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Structural changes in the wheat supply chain and their environmental footprints through satellite yield forecasting

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ABSTRACT

Satellite-based crop forecasting in major exporting regions can trigger production shifts in the opposite hemisphere by leveraging seasonal disparities between the Northern and Southern Hemispheres to stabilize global crop supply and markets. However, the impact of these regional shifts on supply chains and environmental footprint remains unclear. Thus, evaluating the influence of yield forecasts on wheat supply chains and carbon footprints and identifying challenges to and strategies for the sustainable use of satellite-based forecasts are crucial. This study analyzed the structural changes in the wheat supply chain and their environmental impacts resulting from satellite yield forecasting by employing the RAS method and wheat production data. The results indicate that Southern Hemisphere wheat production shifts, triggered by favorable Northern Hemisphere crop information, generate an additional $10.80 billion in value-added and 4.08 Mt of carbon dioxide emissions in a favorable crop year relative to the 2019 base year. Moreover, favorable Northern Hemisphere harvests increase carbon dioxide emissions in countries neighboring Russia and Ukraine, including Turkey, Lebanon, and Egypt. Considering carbon leakage in production forecasts for trading agricultural commodities across hemispheres can stabilize prices and reduce emissions, ultimately improving global food security and environmental sustainability.

1. Introduction

The global food market has become increasingly unstable owing to several notable events such as the 2008 global food crisis, 2020 COVID-19 pandemic, and 2022 Russian invasion of Ukraine (Cariappa et al., 2022). These crises have heightened food price volatility and exacerbated hunger, particularly in developing countries, including those in Africa (World Food Programme, 2023). Furthermore, factors such as climate change, financial market speculation, and biofuel production have exacerbated disruptions to international food markets (Tanaka et al., 2024). Therefore, addressing global food security is crucial. Remote sensing for crop yield forecasting (Becker-Reshef et al., 2010) offers a valuable tool by providing predictive insights to manage food supply and distribution more effectively.

Recent advancements in satellite imagery technology have improved monitoring of the Earth, allowing for more accurate assessments of crop growth conditions and improving the accuracy of harvest predictions (Franch et al., 2019). These advancements have improved the accuracy and timing of forecasting information generation, enabling predictions 1 to 2 months before the onset of the wheat harvest season in the Northern Hemisphere (Franch et al., 2015). Seasonal differences between the hemispheres result in varying schedules for planting and harvesting (Fig. 1). If harvest outcomes can be predicted by May or June in the Northern Hemisphere, wheat farmers in the Southern Hemisphere can anticipate global crop prices and adjust their planting strategies to maximize profitability. Specifically, improved forecasts alter expected price signals, which in turn affect expected returns to wheat cultivation and induce adjustments in planted area and input use. Variations in

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harvest quality in the Northern Hemisphere may lead Southern Hemisphere farmers to modify their cultivation areas, thereby stabilizing the global supply. Tanaka et al. (2023) proposed a system that exploits seasonal differences in crop calendars between the Northern and Southern Hemispheres. This enables farmers to adjust their strategies based on the conditions in the opposite hemisphere, thereby reducing market price volatility.

Global wheat production increased from 732 Mt in 2014 to 791 Mt in 2023, primarily driven by rising global food demand due to population growth (U.S. Department of Agriculture, 2024a). In 2022, agriculture accounted for 10% of U.S. greenhouse gas (GHG) emissions (U.S. Department of Agriculture, 2024b). To mitigate the environmental impacts associated with agricultural products, environmental impacts during production must be minimized (Nasseri, 2019; Pourmehdi and Kheiralipour, 2023) and the environmental footprint throughout the product supply chain must be reduced (Bruckner et al., 2019; Ye et al., 2022). The carbon footprint of wheat production is influenced by various factors, including production region, weather conditions, and farm size (Kashyap and Agarwal, 2021), with nitrogen fertilizer use and straw burning being major contributors (Zhang et al., 2017).

