The Value of Remote Sensing Harvest Forecast Information in Global Food Security

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

Abstract

In recent years, global market shocks have significantly destabilised the international grain market. By capitalising on seasonal differences between the Northern and Southern Hemispheres and utilising early wheat harvest forecast information derived from remotely sensed satellite imagery, farmers in the Southern Hemisphere can respond to timely information to maximise profits. This global hedging mechanism contributes to stabilising the global wheat market. We employ a panel vector error correction model (VECM) to analyse the global agricultural market balancing system using remotely sensed wheat harvest data, focusing on 12 wheat-importing countries. The value of this information is assessed based on profits derived from price stabilisation. The results indicate that import prices in the 12 analysed countries could be stabilised by 10% to 19%, resulting in annual profit gains for importers totaling 364 million USD. When extrapolated globally, the combined profit for exporters and importers is conservatively estimated at approximately 4.98 billion USD.

Keywords Remote sensing forecast information, global agricultural markets, price stabilization, expected utility theory

JEL Codes: Q17, Q18, Q54, D81, C33

1. Introduction

Climate change has increasingly destabilized global grain productivity, with significant impacts observed across multiple regions (Erhan et al., 2017). In Australia, severe droughts in 2006 and 2007 led to catastrophic crop failures, while the La Niña phenomenon brought extraordinary rainfall in 2021 and 2022, resulting in record-breaking harvests. In the United States, widespread droughts across the western and midwestern regions have caused notable yield reductions. Similarly, France faced unprecedented challenges, as torrential rainfall, widespread flooding, and prolonged sunlight deficits during spring and early summer contributed to a staggering 30% decline in wheat production compared to the previous year (Nóia Júnior et al., 2023). These events underscore the vulnerability of global agriculture to increasingly volatile climatic conditions.

Recent advancements in remote sensing technology have significantly enhanced agricultural monitoring capabilities over regional to global scales. Owing to the proliferation of earth observation satellites, increasingly open data policies, standardized satellite image processing techniques, and advancements in AI and cloud computing, agricultural remote sensing research has been substantially advanced in many aspects (Song 2023). Continental to global-scale crop classification maps are being developed and routinely updated (Song et al 2021; van Tricht et al. 2023). Effective methods have been demonstrated to identify crops within the season (e.g. Lin et al 2022), to estimate crop yield in a spatially explicit way (e.g. Lobell et al. 2015; Deines et al. 2021; Song et al. 2022), and to forecast crop production early in the season (e.g. Becker-Reshef et al. 2010; Franch et al. 2015). These innovations have elevated national-level crop yield forecasts, allowing for more efficient predictions across various types of crops as compared to traditional methods. This technology now enables early identification of potential bumper harvests or crop failures. For instance, Russia and Ukraine, two of the world's largest wheat exporters in the Northern Hemisphere, have a harvest season from July to August (Table 1). Using satellite remote sensing, yield forecasts for these regions can be made as early as May or June, providing critical insights for global food supply planning.

Table 1 illustrates the sowing and harvesting periods for wheat globally, revealing substantial timing differences between the Northern and Southern Hemispheres. When harvest outcomes from the Northern Hemisphere are available in July or August, the wheat sowing season in much of the Southern Hemisphere has nearly concluded, leaving little opportunity for production adjustments. However, if early forecasts using remote sensing are accessible by May, many regions in the Southern Hemisphere still have sowing periods underway, allowing farmers to make strategic production adjustments, which is the global hedging mechanism proposed by Tanaka et al. (2023).

With timely access to early data, farmers in the Southern Hemisphere can detect a poor wheat harvest in the Northern Hemisphere, anticipate potential price increases, and allocate a greater portion of their land to wheat than initially planned to capitalize on the projected market demand and subsequently boost income. Conversely, if an abundant harvest is forecasted in the Northern Hemisphere, farmers in the Southern Hemisphere can predict a decline in global wheat prices and reduce their planned wheat acreage to mitigate potential income losses. This responsiveness allows for partial offsetting of Northern Hemisphere shortages through increased Southern Hemisphere production, while surplus harvests in the North can be balanced by adjustments in the South. On a global scale, these adaptations contribute to a more stable and resilient food supply, helping to smooth out fluctuations in wheat availability and prices.

An additional benefit of this mechanism is its potential to reduce volatility driven by financial speculation. By disseminating early forecasts in real time, individuals worldwide, including speculators, can gain equal access to critical market information. In the case of wheat, for instance, speculators can anticipate that Southern Hemisphere farmers will adjust their production in response to poor or abundant harvests in the Northern Hemisphere. This awareness may lead speculators to approach trading with more caution than they might in the absence of such information, reducing impulsive trading based purely on initial supply shocks. As a result, this mechanism can help dampen price swings driven by speculative trading, as well as fluctuations arising from real supply-demand imbalances, providing an additional stabilizing influence on global markets.

