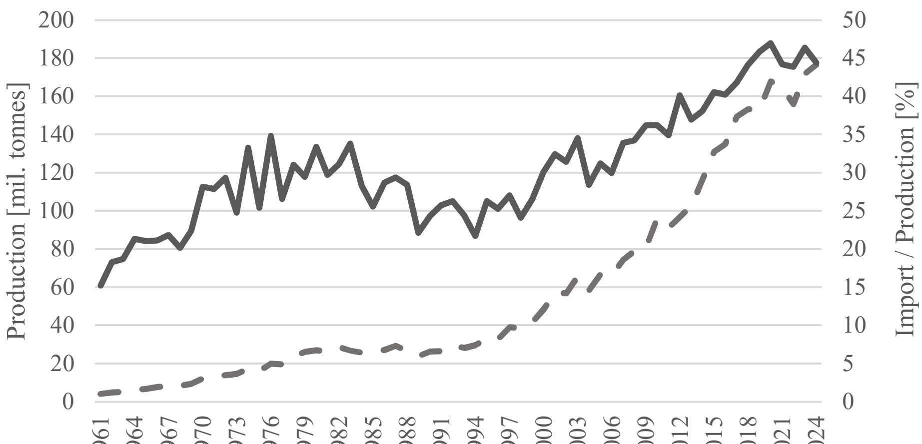


Figure 1. Trends in Global Soybean Production and the Global Import-to-Production Ratio (1961–2024)

Recent advances in remote sensing have markedly enhanced the monitoring of agricultural systems at regional to global scales. The proliferation of Earth observation satellites, together with open data policies, standardized processing workflows, and progress in artificial intelligence and cloud computing, has accelerated developments in agricultural remote sensing (Song, 2023), enabling routine production of continental- and global-scale crop maps (Song et al., 2021; van Tricht et al., 2023). These advances support in-season crop identification (Lin et al., 2022), spatially explicit yield estimation (Lobell et al., 2015; Deines et al., 2021; Song et al., 2022), and early-season production forecasting (Becker-Reshef et al., 2010; Franch et al., 2015), improving the accuracy and timeliness of national-level yield forecasts relative to conventional methods. Importantly, satellite-based monitoring now allows potential harvest shortfalls or surpluses to be identified well before harvest.

Figure 2 summarizes global soybean planting and harvesting calendars, highlighting pronounced differences in production timing between the Northern and Southern Hemispheres. By the time harvest results from the Southern Hemisphere become available in June, soybean planting across much of the Northern Hemisphere (i.e., Canada, EU and USA) is already close to completion, limiting the scope for supply-side responses. In contrast, when yield expectations can be formed as early as April using satellite-based forecasts, sowing activities in many Northern Hemisphere regions are still ongoing. This timing overlap creates an opportunity for farmers to adjust planting decisions in response to anticipated market conditions, forming the basis of the global hedging mechanism proposed by Tanaka et al. (2023).

When early-harvest information is available, farmers in the Northern Hemisphere can infer poor soybean yields in the Southern Hemisphere, anticipate upward pressure on prices, and expand soybean planting beyond initial plans to take advantage of expected market conditions and enhance farm income. Conversely, expectations of a strong Southern Hemisphere harvest signal lower future prices, prompting Northern Hemisphere producers to scale back soybean acreage to limit potential revenue losses. Such adaptive responses enable part of the supply shortfall in the South to be compensated by increased production in the North, while anticipated surpluses in the Southern Hemisphere can be moderated through reduced planting in the Northern Hemisphere. At the global level, these production adjustments contribute to greater stability in soybean supply and prices, enhancing the resilience of the international food system.

A further advantage of this mechanism lies in its capacity to moderate price volatility associated with financial speculation. The real-time dissemination of early yield forecasts allows market participants worldwide, including speculators, to access the same critical information simultaneously. In the soybean market, for example, traders can anticipate that producers in the Northern Hemisphere will adjust planting decisions in response to expected shortages or surpluses in the Southern Hemisphere. Such forward-looking expectations may encourage more measured trading behavior, reducing reactions driven solely by initial supply shocks. Consequently, this information-based mechanism can help attenuate excessive price movements linked to speculative activity, while also smoothing fluctuations arising from underlying supply–demand dynamics, thereby contributing to greater stability in global markets.