Although satellite yield forecasting is anticipated to enhance global food security, its effects on supply chains, particularly regarding changes in regional wheat production and the associated environmental impacts such as carbon dioxide (CO_2) emissions, remain unclear. For example, the carbon footprint of wheat production differs markedly across regions (Zhang et al., 2017), suggesting that changes in regional wheat production resulting from satellite yield forecasting may lead to unforeseen effects on global carbon emissions. Therefore, we address the following research questions:

- How do existing crop pricing and supply/demand adjustment systems affect the wheat supply chain and its carbon footprint when informed by satellite yield forecasts (Tanaka et al., 2023)?
- What are the challenges to and strategies for the sustainable use of satellite yield forecasts?

This study used multi-regional input-output (MRIO) analysis combining the Global Resource Input-Output Assessment (GLORIA) database (Lenzen et al., 2017, 2022) and hypothetical wheat production data (Tanaka et al., 2023). Specifically, we analyzed the effects of both favorable and unfavorable wheat harvests in the Northern Hemisphere on the global supply chain. The results indicated that satellite yield forecasts generate substantial value-added and increase the CO_2 emissions associated with the global wheat supply chain. These findings can inform policies to ensure that satellite yield forecasts enhance the sustainability of wheat production and its associated supply chains. Such policies could help balance economic gains with environmental responsibilities, promoting a more sustainable global food system.

2. Literature review

Tanaka et al. (2023) demonstrated that global agricultural production may stabilize by using production forecast information for wheat and soybeans derived from satellite remote sensing, particularly in regions with varying planting and harvesting seasons. This literature review comprises two sections: one examining studies focusing on remote sensing research and the other on studies analyzing the market impacts of agricultural production forecast information.

2.1. Agricultural production forecast information and its market impacts

Research on the market impacts of World Agricultural Supply and Demand Estimates (WASDE) has largely focused on price discovery and market efficiency. Empirical studies show that price reactions are primarily driven by the "surprise factor," defined as the gap between market expectations and released forecasts (Garcia et al., 1997; Adjemian and Irwin, 2018). Futures prices for major crops such as corn and soybeans exhibit immediate and significant adjustments following report releases, indicating that WASDE announcements function as information shocks. These reports also contribute to the incorporation of supply and demand expectations into prices, thereby enhancing informational efficiency (McKenzie and Holt, 2002).

However, the magnitude of WASDE effects is not uniform. Their impact tends to be stronger during periods of elevated supply uncertainty or weather risk, while incremental informational value declines when market conditions are stable or information is already widely anticipated (Isengildina-Massa et al., 2008; Ding and Katchova, 2024). Overall, the literature suggests that WASDE reports play an important role in price discovery, particularly under heightened uncertainty.

Rigorous causal identification of market reactions to remote sensing information remains limited. Because satellite indicators are generated continuously rather than released at a single, well-defined event date, it is often difficult to implement clean event study designs comparable to those used for United States Department of Agriculture (USDA) crop

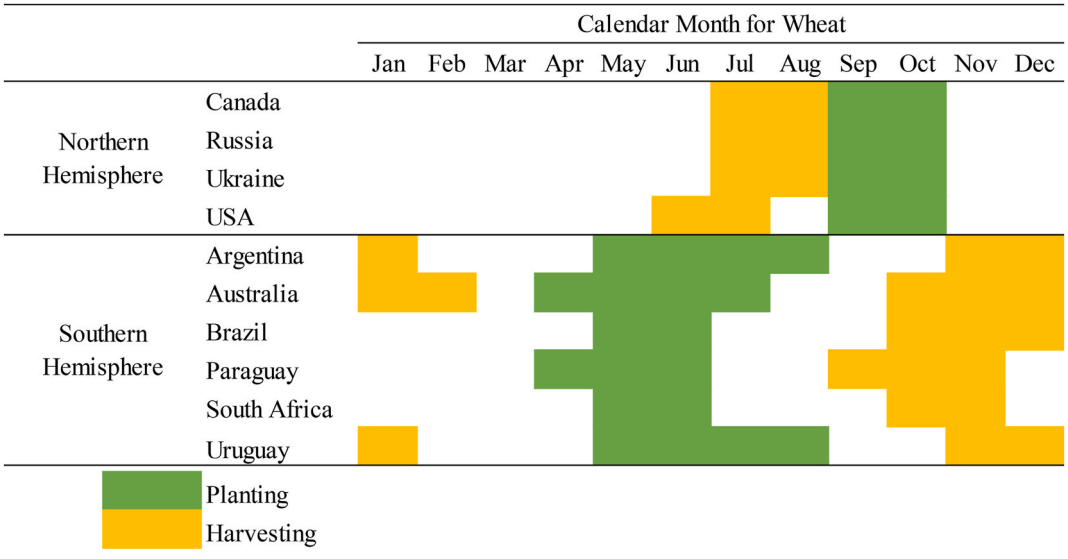

Fig. 1. Crop calendar of wheat in the Northern and Southern Hemispheres.
Data source: Agricultural Market Information System (FAO, 2024).