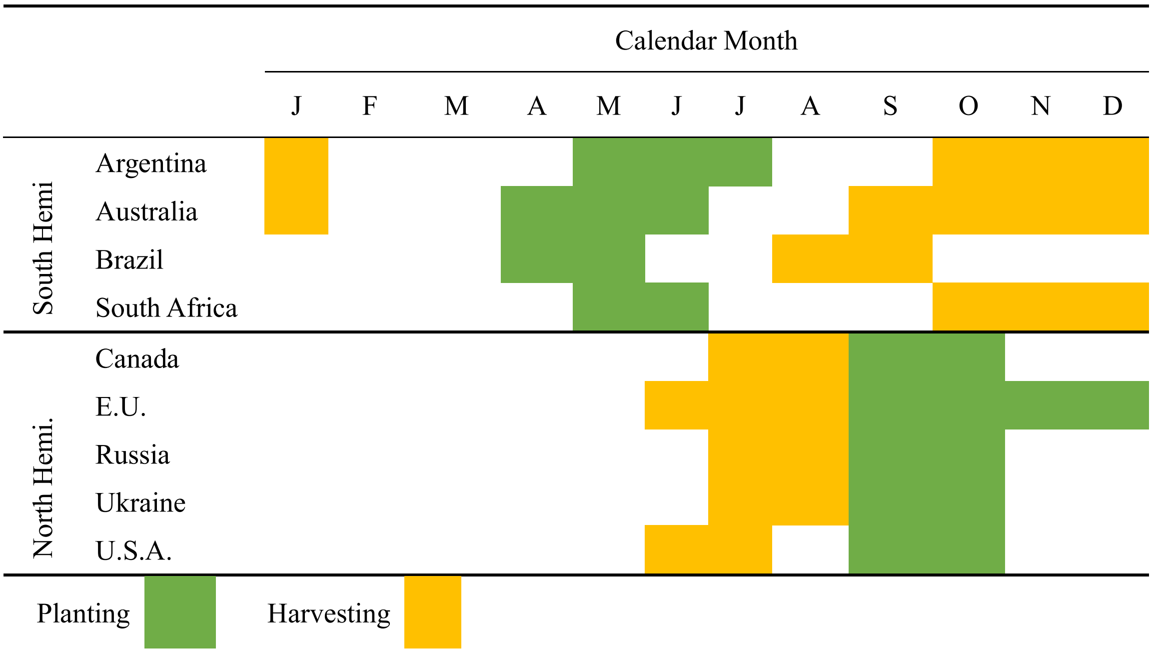
Research analyzing the impact of forecast information on market behavior has frequently focused on the U.S. Department of Agriculture (USDA) crop forecast reports, providing quantitative assessments of price fluctuations and volatility. For instance, Isengildina-Massa et al. (2023) explored how USDA crop forecasts influence futures price volatility, highlighting that market participants' reactions are significantly shaped by the accuracy of the information provided. Banse et al. (2016) employed a Dynamic Conditional Correlation (DCC) model to evaluate market price responses following the release of forecast information, analyzing the degree to which such forecasts contribute to price increases or decreases. Moreover, Han and Huang (2021) emphasized that highly reliable forecast information enhances market stability, whereas inaccurate forecasts can lead to market disruptions. These findings underscore the critical importance of accurate forecast data in informing policy-making and strengthening risk management strategies.

Tanaka et al. (2023) conduct an in-depth analysis of the stability of global wheat and soybean markets using a CGE model informed by remote sensing early crop production forecasts. This pioneering study is the first to examine how international market stability can be enhanced by leveraging remote sensing forecast data alongside the seasonal differences between the Northern and Southern Hemispheres. The research evaluates the impact of forecast information using key case studies, including the bumper and poor wheat harvests in Russia and Ukraine in 2008 and 2012, as well as the soybean shortfall in Brazil in 2012. Although the study successfully estimates the impacts for each specific year, the non-time-series nature of the model leaves the precise extent of price stabilization improvement unquantified.

In this study, we develop an economic model to simulate the stabilization of wheat supply and prices by leveraging seasonal differences between the Northern and Southern Hemispheres. The model specifically examines how wheat production forecasts from major Northern Hemisphere producers—Russia, Ukraine, the United States, and Canada—can be strategically utilized by farmers in key Southern Hemisphere countries, including Argentina, Australia, Brazil, Paraguay, South Africa, and Uruguay, to adjust their production decisions accordingly. This proactive adjustment aims to mitigate supply shocks and price fluctuations. Furthermore, the study quantifies the degree to which this early forecast information can reduce import price volatility for wheat-dependent nations such as Algeria, Cyprus, Egypt, Israel, Jordan, Kuwait, Lebanon, Mozambique, Nigeria, Tunisia, Tanzania, and Yemen, offering insights into the potential for global food price stability through coordinated information-sharing mechanisms. In addition, we estimated the beneficial impacts of the mechanism in monetary terms, using the expected utility theory or a certainty equivalent approach.

The key contribution of our research is the first comprehensive quantification of global wheat supply stabilization and the resulting import price stability. This was achieved through the integration of remote sensing early forecast information with hemispheric seasonality differences, using a robust time-series model. Based on this model, we estimated the beneficial impacts of the prediction information in monetary terms. Unlike Tanaka et al. (2023), who analyzed specific years and therefore left many periods unexamined, our study encompasses all available data periods, enabling a broader assessment of the general value of early forecast information. Specifically, we calculated the standard deviation of import prices for importing countries, clearly illustrating the stabilizing effect of early forecasts on price volatility. Additionally, we measured the stabilizing impact on global wheat supply through Southern Hemisphere adjustments using the Coefficient of Variation. By making the value of remote sensing information more tangible, our research provides justification for the increased investment in remote sensing technology by governments and international organizations, fostering a pathway toward enhanced global food security.

Table 1: Planting and harvesting months of wheat in major exporting countries



Source: The GEOGLAM.

2. Empirical results

2.1 Estimated results of revised global wheat production by using remote sensing data

To introduce the global hedging mechanism into our analysis framework, we divide the wheat-exporting countries into two groups based on their geographic positions: Northern Hemisphere (NH) countries, including Canada, Russia, Ukraine, and the United States, and Southern Hemisphere (SH) countries, including Argentina, Australia, Brazil, Paraguay, South Africa, and Uruguay. Given the hypothesis that SH countries have timely access to remote-sensing information and operate under a perfect forecasting scenario for NH countries, they can predict potential price changes in the global wheat market and adjust their wheat production plans to maximize income.

First, we estimated the hypothetical wheat production of SH countries by incorporating remote-sensing forecasting for NH countries and the responsive production adjustments of SH countries based on the price elasticity of supply. We then combined this with the historical wheat production of NH countries to calculate a new global wheat production, referred to as the revised global wheat production. The detailed process of estimating the revised production is described in the methods section. Due to the availability of remote-sensing data for NH countries' wheat production from 2003 to 2012, our sample period for revised global wheat production is confined to these years. The remote-sensing pre-harvest information of wheat, derived from satellite imagery, was developed by scientists at the Department of Geographical Sciences, University of Maryland College Park.