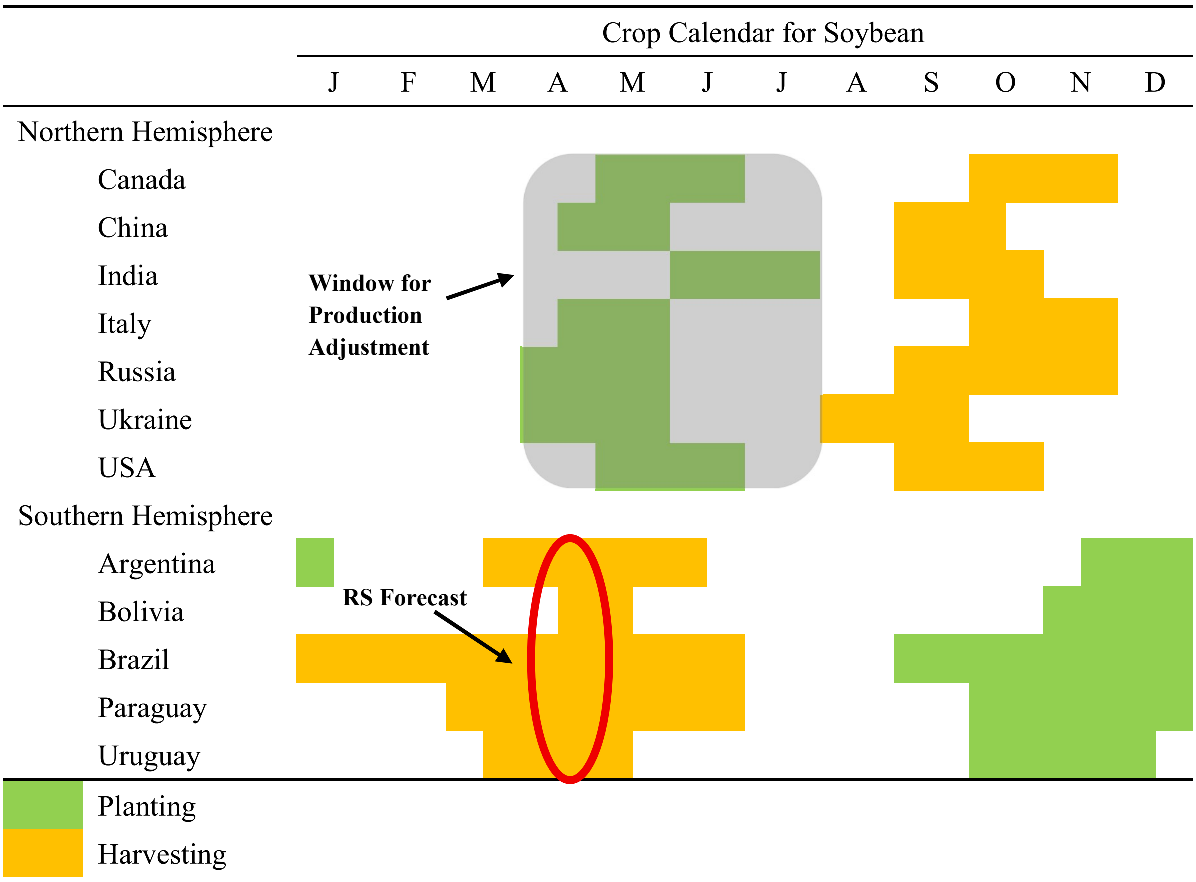
A substantial body of research on the role of forecast information in shaping market behavior has concentrated on crop outlook reports issued by the U.S. Department of Agriculture (USDA), offering empirical evidence on their effects on price movements and volatility. For example, Isengildina-Massa et al. (2008) examined the relationship between USDA crop forecasts and futures market volatility, showing that market responses depend critically on the perceived accuracy of the released information. Using a Dynamic Conditional Correlation (DCC) framework, Banse et al. (2016) analyzed price dynamics surrounding forecast announcements and assessed whether such information tends to amplify or dampen price changes. Similarly, Han and Huang (2021) demonstrated that highly accurate forecasts contribute to market stability, while forecast errors can generate market disturbances. Taken together, these studies highlight the central role of forecast reliability in market functioning, with important implications for policy design and risk management.

Tanaka et al. (2023) investigate the stabilizing role of early crop production forecasts derived from remote sensing within a computable general equilibrium (CGE) framework applied to global wheat and soybean markets. The study makes a novel contribution by demonstrating how international market stability can be improved by combining satellite-based forecast information with seasonal production asymmetries between the Northern and Southern Hemispheres. The analysis focuses on key historical episodes, including bumper and poor wheat harvests in Russia and Ukraine in 2008 and 2012, as well as the soybean production shortfall in Brazil in 2012. While the results provide clear insights into the market impacts of forecast information for each case, the static structure of the model precludes a precise quantification of the overall magnitude of price stabilization effects over time.

In this study, we construct an economic framework to examine how seasonal production differences between the Northern and Southern Hemispheres can be exploited to stabilize global soybean supply and prices. The model analyzes how early-season soybean production forecasts from major Southern Hemisphere producers—Brazil, Argentina, Paraguay, Bolivia and Uruguay—can inform production decisions by farmers in key Northern Hemisphere countries, including Canada, China, India, Italy, Russia, Ukraine and the United States. By adjusting planting decisions in response to anticipated supply conditions, producers in the Northern Hemisphere can partially offset production shocks originating in the South, thereby dampening price volatility.

This study does not rely on a historical before–after comparison of market outcomes following the introduction of remote sensing technology. Instead, it constructs a counterfactual information regime in which early-season remote sensing–based soybean harvest forecasts are hypothetically unavailable at the time of planting decisions, and compares it with an alternative regime in which such information is fully utilized by producers. Within this simulation framework, we quantify how access to early forecast information reduces import price volatility in soybean-dependent countries—including China, Ecuador, Hungary, Indonesia, Iran, Peru, Spain and Thailand—and evaluate the associated welfare gains in monetary terms using risk-premium measures derived from expected utility theory.