reports (Lehecka, 2014; Arnade et al., 2021). Much of the literature on the remote sensing market therefore relies on fixed-effects panel regressions, distributed-lag models, and out-of-sample predictive validation, leaving open concerns about simultaneity and omitted variables such as policy interventions, inventories, exchange rates, and trade restrictions. Tsiboe et al. (2023) showed that official yield news is incorporated into futures prices within a short window and simulated how higher-frequency yield information could alter volatility, suggesting that increasing information frequency may reshape market dynamics, although real-world validation is still needed. Extending the analysis beyond short-term price discovery, Tanaka et al. (2023) used a counterfactual modeling framework to show that satellite-based early harvest forecasts can induce cross-hemispheric production responses that dampen price shocks, thereby quantifying a potential medium-run stabilization effect. Yet this mechanism is demonstrated primarily through simulation rather than direct causal observation. Overall, while predictive evidence linking remote sensing signals to price movements is growing, future research could combine clearly time-stamped remote sensing product releases, high-frequency market microstructure data, and quasi-experimental identification strategies to establish whether changes in the information environment causally improve price discovery, reduce volatility, and enhance market efficiency.

2.2. Carbon footprint analysis in agri-food sectors

The agri-food sector contributes substantially to global GHG emissions, including CO_2, methane (CH_4), and nitrous oxide (N_2O). These emissions result from various activities such as agricultural production, processing, transportation, and waste disposal (Miao et al., 2023). Despite its importance, the definition of "carbon footprint" remains inconsistent, with ongoing debates about the inclusion of soil carbon sequestration and non-CO_2 gases (Wiedmann and Minx, 2009; Fang et al., 2014). Core methodologies for carbon footprint assessment in this sector include life cycle assessment (LCA) and input-output analysis. Process-based LCA offers comprehensive micro-level insights (ISO, 2013), while input-output analysis-based LCA captures macro-level carbon flows across regions and supply chains (Wiedmann, 2009; Ali et al., 2018).

Key studies of process-based LCA have identified livestock production as a major emitter of CH_4, primarily through enteric fermentation and manure management (Mosier et al., 2005). Crop cultivation contributes considerably to N_2O emissions owing to fertilizer use (Mosier et al., 2006; Xue et al., 2014). Geographical and product-specific variations in emissions are evident, with beef production exhibiting notably higher carbon footprints than plant-based foods (Miao et al., 2023). Research has highlighted the interconnectedness of carbon, water, and energy footprints, emphasizing the need for integrated strategies to improve sustainability in the agri-food sector (Silalertruksa and Gheewala, 2018). In addition to process-based LCA, input-output analysis-based LCA has been applied to agri-food systems to trace embodied environmental impacts through international trade linkages. For example, Bruckner et al. (2019) and Ye et al. (2022) integrated agri-food systems into MRIO frameworks to quantify product flows and the associated environmental impacts of product- and country-level along global supply chains, thereby capturing cross-border spillover effects.

These findings have informed policy discussions aimed at promoting sustainable agricultural practices such as employing conservation tillage and precision farming (Bezboruah et al., 2024) and supporting renewable energy adoption in the agricultural sector (Do et al., 2020; CAT, 2023). However, studies have not examined how satellite yield forecasting may alter the allocation of regional production or how such adjustments may propagate through global supply chains to affect embodied carbon emissions. This gap is particularly important given the growing reliance on remote sensing technologies in agricultural decision-making. To address this gap, this study integrates satellite yield forecasting with an MRIO-based carbon accounting framework to quantify how forecast-induced production reallocation affects global supply chain carbon footprints.