Table 2 presents the estimated results of revised global wheat production using remote-sensing data and historical global wheat production. The difference rates between them, ranging from -0.02% to 0.17%, are reported in the last column. The similarity in these values further validates the accuracy and reliability of the remote-sensing data in reflecting actual market conditions. Moreover, we observe that the coefficient of variation of revised global wheat production (0.439) is smaller than that of historical global wheat production (0.503). This suggests that global hedging for wheat production using remote-sensing data could decrease the volatility of global wheat production.

Table 2: The comparison of revised global production and historical wheat production

	Revised global wheat production	Historical global wheat production	Difference rate
2003	18.926	18.912	0.07%
2004	19.09	19.093	-0.02%
2005	19.092	19.09	0.01%
2006	19.021	18.991	0.16%
2007	18.997	18.964	0.17%
2008	19.212	19.236	-0.12%
2009	19.169	19.159	0.05%
2010	19.056	19.027	0.15%
2011	19.178	19.173	0.03%
2012	19.103	19.098	0.03%
CV	0.439	0.503	

Notes: The revised global wheat production is obtained through in subsection 4.1. The value of revised and historical global wheat production is presented in their logarithmic form. CV: Coefficient of Variation = (Standard Deviation / Mean) * 100

2.2 The hedging effectiveness using remote sensing data

In this subsection, we carry out a counterfactual simulation to examine whether remote-sensing forecasts can reduce wheat import price volatility in wheat-importing countries. We chose 12 net wheat-importing countries whose wheat consumption heavily depends on imports: Algeria, Cyprus, Egypt, Israel, Jordan, Kuwait, Lebanon, Mozambique, Nigeria, Tunisia, Tanzania, and Yemen. Due to the limitations of yearly wheat production data, a panel VECM is used to simulate the different effects between revised and historical global wheat production on the wheat import price in these countries. It is worth mentioning that our simulation assumes that domestic production and consumption in wheat-importing countries, as well as global production in exporting countries, can influence import prices in wheat-importing countries. Although import prices are also subject to unpredictable changes due to factors like weather conditions, geopolitical events, market speculation, etc., these factors are assumed to be constant in our analysis.

We estimate the unhedged and hedged import prices based on the panel VECM and apply standard deviations to define the import price volatility of each country from 2005 to 2012. Figure 1 reports the comparison of the unhedged and hedged volatility for wheat import prices in wheat-importing countries. Unhedged volatility refers to the fluctuations in wheat import prices without any hedging strategies in place, which are typically higher due to exposure to market risks. In contrast, hedged volatility represents the fluctuations in wheat import prices when hedging strategies, such as the use of remote-sensing data for better forecasting and production adjustments, are applied. From the comparison in Figure 1, it is evident that the standard deviation of wheat import prices is lower in the hedged scenario compared to the unhedged scenario. For example, the standard deviation decreases from 0.220 (unhedged) to 0.179 (hedged) in Yemen, indicating the largest reduction in import price volatility. Similarly, the standard deviation decreases from 0.301 (unhedged) to 0.270 (hedged) in Kuwait, which is the smallest reduction. Overall, the hedged scenario demonstrates a lower standard deviation in all the wheat-importing countries, suggesting that hedging strategies mitigate market risks such as supply shocks and stabilize import prices.

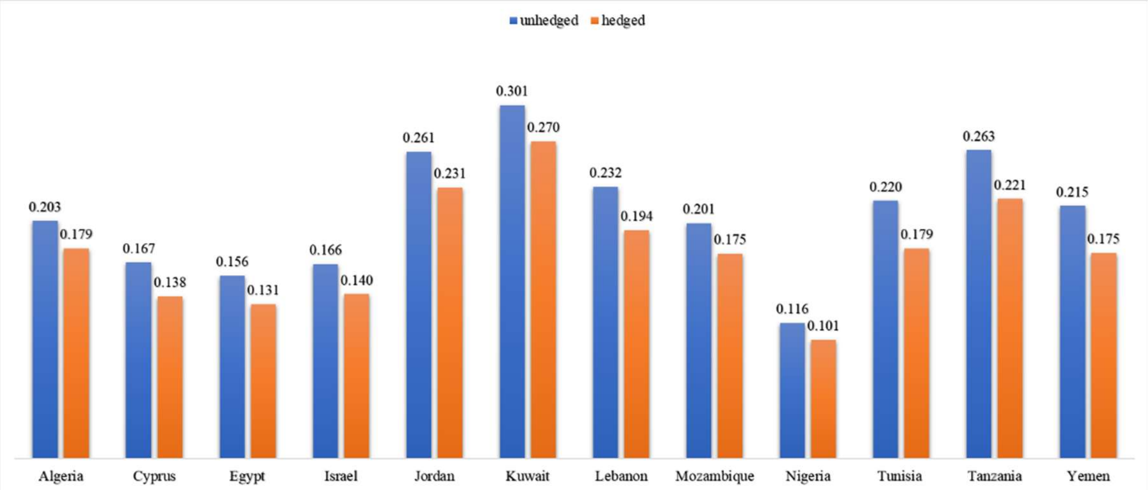


Figure 1: The comparison of hedged and unhedged wheat imports price volatility in wheat-importing countries

Notes: Blue bars indicate the unhedged wheat import prices using historical global wheat production. Red bars show the hedged wheat import prices using revised global wheat production.