Figure 2. Global Planting and Harvesting Seasons for Soybean



Source: Compiled by authors based on USDA International Production Assessment Division and TESEO crop calendars.

2. Results

Price volatility is measured using the standard deviation of annual soybean import prices. Although higher-frequency measures of conditional volatility are well suited to analyzing short-term price discovery around information releases, the annual aggregation adopted here is intended to capture medium- to long-run stabilization effects arising from production adjustments that operate through planting decisions. Accordingly, the volatility metric employed in this study reflects cumulative stabilization over the production cycle rather than immediate market reactions to forecast announcements.

The use of annual data is motivated by two practical and conceptual considerations. First, consistent high-frequency import price series are unavailable for many of the countries examined, and restricting the analysis to a small subset with monthly or weekly data would compromise cross-country comparability. Second, soybean production decisions are inherently annual, as planting and harvesting typically occur once per year. Accordingly, annual price volatility provides the appropriate temporal aggregation for capturing stabilization effects that operate through production adjustments.

2.1. Effects of Timely Harvest Forecast Information on Price Volatility

In the following analysis, “with RS” and “without RS” do not refer to observed market outcomes before and after the historical introduction of remote sensing technology. Instead, they represent two simulated information regimes within a counterfactual framework. The “without RS” scenario corresponds to a baseline world in which planting decisions are formed solely on the basis of historical production information, whereas the “with RS” scenario incorporates early-season remote sensing–based harvest forecasts into producers’ expectations while holding all other conditions constant.

Panel (a) of Figure 3 illustrates the standard deviation (SD) of soybean import prices across eight sample countries under the two simulated information regimes. The comparison highlights differences in price volatility between a counterfactual world without access to early-season remote sensing forecasts and an alternative regime in which such information is incorporated into production decisions. As a general trend, the utilization of RS information ("With RS") resulted in a reduction of the standard deviation in all countries, confirming its effect in mitigating price volatility. Notably, in Iran, where the standard deviation was the highest at approximately 250 under the counterfactual regime without RS information, there was a marked decline under the simulated regime with RS information. Conversely, the data also indicates that the information consistently contributed to price stabilization even in countries with initially low volatility, such as Thailand and Ecuador.

Panel (b) in Figure 3 illustrates the percentage change in the standard deviation (SD) of soybean import prices following the implementation of hedging strategies. Notably, all eight surveyed countries exhibited negative change rates, confirming that hedging consistently contributes to the mitigation of price volatility. The degree of reduction varied across countries; Hungary recorded the most significant decline at approximately 5.4%, followed by China and Indonesia, both at 4.2%. In contrast, the reduction rates for Spain (1.2%), Ecuador (1.3%), and Iran (1.3%) remained relatively modest. These disparities may reflect differences in market structures, import dependency on soybeans, and the quality of existing information infrastructure in each nation.