3. Materials and methods

3.1. Data sources

This study employed GLORIA (Lenzen et al., 2017, 2022), encompassing 164 regions and 120 sectors (including all countries relevant to this study in the Northern and Southern Hemispheres and the wheat sector). Data from 2019 were used as the base year, while data from 2008 to 2010 represented years of favorable and unfavorable harvests, respectively, as wheat-producing Northern Hemisphere countries experienced relatively good and bad crop yields in those respective years. Based on Tanaka et al. (2024), we hypothesized that farmers in Southern Hemisphere countries such as Argentina, Australia, Brazil, Paraguay, South Africa, and Uruguay would adjust their wheat production levels in response to wheat production forecasts derived from remote sensing data in Northern Hemisphere countries such as the United States, Canada, Russia, and Ukraine. This study integrated hypothetical data on production adjustments in the Southern Hemisphere with actual wheat production data for these countries from the Food and Agriculture Organization (FAO, 2023).

This study analyzed the production spillovers and associated changes in GHG emissions across multiple industries through global supply chains under favorable and unfavorable harvest scenarios and derived corresponding policy implications. In this context, we focused on CO_2 emissions, as they represent the most widely affected component of GHGs across industries. The analysis used sector- and country-level direct CO_2 emission data stored in the satellite accounts of the GLORIA database, which are based on the EDGAR database (European Commission, 2021a).

The wheat production forecasts based on remote sensing were derived using the methodology originally developed by Becker-Reshef et al. (2010) and refined by Franch et al. (2015). This method relies on the positive and linear relationship between the satellite-derived seasonal maximum normalized difference vegetation index (NDVI) and wheat yield at the country scale to establish a regression-based model (Becker-Reshef et al., 2010). The evolution of NDVI values throughout the growing season is primarily influenced by accumulated growing degree days (GDDs). Consequently, seasonal maximum NDVI values can be predicted using GDDs approximately 40 days before the observed NDVI peak date, thereby improving the timeliness of yield forecasting (Franch et al., 2015). Daily bidirectional reflectance distribution function-corrected surface reflectance data from the Moderate Resolution Imaging Spectroradiometer, air temperature reanalysis data from the National Centers for Environmental Prediction and the National Center for Atmospheric Research, satellite-based wheat crop masks, and administrative wheat yield statistics were combined to generate wheat yield forecasts at the county scale. These forecasts were subsequently combined with harvested area statistics to generate national-scale wheat production forecasts. The methods were evaluated across the United States, Ukraine, and China, demonstrating an error margin of 7–10% relative to official statistics. The methods were applied to Russia, Ukraine, the United States, and Canada to generate the wheat forecasts from 2003 to 2012 employed in this study.

3.2. MRIO analysis

An MRIO table illustrates the domestic and international transactions among various industries (or commodities). This model is used to analyze the direct and indirect effects of production changes in various industries across different countries and regions. The intermediate transaction matrix is defined as $\mathbf{Z} = \left(z_{ij}^{rs}\right)$, final demand matrix as $\mathbf{Y} = \left(y_i^{rs}\right)$, value-added vector as $\mathbf{v} = \left(v_i^{r}\right)$, and total output vector as $\mathbf{x} =$

(x_i^r). Here, $r, s = \{1, 2, \ldots, M\}$ and $i, j = \{1, 2, \ldots, N\}$ represent specific regions and products, respectively, where M and N denote the number of regions and products in the MRIO table, respectively. The structure of an MRIO model with M regions and N products is illustrated in Fig. 2.

If we define the input coefficient matrix as $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$, the total output $\mathbf{x}$ can be expressed as follows (Miller and Blair, 2009). Here, denotes the diagonal matrix.

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} \tag{1}$$

where $\mathbf{y} = \mathbf{Yi}$ is the total final demand vector and $\mathbf{i}$ is the summation vector. The matrix $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is referred to as the Leontief inverse matrix (Leontief, 1936). The Leontief model is a demand-driven model that describes total production as the spillover effect of demand to upstream industries, allowing for tracking changes in the input variations associated with changes in total production. Similar to upstream spillover effects, we also adopted the Ghosh model (Ghosh, 1958) to approximate the spillover effects of supply on downstream industries. Using the production coefficient matrix $\mathbf{B} = \hat{\mathbf{x}}^{-1}\mathbf{Z}$ and Ghosh inverse matrix $\mathbf{G} = (\mathbf{I} - \mathbf{B})^{-1}$, the total output $\mathbf{x}$ can be rewritten as

$$\mathbf{x}' = \mathbf{v}(\mathbf{I} - \mathbf{B})^{-1} = \mathbf{vG} \tag{2}$$

where ' denotes the transportation of the matrix.