Furthermore, to understand the role of the global hedging mechanisms, it is crucial to investigate the hedging effectiveness of revised global production. The hedging effectiveness (*HE*) ratio of considering the remote sensing forecasts information are determined as follows:

$$HE = \frac{IMP^{V}_{Unheged} - IMP^{V}_{Hedged}}{IMP^{V}_{Unheged}}, \tag{1}$$

where $IMP^{V}_{Unhedged}$ and IMP^{V}_{Hedged} indicate the unhedged and hedged import price, respectively. This ratio quantifies the reduction in price volatility due to the implementation of hedging strategies based on remote sensing forecasts. A higher HE ratio indicates greater effectiveness in reducing price volatility. Table 3 summarizes the comparison, showing the effectiveness of remote-sensing forecast information in reducing the volatility of wheat import prices in each wheat-importing country. From Table 3, we can observe that HE ratios are positive in all countries, although the values vary across countries. Consistent with Figure 1, the volatility reduction ranges from a low of 10.254% in Kuwait to a high of 18.683% in Yemen. More specifically, countries like Algeria, Lebanon, Tunisia, and Tanzania have higher HE ratios, while Mozambique exhibits a lower HE ratio. These results highlight the substantial role that remote-sensing forecast data can play in mitigating market risks and stabilizing import prices in wheat-importing countries.

Table 3: Results of hedging effectiveness

	$IMP^{V}_{Unheged}$	IMP^{V}_{Hedged}	Hedge effectiveness (%)
Algeria	0.203	0.179	11.526
Cyprus	0.167	0.138	17.391
Egypt	0.156	0.131	15.586
Israel	0.166	0.140	15.444
Jordan	0.261	0.231	11.627
Kuwait	0.301	0.27	10.254
Lebanon	0.232	0.194	16.048
Mozambique	0.201	0.175	12.932
Nigeria	0.116	0.101	12.364
Tunisia	0.22	0.179	18.526
Tanzania	0.263	0.221	15.797
Yemen	0.215	0.175	18.638

Notes: The hedge effectiveness are computed using Eq. (1).

Our results show that implementing a global hedging mechanism using remote-sensing data can significantly reduce the volatility of wheat import prices in wheat net-importing countries. By decreasing this volatility, wheat-importing countries can benefit from more predictable and stable food costs, which is particularly important for low-income and food-deficit regions. This stability can lead to improved food security and economic stability, highlighting the importance of integrating advanced forecasting techniques and hedging mechanisms in global agricultural trade policies.

2.3 Effects on risk premium

Our analysis revealed a clear reduction in the volatility of import prices based on our calculations. This section evaluates the economic benefits derived from the stabilization of import prices across various countries. Specifically, we estimated the risk premium (RP) associated with import price fluctuations by categorizing the analysis into scenarios without production adjustment (Unhedged) and those with adjustment (Hedged), as presented in Table 4.

The reduction in volatility was observed across all countries, resulting in a decrease in the corresponding risk premium. Although the extent of this reduction varied by country, Nigeria exhibited the smallest decline, with an RP of 5.3 USD, while Tanzania showed the largest decrease, reaching 24.3. This figure represents the amount a country would be willing to pay to avoid price fluctuations. For instance, in the absence of timely utilization of remote sensing forecast information, Tanzania's willingness to pay for stabilized wheat prices could be interpreted as 96.8 USD per ton.

The adoption of remote sensing information contributes to reduced volatility and a subsequent decrease in the risk premium. The difference between the original and reduced risk premium reflects the per-ton economic gain for importing countries. By multiplying this difference by the average import volume from 2005 to 2012, we can estimate the annual economic benefits for each country (i.e., beneficial impacts).

As a result, Egypt stands out among the 12 countries, reaping the highest benefit at 104 million USD, while Cyprus receives the smallest gain. Table 4 indicates that this outcome is primarily influenced by the substantial volume of wheat imports rather than the impact of reduced risk premiums. Collectively, the importers from these 12 countries achieve a total profit of 364 million USD. As elaborated in the Discussion section, the beneficiaries of this price stabilization extend beyond global importers and exporters to include consumers and agricultural producers, making this estimate notably conservative.

Table 4: Risk premium and economic impacts

	Unhedged RP [USD] (1)	Hedged RP [USD] (2)	Changes in RP [USD] (1) − (2)	Beneficial impacts [mil. USD] (1) − (2)×import
Algeria	60.6	48.5	12.0	70.1
Cyprus	44.4	31.1	13.3	1.5
Egypt	43.6	31.9	11.7	104.1
Israel	49.5	36.5	13.0	20.3
Jordan	105.9	87.5	18.4	15.6
Kuwait	124.9	106.3	18.7	5.9
Lebanon	84.7	63.0	21.7	9.7
Mozambique	71.3	56.3	15.0	6.5
Nigeria	23.6	18.3	5.3	19.1
Tunisia	72.6	50.5	22.1	33.7
Tanzania	96.8	72.5	24.3	19.5
Yemen	71.7	49.8	21.9	58.0

3. Discussions

This study focuses solely on production fluctuations, estimating the impact of remote sensing forecast information. However, in reality, non-commercial speculators also play a significant role in the market. Previous research has shown that markets react instantly to the release of USDA's WASDE reports (e.g., McKenzie & Holt, 2002; Isengildina-Massa et al., 2008). If early forecast information like this were widely accessible, speculators would likely adjust their strategies, factoring in production changes made by farmers in the Southern Hemisphere. As a result, speculators might operate with smaller positions than they currently do, even as they respond to the same market dynamics. This suggests that the real-world value of remote sensing information could exceed the estimates provided in this study. Furthermore, such forecast data could help diminish the market influence of speculators.

To maximize the benefits of this system, it is crucial to establish a platform for sharing early harvest forecast information. Ensuring that real-time production forecasts are freely and easily accessible to everyone is key to making the global hedging system effective. Since this system benefits people worldwide, the information should be shared openly among farmers and other stakeholders. International organizations such as the World Bank, IMF, or the United Nations could play a leading role in creating and maintaining such a platform.