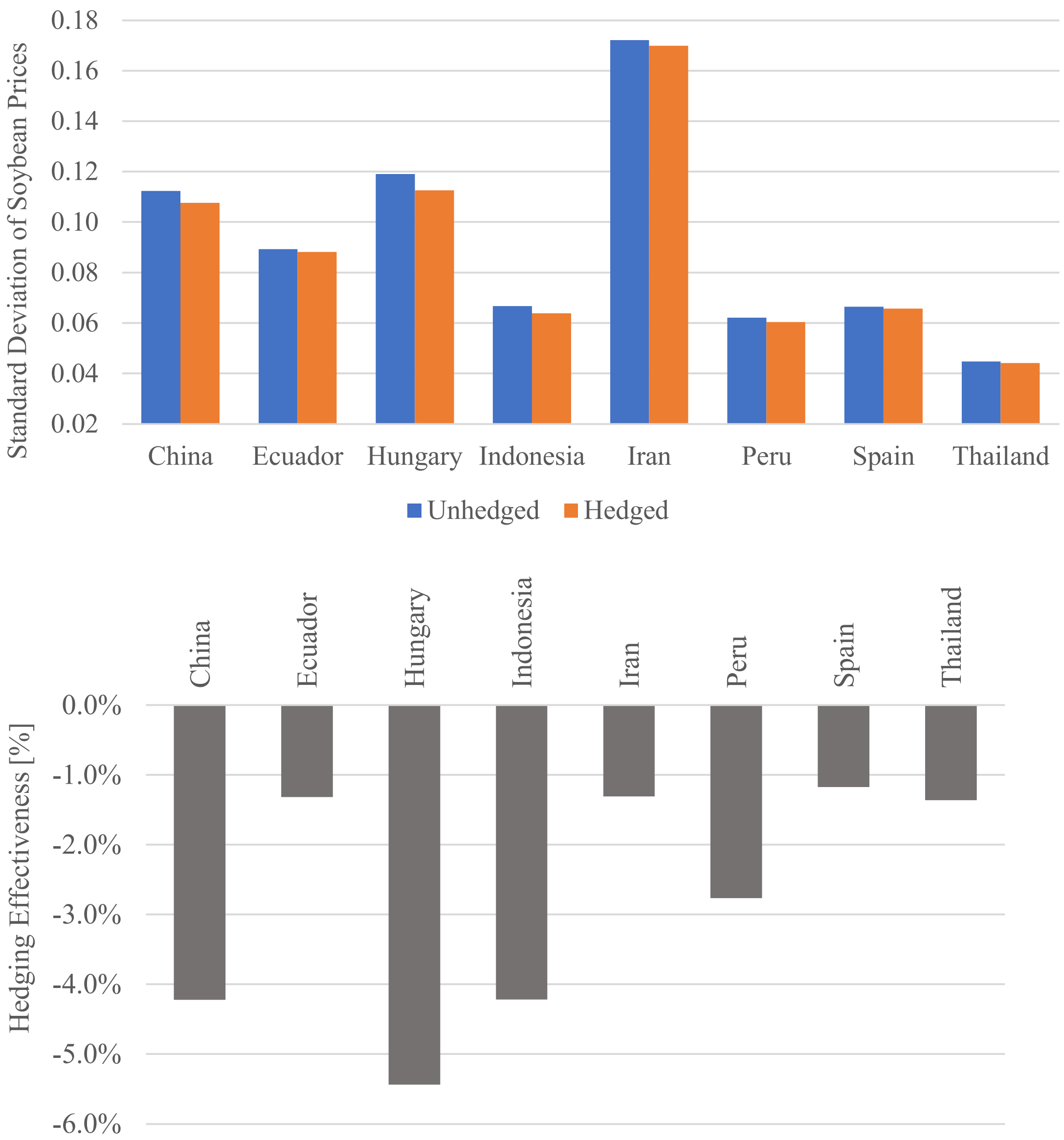


Figure 3. Variation in Price Volatility with/without Remote Sensing Harvest Information

2.2. Beneficial Effects from Reduced Price Volatility

Tables 1–3 quantify the economic value of early soybean harvest forecast information obtained through remote sensing within a global market framework that explicitly exploits seasonal differences between the Northern and Southern Hemispheres. In this mechanism, early production signals from major Southern Hemisphere producers are transmitted to Northern Hemisphere countries—most notably Brazil—prior to their planting decisions, enabling farmers to adjust soybean production upward or downward in anticipation of global supply conditions. This anticipatory adjustment mitigates aggregate supply uncertainty and contributes to the stabilization of world soybean markets.

Across all three behavioral specifications—constant absolute risk aversion (CARA), constant relative risk aversion (CRRA), and prospect theory—the results consistently indicate that early forecast information generates substantial welfare gains by reducing uncertainty in global soybean supply and prices. These gains arise not from ex post market interventions, but from ex ante production responses by farmers who incorporate remote sensing–based information into their decision-making processes.

Table 1 presents the estimated benefits under CARA preferences. The results exhibit an approximately linear increase in benefits with respect to the coefficient of absolute risk aversion, consistent with the theoretical prediction that the risk premium is proportional to risk aversion under CARA utility. Countries with larger soybean consumption and higher exposure to international price volatility experience greater benefits, while the global benefit—extrapolated from the sample countries to world soybean consumption—exceeds USD 95 million even under a low risk-aversion scenario and approaches USD 1 billion under higher risk aversion.

Table 2 reports the corresponding estimates under CRRA utility, where the benefits of early information increase more rapidly as relative risk aversion rises. This nonlinear amplification reflects the heightened sensitivity of welfare to consumption uncertainty under CRRA preferences.

Nevertheless, the qualitative implication remains unchanged: by enabling Southern Hemisphere producers to respond proactively to anticipated Northern Hemisphere harvest outcomes, early forecast information significantly dampens global price fluctuations and improves economic welfare.

Table 3 extends the analysis to a prospect theory framework, allowing for loss aversion and asymmetric valuation of downside risks. The resulting welfare gains are substantially larger than those obtained under expected utility models, indicating that when farmers and market participants place greater weight on adverse outcomes, the stabilizing role of early information becomes even more pronounced. Under this behavioral setting, early harvest forecasts sharply reduce perceived downside risk, leading to sizeable global welfare improvements measured in several billion U.S. dollars.

Overall, these results demonstrate that remote sensing–based early harvest forecasts function as a coordination mechanism across hemispheres, aligning production decisions with anticipated global supply conditions. By reducing uncertainty before planting decisions are made, the information system stabilizes world soybean markets and generates robust welfare gains across countries, particularly in environments characterized by high volatility and strong aversion to downside risk.