3.3. Analysis of upstream and downstream impacts

This study is based on the following settings and assumptions:

1. **Inputs to wheat production in Northern Hemisphere countries:** These inputs are assumed to remain constant irrespective of the yield level (i.e., set as in the base year) because wheat production is indeterminate at the time of planting. Conversely, wheat-producing Southern Hemisphere countries can adjust their inputs (i.e., influence upstream) by using remote sensing information on wheat production in the Northern Hemisphere (Eq. [3]).
2. **Changes in wheat production in Northern Hemisphere countries:** These changes are defined as the rate of change between the favorable/unfavorable harvest year and the preceding year (first line of Eq. [4]).
3. **Changes in wheat production in Southern Hemisphere countries:** These changes are defined as the rate of change between the actual yield and the yield adjusted by the cross-hemisphere production response for the year (second line of Eq. [4]).

If we define $q_i^r(t)$ and $\theta_i^r(t)$ as the actual yield and the yield adjusted for cross-hemisphere production response in country r during year t, respectively, the rates of change in upstream $\mathbf{c}^{UP} = \left\{c_i^{UP,r}\right\}$ and downstream production $\mathbf{c}^{DOWN} = \left\{c_i^{DOWN,r}\right\}$ can be derived as follows:

$$c_i^{UP,r} = \begin{cases} \dfrac{\theta_i^r(t)}{q_i^r(t)} \ (r \in SH) \\ 1 \ (otherwise) \end{cases} \tag{3}$$

$$c_i^{DOWN,r} = \begin{cases} \dfrac{q_i^r(t)}{q_i^r(t-1)} \ (r \in NH) \\ \dfrac{\theta_i^r(t)}{q_i^r(t)} \ (r \in SH) \\ 1 \ (otherwise) \end{cases} \tag{4}$$

where NH and SH are the sets of target countries in the Northern and Southern Hemispheres, respectively. Therefore, the upstream effect $\boldsymbol{\varepsilon}^{up}$ and downstream effect $\boldsymbol{\varepsilon}^{down}$ are calculated as follows:

$$\boldsymbol{\varepsilon}^{up} = \mathbf{L}\hat{\mathbf{c}}^{UP}\mathbf{y} - \mathbf{x} \tag{5}$$

$$\boldsymbol{\varepsilon}^{down} = \mathbf{v}\hat{\mathbf{c}}^{DOWN}\mathbf{G} - \mathbf{x}' \tag{6}$$

The hypothetical total output, incorporating the cross-hemisphere production response $\mathbf{x}^{RS} = \left\{x_i^{RS,r}\right\}$, is defined as follows:

$$\mathbf{x}^{RS} = \mathbf{x} + \boldsymbol{\varepsilon}^{up} + \boldsymbol{\varepsilon}^{down'} \tag{7}$$

In this study, changes in global supply chain networks were estimated using the generalized RAS method (Stone, 1961; Junius and Oosterhaven, 2003; Lenzen et al., 2007; Zhang et al., 2017). This study then iteratively adjusted the input coefficient matrix to match the new total output $\mathbf{x}^{RS}$ estimated above and approximated changes in the input structure (details in Supplementary Information).