This study did not encompass all wheat-importing countries; the 12 countries analyzed in 2022 represented only 16% of the global wheat import volume (FAOSTAT). The total profit for these 12 countries was estimated at 364 million USD, with an average import volume of 27 million tons from 2005 to 2012, resulting in a profit of 13.5 USD per ton (364 million USD / 27 million tons). Considering the global total wheat import volume of 184.5 million tons, the estimated annual global profit would be 2,488 million USD (13.5 USD × 184.5 million tons). Additionally, if exporters also possess risk-averse utility functions, the total profit could potentially double, reaching 4,976 million USD. Since consumers and agricultural producers are also expected to gain from price stability, the potential benefits could be even higher. Therefore, the 364 million USD or even 4,976 million USD figure reported in this study is a highly conservative estimate.

4. Methodology and data

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 Wheat Prices Using Remote Sensing Data

First, we estimate the relationship between wheat's production of NH countries and international wheat price based on the historical data. Considering that agricultural crops are harvested in year *t* and traded in year $t+1$, a one-year lag length is assumed for the production variable. The first order logarithmic difference data are used to estimate the change rate of the global wheat price with the following ordinary least squares (OLS) regression model:

$$p_t^{HisG} = \alpha + \beta_1 Q_{t-1}^{HisNH} + \beta_2 Q_{t-1}^{HisSH} + \beta_3 OIL_t + \beta_4 SOYBEAN_t + \beta_5 RICE_t + \varepsilon_t, \quad (2)$$

where p_t^{HisG} is the global wheat price change rate in period t. Q_{t-1}^{HisNH} signify the combined historical wheat production change rate in year $t-1$ of the four NH countries (Russia, Ukraine, United States and

Canada) and Q_{t-1}^{HisSH} is that for six SH countries (Argentina, Australia, Brazil, Paraguay, South Africa and Uruguay). The explanatory variables such as OIL_t(global crude oil price change rate), $SOYBEAN_t$ (global soybean price change rate) and $RICE_t$ (global rice price change rate) in period t are considered to influence the p_t^{HisG}. The data period spans from 1992 to 2021.

In the next step, assuming that wheat producing countries of SH can access the remote-sensing forecast data for NH countries. The hypothetical wheat's production change rate of NH countries Q_t^{HypNH} can be calculated by taken the logarithmic difference between the remote sensing wheat production data for NH countries in year t and the historical wheat production for NH countries in year $t-1$. Then, based on prediction of wheat price change rate for NH countries and the relationship in equation (1), SH countries can estimate the hypothetical international wheat price change rate $\hat{p}_t^{HypG}$ as follow:

$$\hat{p}_t^{HypG} = \hat{\alpha} + \widehat{\beta_1} Q_{t-1}^{HypNH} + \widehat{\beta_2} Q_{t-1}^{HisSH} + \widehat{\beta_3} OIL_t + \widehat{\beta_4} SOYBEAN_t + \widehat{\beta_5} RICE_t \,, \tag{3}$$

where $\hat{\alpha}$ and $\hat{\beta}$ is the OLS estimator of equation (2). Here, since we are focusing solely on the relationship between wheat production in NH countries and the global wheat price, it is necessary to assume that other conditions remain constant. Due to the limitation of remote sensing data, which spans from 2003 to 2012, the hypothetical global wheat price data will cover the period from 2004 to 2013.

4.3 Revised Estimation of Global Wheat Production Using Price Elasticity of Supply

Given the hypothesis that SH countries have timely access to remote sensing information and possess a perfect forecasting scenario for NH countries, they can predict potential price changes in the global wheat price and adjust their wheat production plans to maximize income. Based on the estimated hypothetical change in global wheat price $\hat{p}_t^{HypG}$, we can calculate the hypothetical change rate of wheat production by applying the price elasticity of supply for wheat in each SH country as follows:

$$Q_{i,t-1}^{HypSH} = \hat{p}_t^{HypG} \times e_i, \tag{4}$$

where $Q_{i,t-1}^{HypSH}$ is hypothetical change rate of wheat production of SH countries in year $t-1$ and e_i is the price elasticity of supply for wheat in SH country *i*. Then, the hypothetical wheat production for each SH country can be calculated using the historical wheat production data of SH countries. The total hypothetical wheat production for all SH countries is calculated by aggregating the data from these countries. Finally, the revised global wheat production is determined by combining the hypothetical wheat production of SH countries with the historical wheat production of NH countries. Here, we use EXQ_{t-1}^{HisG} and EXQ_{t-1}^{HypG} to definite the historical global wheat production and revised global wheat production in period $t-1$, respectively. Both variables are in logarithmic form.

4.4 The estimation of the unhedged and hedged volatility for wheat import price by using panel VECM

Since yearly data are used in our study, we apply a panel model to address the issue of data limitation. Prior to performing the panel data analysis, it is necessary to check the stationarity of each variable and the existence of a cointegrating relationship among variables. The panel unit root test and cointegration test indicate that all the variables are integrated at I (1) and there is evidence of a cointegrating relationship among variables in our panel analysis[1]. Given the presence of cointegration, we employ the Pooled Mean Group (PMG) approach developed by Pesaran, Shin, and Smith (1999), which has been widely applied in panel empirical studies. The PMG model has the advantage of imposing homogeneity in the long-run coefficients across countries while allowing for possible

---

[1] To save space, we do not present the results of panel unit root test and cointegration test, but these are available from the authors on request.

heterogeneity in the short-run coefficients and error variances. Furthermore, this approach treats the explanatory variables as exogenous because the error terms are distributed independently of the regressors.