Table 1. Impacts of Early Forecast Information on Risk Premium under CARA

	Benefit from Early Information [USD]			
	α=1	α=2	α=4	α=10
China	16,730,894	33,461,770	66,923,540	167,308,940
Ecuador	18,031	36,063	72,125	180,313
Hungary	270,687	541,373	1,082,746	2,706,866
Indonesia	837,862	1,675,723	3,351,446	8,378,615
Iran	9,611,237	19,222,470	38,444,950	96,112,370
Peru	93,817	187,634	375,268	938,170
Spain	1,040,846	2,081,691	4,163,382	10,408,460
Thailand	678	1,357	2,713	6,783
Total	28,604,052	57,208,081	114,416,170	286,040,517
Global Benefit	95,361,600	190,723,122	381,446,271	953,615,985

Table 2. Impacts of Early Forecast Information on Risk Premium under CRRA

	Benefit from Early Information [USD]			
	γ=1	γ=5	γ=10	γ=20
China	16,730,886	83,654,428	167,308,857	334,617,714
Ecuador	18,031	90,156	180,313	360,625
Hungary	270,687	1,353,433	2,706,866	5,413,732
Indonesia	837,861	4,189,307	8,378,615	16,757,230
Iran	9,611,237	48,056,184	96,112,368	192,224,736
Peru	93,817	469,085	938,170	1,876,340
Spain	1,040,846	5,204,228	10,408,455	20,816,911
Thailand	678	3,392	6,783	13,566
Total Benefit	28,604,043	143,020,213	286,040,427	572,080,854
Global Benefit	95,361,570	476,807,841	953,615,685	1,907,231,370

Table 3. Beneficial Effects of Early Forecast Information with Prospect Theory

	Benefit from Early Information [USD]			
	γ=1	γ=5	γ=10	γ=20
China	312,223,442	1,000,489,376	1,860,821,795	3,581,486,631
Ecuador	240,403	1,017,418	1,988,686	3,931,223
Hungary	1,145,764	5,182,060	10,227,430	20,318,169
Indonesia	10,712,073	43,798,896	85,157,425	167,874,483
Iran	30,895,030	141,285,209	279,272,933	555,248,380
Peru	963,446	3,916,083	7,606,880	14,988,474
Spain	14,495,918	56,683,009	109,416,872	214,884,598
Thailand	7,787,629	23,774,591	43,758,293	83,725,698
Total Benefit	378,463,705	1,276,146,642	2,398,250,314	4,642,457,656
Global Benefit	1,261,740,968	4,254,480,624	7,995,405,196	15,477,254,333

3. Discussion

This study provides quantitative evidence that remote sensing–based early soybean harvest forecasts can stabilize global agricultural markets by inducing ex ante production adjustments rather than relying on ex post market interventions. Exploiting the seasonal asymmetry between the Southern and Northern Hemispheres, early information enables farmers to revise planting decisions in anticipation of global supply conditions, thereby reducing aggregate uncertainty and dampening price volatility in world soybean markets.

A central contribution of this study lies in identifying production adjustment as the primary transmission channel through which information enhances market stability. Unlike conventional stabilization mechanisms—such as public stockholding, export restrictions, or emergency trade measures—this information-based mechanism operates before supply shocks are fully realized. When early signals indicate a poor harvest in the Southern Hemisphere, Northern Hemisphere producers can expand soybean acreage to partially offset the anticipated shortfall. Conversely, expectations of abundant Southern Hemisphere production induce a contraction in planting, mitigating surplus-driven price declines. These decentralized yet coordinated responses transform dispersed private decisions into a system-level stabilizing force.

The magnitude of the estimated welfare gains reflects the importance of timing in agricultural decision-making. Remote sensing forecasts differ fundamentally from traditional market signals or official reports in that they provide actionable information while planting decisions are still reversible. This temporal advantage allows supply responses to occur at the production stage, rather than through delayed price adjustments or costly policy interventions. As a result, uncertainty is reduced at its source, lowering risk premiums faced by import-dependent countries and improving economic welfare.

The comparison across behavioral frameworks further underscores the robustness of this mechanism. While expected utility models with CARA and CRRA preferences already indicate substantial benefits from early information, the markedly larger gains obtained under prospect theory highlight the critical role of downside risk perceptions. When agents exhibit loss aversion and place disproportionate weight on adverse price outcomes, early forecasts generate particularly large welfare improvements by reducing the likelihood and severity of price spikes. This finding suggests that conventional welfare analyses may systematically underestimate the social value of early information in volatile food markets.

The stabilization effects identified in this study are primarily driven by production adjustments at the planting stage. Early harvest forecasts alter producers' expectations about global supply conditions, leading to acreage expansion or contraction before output is realized. This ex ante supply response constitutes the central mechanism through which remote sensing information stabilizes world soybean markets in the model framework.

In addition to production adjustments, improved information transparency may also influence speculative behavior by reducing uncertainty and limiting the scope for self-reinforcing price dynamics. However, speculation-related effects are treated as complementary rather than primary channels in this study.

Beyond production decisions, early and widely accessible forecast information may also moderate speculative dynamics in commodity markets. When market participants anticipate that producers will adjust planting in response to expected supply shocks, the scope for self-reinforcing price movements driven purely by initial shocks is reduced. Although speculation is not the primary focus of this study, the results indicate that transparent and credible information can attenuate the amplification of price volatility arising from both physical supply uncertainty and financial market behavior.

While this analysis focuses on soybeans, the underlying mechanism is not crop-specific.