Since the lag length in the autoregressive distributed lag model should be determined, we use the Bayesian information criterion (BIC) to choose the appropriate lag length (*p, q*). Our results show that the optimal lag is 1 (p = 1, q=1) for the model[2]. Then, based on panel VECM framework, the unhedged wheat import price in net wheat-importing countries using historical global wheat production is estimated by:

$$\Delta IMP_{i,t}^{Unhedged} = \pi_i\left(IMP_{i,t} - \delta_{0i} - \delta_{1i}IMQ_{i,t} - \delta_{2i}IMC_{i,t} - \delta_{3i}EXQ_{t-1}^{HisG}\right) - \theta_{11i}\Delta IMQ_{i,t} - \theta_{21i}\Delta IMC_{i,t} - \theta_{31i}\Delta EXQ_{t-1}^{HisG} + \varepsilon_{i,t} \quad (5)$$

Considering that agricultural crops are harvested in year t and traded in year $t+1$, a one-year lag length is assumed for the EXQ_{t-1}^{HisG} impacting wheat import price in wheat-importing countries. The error correction term π, long-run coefficients δ, and short-run coefficients θ will be estimated by using maximum likelihood procedure. On the other hand, the hedged wheat import price in net wheat importing countries using revised global wheat production is estimated by:

$$\Delta IMP_{i,t}^{Hedged} = \pi_i\left(IMP_{i,t} - \delta_{0i} - \delta_{1i}IMQ_{i,t} - \delta_{2i}IMC_{i,t} - \delta_{3i}EXQ_{t-1}^{HypG}\right) - \theta_{11i}\Delta IMQ_{i,t} - \theta_{21i}\Delta IMC_{i,t} - \theta_{31i}\Delta EXQ_{t-1}^{HypG} + \varepsilon_{i,t} \quad (6)$$

Based on equations (5) and (6), we calculate the standard deviations of unhedged and hedged wheat import prices for each net wheat-importing country from 2005 to 2012. Finally, we compare the volatility of unhedged and hedged wheat import prices to evaluate the extent to which remote-sensing forecast information improves the stability of wheat import prices in net wheat-importing countries.

4.5 Estimating risk premium

[2] The results are not provided here to save space but are available upon request from the authors.

In economics, the theoretical understanding of attitudes toward risk has been shaped by the contributions of Bernoulli (1738) and Von Neumann & Morgenstern (1944). First, we assume the utility function of the importer (or consumer). The logarithmic utility function has been widely used in numerous studies in economics and finance to model risk aversion (Mehra and Prescott, 1985), which is defined as follows:

$$U(w) = log(w), \tag{7}$$

where w represents the price paid by the importer. Next, we calculate the expected utility. Let μ denote the expected value of the price and denote σ the standard deviation of the price. Assuming that the price follows a normal distribution, the expected utility is expressed as:

$$E[U(w)] = log(\mu) - \frac{2\mu}{2\sigma^2}, \tag{8}$$

where μ and σ represent the mean and standard deviation of import price. To determine the certainty equivalent (CE), which is the guaranteed price that provides the same utility as the expected utility, we define CE as:

$$CE = \mu exp(-\frac{2\mu}{2\sigma^2}). \tag{9}$$

The risk premium (RP) is then calculated by:

$$RP = \mu - CE. \tag{10}$$

4.6 Data for the counterfactual simulation

The data analysis consists of two parts. In the first part, we introduce the data used to calculate the revised global wheat price and production, incorporating the responses of SH farming operators to remote sensing data. Because the wheat production data for the former Soviet Union regions are available from 1992, the historical wheat's production for NH countries coverage is limited between 1992 and 2021. We take the hard red winter wheat (sourced from the IMF Commodity Prices) as the international price of wheat. The remote sensing data for NH regions (Russia, Ukraine, United States and Canada) is from 2003 to 2012. The remote sensing-based early crop forecasting information of wheat retrieved from satellite imageries was developed by scientists at Department of Geographical Sciences, University of Maryland College Park

We use the price elasticity of supply to represent the degree of response to changes in global wheat prices by SH farmers in South Africa, Uruguay, Paraguay, Argentina, and Brazil, respectively (Brescia and Lema, 2007; Griffith et al., 2001; Meyer, 2002) [3]. The total SH production altered is merged with historical production in NH to compose the revised global wheat production. Finally, the historical global wheat production is replaced by the modified global wheat production to simulate the virtual impacts of remote sensing-based early crop forecasting information on import prices in wheat-importing countries.

In the second part, we present the data used in the panel VECM analysis to investigate the long- and short-term relationships among wheat import price, domestic consumption and production of wheat in net wheat-importing countries, and aggregated global wheat production of net wheat-exporting countries. Algeria, Cyprus, Egypt, Israel, Jordan, Kuwait, Lebanon, Mozambique, Nigeria, Tunisia, United Republic of Tanzania, and Yemen are chosen as the net wheat-importing countries. Data for the four variables are obtained from the FAOSTAT. Import price is calculated as import value divided by import quantity in USD. The aggregated global wheat production is composed of the 10 largest net wheat-exporting countries, including Argentina, Australia, Brazil, Canada, Paraguay, Russia, South Africa, Ukraine, USA, and Uruguay. Table 5 presents the definitions and data sources of the variables used in our panel analysis. International prices of rice, soybean and oil are retrieved from the IMF Commodity Prices.

---

[3] The elasticity for Uruguay is applied to that for Paraguay with unavailability of the data.

Table 5: Definitions of the variables used in the panel data analysis.

Variable Symbol	Definition	Type	Source
p_t^{HisG}	Global wheat price change rate in period t	Monthly historical data converted to yearly data (No.1 Hard Red Winter, ordinary protein, Kansas City)	IMF Commodity Prices
Q_{t-1}^{HisNH}	Wheat production change rate of 4 NH net wheat-exporting countries in period $t-1$.	Yearly historical data (Sum of Canada, Russia, Ukraine and USA)	FAOSTAT
Q_{t-1}^{HisSH}	Wheat production change rate of 6 SH net wheat-exporting countries in period $t-1$.	Yearly historical data (Sum of Argentina, Australia, Brazil, Paraguay, South Africa, and Uruguay)	FAOSTAT
OIL_t	Crude oil price change rate in period t.	Monthly historical data converted to yearly data	IMF Commodity Prices
$SOYBEAN_t$	Global soybean price change rate in period t	Monthly historical data converted to yearly data	IMF Commodity Prices
$RICE_t$	Global rice price change rate in period t	Monthly historical data converted to yearly data	IMF Commodity Prices
Q_{t-1}^{HypNH}	Hypothetical NH wheat production change rate in period $t-1$.	Yearly hypothetical data	Estimated
$\hat{p}_t^{HypG}$	Hypothetical global wheat price change rate in period $t-1$.	Yearly hypothetical data	Estimated
$Q_{i,t-1}^{HypSH}$	Hypothetical SH wheat production change rate for country i in period $t-1$.	Yearly hypothetical data	Estimated
e_i	Price elasticity of supply for country i	Estimated in past studies	Brescia and Lema, 2007; Griffith et al., 2001; Meyer, 2005.
EXQ_{t-1}^{HisG}	Historical global wheat production (SH+NH) in period $t-1$.	Yearly historical data	FAOSTAT
EXQ_{t-1}^{HypG}	Revised global wheat production (SH+NH) in period $t-1$.	Yearly hypothetical data	Estimated
$IMP_{i,t}$	Wheat import price of net wheat-importing country i in period t.	Yearly historical data estimated from import value divided by import quantity in logarithmic form	FAOSTAT
$IMQ_{i,t}$	Wheat production of net wheat-importing country i in period t.	Yearly historical data in logarithmic form	FAOSTAT
$IMC_{i,t}$	Wheat consumption of net wheat-importing country i in period t.	Yearly historical data in logarithmic form	FAOSTAT

5. Limitation

This study focuses exclusively on the major wheat-producing countries in the Northern Hemisphere—Russia, Ukraine, the United States, and Canada—by utilizing remote sensing data. However, wheat is also cultivated extensively across numerous European countries and other regions. Incorporating these regions into the model would capture additional benefits. Consequently, the estimates presented in this study are likely conservative when compared to the actual benefits.

Similarly, the analysis in the Southern Hemisphere is restricted to a limited number of wheat-producing countries, leaving out several other producers. If all wheat-supplying countries were assumed to respond, the adjustments in global wheat supply would be more substantial. As a result, the price stabilization effects and associated benefits estimated in this study are also likely to be conservative relative to actual outcomes.

Farmers' responses were modeled using price elasticity of demand estimates from prior studies. However, it is plausible that some farmers may lack the capacity to adjust their production within a short time frame. This limitation suggests that the production adjustments estimated in this study could be overstated. Future research is needed to quantify the proportion of farmers who are capable of making short-term production adjustments.

Reference

Adjemian, M.K. (2012). Quantifying the WASDE Announcement Effect. American Journal of Agricultural Economics, 94(1), pp.238–256. doi: https://doi.org/10.1093/ajae/aar131.

Adjemian, M.K., Johansson, R., McKenzie, A. and Thomsen, M. (2017). Was the Missing 2013 WASDE Missed? Applied Economic Perspectives and Policy, 40(4), pp.653–671. doi: https://doi.org/10.1093/aepp/ppx049.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of errorcomponents model. Journal of Econometrics, 68, pp.29–51.

Banse, M., Janzen, N., Junker, F., Kreins, P., Offermann, F., Salamon, P. and Weimar, H. (2016). Modelling the bioeconomy: Linkages between agricultural, wood and energy markets. Paper prepared for the 19th Annual Conference on Global Economic Analysis. Available at: https://www.semanticscholar.org/paper/Modelling-the-bioeconomy%3A-linkages-between-wood-and-Banse-Janzen/c27d214cf27a84caedec713010c154695a527dce.

Becker-Reshef, I., Vermote, E., Lindeman, M. and Justice, C. (2010). A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. Remote Sensing of Environment, 114, pp.1312–1323.

Bernoulli, D. (1738). Specimen Theoriae Novae de Mensura Sortis. Commentarii Academiae Scientiarum Imperialis Petropolitanae, 5, pp.175–192. (English translation: Bernoulli, D. (1954). Exposition of a New Theory on the Measurement of Risk. Econometrica, 22(1), pp.23–36.)

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87, pp.115–143.

Breusch, T.S. and Pagan, A.R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies, 47, pp.239–253.

Brescia, V. and Lema, D. (2007). Supply Elasticities for Selected Commodities in MERCOSUR and Bolivia. EC Project EUMercoPol (2005–08). Available at: https://inta.gob.ar/sites/default/files/script-tmp-mercosur-supply_elasticities.pdf.

Colling, P.I. and Irwin, S.H. (1990). The Reaction of Live Hog Futures Prices to USDA “Hogs and Pigs Reports.” American Journal of Agricultural Economics, 72(1), pp.84–94.

Dasgupta, P., Morton, J.F., Dodman, D., et al. (2014). Rural areas. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Deines, J.M., Patel, R., Liang, S.-Z., Dado, W. and Lobell, D.B. (2021). A million kernels of truth: Insights into scalable satellite maize yield mapping and yield gap analysis from an extensive ground dataset in the US Corn Belt. Remote Sensing of Environment, 253, 112174.

Dickey, D.A. and Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, pp.427–431.

Du, X., Yu, C.L. and Hayes, D.J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. Energy Economics, 33, pp.497–503.

Erhan Ünal, G., Karapinar, B. and Tanaka, T. (2017). Welfare-at-Risk and Extreme Dependency of Regional Wheat Yields: Implications of a Stochastic CGE Model. Journal of Agricultural Economics, 69(1), pp.18–34. doi: https://doi.org/10.1111/1477-9552.12229.

Fortenbery, R.T. and Summer, D.A. (1990). The Effects of USDA Reports in Futures and Options Markets. Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL.

Franch, B. et al. (2015). Improving the timeliness of winter wheat production forecast in the United States of America, Ukraine and China using MODIS data and NCAR Growing Degree Day information. Remote Sensing of Environment, 161, pp.131–148.