Any agricultural commodity characterized by pronounced seasonal asymmetries, significant international trade, and climate-sensitive yields may benefit from similar information-based stabilization. Extending this framework to other globally traded crops, such as maize or wheat, represents a promising avenue for future research.

Several limitations merit consideration. The analysis assumes that early forecast information is credible, widely disseminated, and effectively incorporated into farmers' decision-making. In practice, production responses may be constrained by local agro-climatic conditions, institutional settings, and access to information. Consequently, the estimated benefits should be interpreted as a conservative lower bound of the true social value of early harvest forecasts.

While the model-based analysis is consistent with a stabilization mechanism operating through planting-stage production responses, this study does not directly estimate acreage adjustments or speculative trading behavior. Empirically identifying these channels using acreage data, futures-market indicators, or forecast-release event studies represents an important avenue for future research.

The annual frequency adopted in this study reflects both data availability and the economic structure of agricultural production. For many countries, reliable monthly or weekly import price data do not exist, and restricting the analysis to a limited subset would undermine cross-country comparability. Moreover, because soybean production decisions are made on an annual planting cycle, annual price volatility is the most relevant measure for evaluating stabilization mechanisms that operate through production adjustments rather than short-term price discovery.

Another important limitation concerns the assumption of perfect early harvest forecasts. In reality, remote sensing–based predictions are subject to measurement error and uncertainty, and producers may respond to noisy signals rather than fully accurate information. The perfect-forecast assumption adopted here is therefore not intended to represent a realistic forecasting environment, but to isolate the upper-bound effect of timely information on production decisions and market stability.

Introducing noisy forecast signals and explicit constraints on supply responses would be a natural extension of this framework and could further refine the magnitude of the estimated welfare gains.

From a policy perspective, these findings have direct implications. Investments in national and international remote sensing infrastructure, open-access data platforms, and institutional mechanisms for rapid information dissemination can yield substantial social returns by stabilizing food markets at their source. In an era of increasing climate-induced yield volatility, early harvest information should be recognized as a global public good. Integrating information-based stabilization mechanisms into international food and agricultural policy—through organizations such as FAO, GEOGLAM, and G20 agricultural cooperation frameworks—offers a cost-effective and market-compatible strategy for enhancing global food system resilience.

4. Methodology and data

Counterfactual information regime

Before introducing the econometric and simulation procedures, it is important to clarify the counterfactual structure underlying the analysis. This study does not exploit a historical policy change or a discrete adoption of remote sensing technology. Instead, it constructs two counterfactual information regimes that differ only in the availability of early-season remote sensing–based harvest forecasts at the time of planting decisions. In the baseline regime ("without RS"), producers form expectations solely on the basis of historical production information. In the alternative regime ("with RS"), historical expectations are replaced by remote sensing–based early harvest forecasts, while all other market conditions—including demand, trade structure, and policy environment—are held constant. All subsequent estimations and simulations are conducted by comparing outcomes across these two information regimes.

4.1. Remote sensing data.

The remote sensing-based wheat production forecasts were derived using the methodology originally developed by Becker-Reshef et al. (2010) and improved by Franch et al. (2015). The method relies on the positive and linear relationship between satellite-observed seasonal maximum normalized difference vegetation index (NDVI) and wheat yield at the county scale to establish a regression-based model (Becker-Reshef et al. 2010). Since the evolution of NDVI values throughout the growing season is largely determined by the accumulated growing degree days (GDD), seasonal maximum NDVI values can be predicted using GDD approximately 40 days before the observed NDVI peak date, and thereby improving the timeliness of yield forecasting (Franch et al. 2015). Daily bidirectional reflectance distribution function (BRDF)-corrected surface reflectance data from the Moderate Resolution Imaging Spectroradiometer (MODIS), air temperature reanalysis data from the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR), satellite-based wheat crop masks and administrative wheat yield statistics were combined to generate wheat yield forecasts at the county scale, which were subsequently combined with harvested area statistics to generate national-scale wheat production forecasts. The methods were tested over the United States, Ukraine and China and the results were proved to have 7%-10% error against official statistics. The methods were applied to Russia, Ukraine, the United States and Canada to produce wheat forecasts from 2003 to 2012 that are used in this study.

4.2. Revised Estimation of Global Soybean Prices Using Remote-Sensing Information

We begin by examining the relationship between soybean production in the northern hemisphere (NH) and southern hemisphere (SH) and the international soybean price using historical data. Because soybean output is harvested in year t but enters international markets in year $t + 1$, production variables are incorporated with a one-year lag. To capture price dynamics and ensure stationarity, all variables are expressed in first-order logarithmic differences[1]. The growth rate of the global soybean price is estimated using the following ordinary least squares (OLS) specification:

$$\Delta lnp_t^{HisG} = \alpha + \beta_1 \Delta lnQ_{t-1}^{HisSH} + \beta_2 \Delta lnQ_{t-1}^{HisNH} + \beta_3 \Delta lnDXY_t + \beta_4 \Delta lnCORN_t + \beta_5 \Delta lnCSO_t + \varepsilon_t \quad (1)$$

where Δlnp_t^{HisG} denotes the change rate of the global soybean price in period *t*. ΔlnQ_{t-1}^{HisNH} represents the combined soybean production growth rate of NH countries (Canada and the United States), while ΔlnQ_{t-1}^{HisSH} captures production growth in SH countries (Argentina, Bolivia, Brazil, Paraguay, and Uruguay). The other variables include the U.S. Dollar Index ($\Delta lnDXY_t$), the global corn price ($\Delta lnCORN_t$), and soybean oil production in China ($\Delta lnCSO_t$), all of which may affect soybean prices through cost, substitution, and demand channels. The estimation sample spans 1990–2022.