Griffith, G., I'Anson, K., Hill, D. and Vere, D. (2001). Previous Supply Elasticity Estimates for Australian Broadacre Agriculture. Economic Research Report No.6. NSW Agriculture, Orange.

Han, E. and Huang, Q. (2021). Global Commodity Markets, Chinese Demand for Maize, and Deforestation in Northern Myanmar. Land, 10(11), pp.1232–1232. doi: https://doi.org/10.3390/land10111232.

Im, K.S., Pesaran, M.H. and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, pp.53–74.

Isengildina-Massa, O., Irwin, S.H., Good, D.L. and Gomez, J.K. (2008). Impact of WASDE reports on implied volatility in corn and soybean markets. Agribusiness, 24(4), pp.473–490. doi:

https://doi.org/10.1002/agr.20174.

Karali, B. (2012). Do USDA Announcements Affect Comovements Across Commodity Futures Returns? Journal of Agricultural and Resource Economics, 37(1), pp.77–97.

Lautze, S., Bell, W., Alinovi, L. and Russo, L. (2012). Early warning, late response (again): The 2011 famine in Somalia. Global Food Security, 1, pp.43–49.

Levin, A., Lin, C.F. and Chu, C. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108, pp.1–24.

Lin, C., Zhong, L., Song, X.-P., Dong, J., Lobell, D.B. and Jin, Z. (2022). Early- and in-season crop type mapping without current-year ground truth: Generating labels from historical information via a topology-based approach. Remote Sensing of Environment, 274, 112994.

Lobell, D.B., Thau, D., Seifert, C., Engle, E. and Little, B. (2015). A scalable satellite-based crop yield mapper. Remote Sensing of Environment, 164, pp.324–333. doi: https://doi.org/10.1016/j.rse.2015.04.021.

Love, I. and Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from Panel VAR. The Quarterly Review of Economics and Finance, 46, pp.190–210.

Marone, H. (2008). How Do Wheat Prices React to USDA Reports? A UNDP/ODS Working Paper.

McKenzie, A.M. (2008). Pre-Harvest Price Expectations for Corn: The Information Content of USDA Reports and New Crop Futures. American Journal of Agricultural Economics, 90(2), pp.351–366.

McKenzie, A.M. and Holt, M.T. (2002). Market efficiency in agricultural futures markets. Applied Economics. doi: https://doi.org/10.1080//00036840110102761.

McKenzie, A.M. and Singh, N. (2011). Hedging Effectiveness Around U.S. Department of Agriculture Crop Reports. Journal of Agricultural and Applied Economics, 43(1), pp.77–94.

Mehra, R. and Prescott, E.C. (1985). The equity premium: A puzzle. Journal of Monetary Economics, 15(2), pp.145–161. doi: https://doi.org/10.1016/0304-3932(85)90061-3.

Meyer, F. (2002). Modelling the Market Outlook and Policy Alternatives for the Wheat Sector in South Africa. Department of Agricultural Economics, Extension, and Rural Development, Faculty of Natural and Agricultural Sciences, University of Pretoria. Available at: https://repository.up.ac.za/bitstream/handle/2263/28109/00dissertation.pdf?sequence=1.

Milonas, N. (1987). The Effects of USDA Crop Announcements on Commodity Prices. The Journal of Futures Markets, 7(5), pp.571–589.

Newey, W.K. and West, K.D. (1994). Automatic lag selection in covariance matrix estimation. Review of Economic Studies, 61, pp.631–653.

Nóia Júnior, R. de S., Deswarte, J., Cohan, J., et al. (2023). The extreme 2016 wheat yield failure in France. Global Change Biology, 29(11), pp.3130–3146. doi: https://doi.org/10.1111/gcb.16662.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61(4), pp.5–49.

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to PPP hypothesis: New results. Econometric Theory, 20(3), pp.597–627.

Pesaran, M.H., Shin, Y. and Smith, R. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94, pp.621–634.

Pesaran, M.H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics No. 0435. University of Cambridge.

Pesaran, M.H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22, pp.265–312.

Phillips, P.C. and Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75, pp.335–346.

Song, X.-P. (2023). The future of global land change monitoring. International Journal of Digital Earth, 16, pp.2279–2300.

Song, X.-P., Li, H., Potapov, P. and Hansen, M.C. (2022). Annual 30 m soybean yield mapping in Brazil using long-term satellite observations, climate data and machine learning. Agricultural and Forest Meteorology, 326, pp.109186–109186. doi:https://doi.org/10.1016/j.agrformet.2022.109186.

Song, X.-P., Hansen, M.C., Potapov, P.V., et al. (2021). Massive soybean expansion in South America since 2000 and implications for conservation. Nature Sustainability, 4, pp.784–792.

Tanaka, T., Sun, L., Becker-Reshef, I., Song, X.-P. and Puricelli, E. (2023). Satellite forecasting of crop harvest can trigger a cross-hemispheric production response and improve global food security. Communications Earth & Environment, 4(1). doi: https://doi.org/10.1038/s43247-023-00992-2.

Taylor, C.W. (2012). Market Reactions to USDA Reports: State Analysis of Corn Price Response. The Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12–14, 2012.

Ünal, G.E., Karapinar, B. and Tanaka, T. (2018). Welfare-at-Risk and Extreme Dependency of Regional Wheat Yields: Implications of a Stochastic CGE Model. Journal of Agricultural Economics, 69(1), pp.18–34. doi: https://doi.org/10.1111/1477-9552.12229.

Van Tricht, K., Degerickx, J., Gilliams, S., et al. (2023). WorldCereal: A dynamic open-source system for global-scale, seasonal, and reproducible crop and irrigation mapping. Earth System Science Data, 15, pp.5491–5515.

Von Neumann, J. and Morgenstern, O. (1944). Theory of Games and Economic Behavior. Princeton University Press.

Zin, S.E. and Liu, Y. (2006). Understanding Stock Returns and Volatility in Emerging Markets. Journal of Economic Dynamics and Control, 30(8), pp.1151–1170.