4.3 Construction of Hypothetical Global Soybean Prices Based on Remote-Sensing Forecasts

We next consider a counterfactual scenario in which NH countries have real-time access to remote-sensing-based production forecasts for SH soybean producers. Under this assumption, the hypothetical growth rate of SH soybean production is defined as the logarithmic difference between remotely sensed production in year *t* and a trimmed average of historical production over the preceding five years. Using the estimated coefficients from equation (1), NH countries can then infer a hypothetical global soybean price change rate as follows:

$$\Delta ln\hat{p}_t^{HypG} = \hat{\alpha} + \widehat{\beta_1} \Delta lnQ_{t-1}^{HypSH} + \widehat{\beta_2} \Delta lnQ_{t-1}^{HisNH} + \widehat{\beta_3} \Delta lnDXY_t + \widehat{\beta_4} \Delta lnCORN_t + \widehat{\beta_5} \Delta lnCSO_t \quad (2)$$

where $\hat{\alpha}$ and $\hat{\beta}$ are OLS estimates obtained from equation (1). To isolate the informational role of SH production forecasts, all other explanatory variables are held constant. Due to data constraints, remote-sensing soybean production data are available from 2001 onward, resulting in a hypothetical price series covering 2002–2022.

[1] The results of the unit root tests suggest that all variables are stationary in logarithmic first differences. The corresponding results are available upon request.

4.4 Revised Estimation of Global Soybean Production Using Supply Elasticity

Assuming that NH producers can accurately anticipate price movements using remote-sensing information, they adjust soybean production decisions to maximize expected revenue. The hypothetical growth rate of soybean production in NH country *i* is derived using the price elasticity of supply:

$$\Delta lnQ_{i,t-1}^{HypNH} = e_i \times \Delta \ln\hat{p}_t^{HypG}, \tag{3}$$

where e_i denotes the soybean supply elasticity for NH country *i*. Hypothetical production levels are computed using historical production data and aggregated across NH countries. Revised global soybean production is then obtained by combining hypothetical NH production with observed historical SH production. Let Q_{t-1}^{HisG} and Q_{t-1}^{HypG} denote historical and revised global soybean production, respectively. Both variables are expressed in logarithmic form for subsequent analysis.

4.5 Estimation of Unhedged and Hedged Soybean Import Price Volatility

To assess whether remote-sensing-based forecasts contribute to greater import price stability, we estimate unhedged and hedged soybean import prices using a panel vector error correction model (VECM). Given the annual frequency of the data, a panel framework is employed to improve estimation efficiency. Panel unit root and cointegration tests confirm that all variables are integrated of order one and share a long-run equilibrium relationship. We apply the pooled mean group (PMG) estimator of Pesaran, Shin, and Smith (1999), which imposes homogeneity on long-run coefficients while allowing short-run dynamics to vary across countries. Lag length selection based on the Bayesian Information Criterion indicates an optimal ARDL specification of (1,1). The unhedged soybean import price equation, based on historical global production, is specified as:

$$\Delta SPP_{i,t}^{Unhedged} = \phi_i\left(SPP_{i,t} - \lambda_{0i} - \lambda_{1i}IMQ_{i,t} - \lambda_{2i}IMC_{i,t} - \lambda_{3i}Q_t^{HisG} - \lambda_{4i}CSI_t\right) \tag{4}$$
$$-\xi_{11i}\Delta IMQ_{i,t} - \xi_{21i}\Delta IMC_{i,t} - \xi_{31i}\Delta Q_t^{HisG} - \xi_{41i}\Delta CSI_t + \upsilon_{i,t}$$

The error correction term ϕ_i, long-run coefficients λ, and short-run coefficients ξ will be estimated by using maximum likelihood procedure. On the other hand, the hedged import price equation replaces historical production with revised global production:

$$\Delta SPP_{i,t}^{hedged} = \phi_i\left(SPP_{i,t} - \lambda_{0i} - \lambda_{1i}IMQ_{i,t} - \lambda_{2i}IMC_{i,t} - \lambda_{3i}Q_t^{HpyG} - \lambda_{4i}CSI_t\right) \tag{5}$$
$$-\xi_{11i}\Delta IMQ_{i,t} - \xi_{21i}\Delta IMC_{i,t} - \xi_{31i}\Delta Q_t^{HpyG} - \xi_{41i}\Delta CSI_t + \upsilon_{i,t}$$

Standard deviations of unhedged and hedged soybean import prices are computed for each net soybean-importing country over the sample period. Comparing these volatilities allows us to evaluate whether access to remote-sensing-based production forecasts enhances price stability in international soybean markets.

4.3. Risk Premium Under CARA

In this study, as part of the risk assessment regarding wheat import price fluctuations, we employ a Constant Absolute Risk Aversion (CARA) utility function to incorporate the risk-averse behavior of importers or consumers. The CARA utility function is defined as follows:

$$U(w) = -\exp(-\alpha w), (\alpha > 0) \tag{7}$$

where w represents the purchase price (or its reciprocal, representing purchasing power), and α denotes the coefficient of absolute risk aversion. This exponential utility function is commonly used in economic analysis to represent scenarios where risk attitudes remain constant regardless of the level of wealth or price.

Assuming that prices follow a normal distribution with mean μ and variance σ^2, the expected utility $E[U(w)]$ is derived as follows, based on the properties of the moment-generating function:

$$E[U(w)] = -exp\left[-\alpha\left(\mu - \frac{1}{2}\alpha\sigma^2\right)\right] \tag{8}$$

The Certainty Equivalent (CE), which provides a utility level equivalent to this expected utility, is defined as follows:

$$CE = \mu - \frac{1}{2}\alpha\sigma^2 \tag{9}$$

Then, the Risk Premium (RP) is calculated as the difference between the expected price and the certainty equivalent:

$$RP = \mu - CE = \frac{1}{2}\alpha\sigma^2 \tag{10}$$

Employing expected utility theory to evaluate the monetary value of risk, this approach is extensively applied across the fields of agricultural economics, financial economics, and environmental policy research (Pratt, 1964; Arrow, 1965; Gollier, 2001). Following the seminal work of Arrow (1965), we characterize the risk preference of market participants using the coefficient of absolute risk aversion, α.

4.6 Risk Premium Under CRRA

In this study, we adopt a Constant Relative Risk Aversion (CRRA) utility function to model risk-averse behavior under proportional price uncertainty. The CRRA specification assumes that agents' risk preferences depend on relative, rather than absolute, changes in prices or income, making it suitable for analyzing multiplicative price shocks.

The CRRA utility function is given by

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}, \qquad \gamma \neq 1,$$

where x denotes purchasing power (or its inverse price measure) and γ is the coefficient of relative risk aversion. A higher γ indicates greater aversion to relative risk. A key property of this utility function is that relative risk aversion is constant, while absolute risk aversion declines as $x$increases. The CRRA framework is widely used in agricultural and financial economics to evaluate welfare losses and risk premia arising from price volatility (Arrow, 1965; Pratt, 1964; Gollier, 2001).

4.7 Beneficial Effect Estimation with Prospect Theory

To account for the asymmetric sensitivity of consumers toward price fluctuations, this study employs a welfare evaluation approach based on Prospect Theory (Kahneman and Tversky, 1979). Unlike traditional Expected Utility Theory, this approach assumes that consumers evaluate their utility based on changes relative to a specific reference point rather than absolute wealth levels.

The reference point R is defined as the mean payment in the unhedged scenario ($R = \bar{P}_{unhedged}$). For the actual payment P_t in year t, the deviation from the reference point, x_t, is defined as follows:

$$x_t = R - P_t$$

Here, $x_t > 0$ represents "Gains" (payments lower than the average), while $x_t < 0$ represents "Losses" (payments exceeding the average).

To reflect the psychological trait of loss aversion, we adopt the following linear value function x_t:

$$v(x_t) = \begin{cases} x_t & (x_t \geq 0) \\ \gamma \cdot x_t & (x_t < 0) \end{cases}$$

In this formulation, γ denotes the loss aversion coefficient. This coefficient represents the psychological reality that the disutility (pain) from a loss is perceived to be γ times stronger than the utility (joy) derived from an equivalent gain.

The expected value V for both the hedged (H) and unhedged (U) scenarios is calculated as the mean value over the sample period ($n = 20$):

$$V = \frac{1}{n}\sum_{t=1}^{n} v(x_t)$$

The stabilization benefit is estimated as the difference between these expected values (\$$V_H - V_U$). This metric quantifies the impact of avoiding price spikes—the "losses"—on consumer welfare in monetary terms.

4.4. Data for the counterfactual simulation

Early-season soybean crop forecasts for the period 2001–2023 were derived from satellite imagery and remote sensing data developed by the Department of Geographical Sciences at the University of Maryland, College Park. To estimate the econometric models, we supplemented these forecasts with data on soybean production, harvested area, and producer prices from FAOSTAT. International price indices for soybeans, corn, wheat, rice, and crude oil were retrieved from the International Monetary Fund (IMF) Commodity Price database. Furthermore, to calculate risk premium effects on a per-capita basis, we integrated population and consumption data from FAOSTAT with the estimated price series. Regarding the cross-hemisphere supply responses, price elasticities for Northern Hemisphere countries—specifically Canada, the USA, China, India, Ukraine, Russia, and Italy—were sourced from the existing literature, including Guyomard et al. (1996), Colby et al. (2000), Kumar et al. (2010), Haile et al. (2016), and Varacca and Sckokai (2020).

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