3.4. Generalized RAS method

The RAS algorithm (Stone, 1961; Zhang et al., 2017) iteratively adjusts an old intermediate transaction matrix $\mathbf{Z}$, which has specified row and column sums, to produce a "new" intermediate transaction matrix $\mathbf{Z}^{RS}$ that conforms to a "new" set of given row sums $\boldsymbol{\rho}$ and column sums $\boldsymbol{\sigma}$. In addition, Junius and Oosterhaven (2003) and Lenzen et al. (2007) developed the generalized RAS method for computing a matrix with

		Intermediate input								Final demand				Total output
		Region 1			Region 2			...	Region M	Region 1	Region 2	...	Region M	
		Product 1	...	Product N	Product 1	...	Product N							
Region 1	Product 1	Z_{11}^{11}	$\cdots$	Z_{1N}^{11}	Z_{11}^{12}	$\cdots$	Z_{1N}^{12}	$\cdots$	Z_{1N}^{1M}	y_1^{11}	y_1^{12}	$\cdots$	y_1^{1M}	x_1^1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$			$\vdots$	$\vdots$		$\vdots$	$\vdots$
	Product N	Z_{N1}^{11}	$\cdots$	Z_{NN}^{11}	Z_{N1}^{12}	$\cdots$	Z_{NN}^{12}			y_N^{11}	y_N^{12}	$\cdots$	y_N^{1M}	x_N^1
Region 2	Product 1	Z_{11}^{21}	$\cdots$	Z_{1N}^{21}	Z_{11}^{22}	$\cdots$	Z_{1N}^{22}			y_1^{21}	y_1^{22}	$\cdots$	y_1^{2M}	x_1^2
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$			$\vdots$	$\vdots$		$\vdots$	$\vdots$
	Product N	Z_{N1}^{21}	$\cdots$	Z_{NN}^{21}	Z_{N1}^{22}	$\cdots$	Z_{NN}^{22}			y_N^{21}	y_N^{22}	$\cdots$	y_N^{2M}	x_N^2
$\vdots$		$\vdots$						$\ddots$		$\vdots$	$\vdots$		$\vdots$	$\vdots$
Region M		Z_{N1}^{M1}							Z_{NN}^{MM}	y_N^{M1}	y_N^{M2}	$\cdots$	y_N^{MM}	x_N^M
Value-added		v_1^1	$\cdots$	v_N^1	v_1^2	$\cdots$	v_N^2	$\cdots$	v_N^M					
Total output		x_1^1	$\cdots$	x_N^1	x_1^2	$\cdots$	x_N^2	$\cdots$	x_N^M					

Fig. 2. Structure of the MRIO model.

negative values. Using the generalized RAS method and hypothetical total production calculated above, we adjusted the input transaction matrix of the MRIO table to analyze structural changes in the wheat supply chain and their impacts on the environmental footprint of wheat.

We defined a "new" set of given row sums column vector $\boldsymbol{\rho} = \{\rho_i^r\}$ and column sums row vector $\boldsymbol{\sigma} = \{\sigma_i^r\}$ as follows:

$$\rho_i^r = \left(\frac{\sum_{s,j} z_{ij}^{rs}}{x_i^r}\right) \times x_i^{RS,r} \tag{8}$$

$$\sigma_j^s = \begin{cases} \sum_{r,i} z_{ij}^{rs} \ (s \in NH, j = \text{wheat}) \\ \left(\frac{\sum_{r,i} z_{ij}^{rs}}{x_j^s}\right) \times x_j^{RS,s} \ (otherwise) \end{cases} \tag{9}$$

Northern Hemisphere countries adjust their wheat production but demand for intermediate goods remains consistent with that of the base year (first line of Eq. S(2)). Therefore, the value-added coefficient (productivity) of the wheat sector in Northern Hemisphere countries increases (decreases) when their harvest is favorable (unfavorable).

Using the new intermediate transaction matrix $\mathbf{Z}^{RS} = \left\{z_{ij}^{RS,rs}\right\}$, we derived a new final demand matrix $\mathbf{Y}^{RS} = \left\{y_i^{RS,rs}\right\}$ and a value-added vector $\mathbf{v}^{RS} = \left\{v_i^{RS,r}\right\}$ as follows:

$$y_i^{RS,rs} = \frac{y_i^{rs}}{\sum_s y_i^{rs}} \times \left(x_i^{RS,r} - \sum_{s,j} z_{ij}^{RS,rs}\right) \tag{10}$$

$$v_j^{RS,s} = x_j^{RS,s} - \sum_{r,i} z_{ij}^{RS,rs} \tag{11}$$

3.5. Change in carbon footprint

From Eq. (7), the global CO_2 emissions associated with the change in wheat production can be calculated as follows:

$$E^{RS} = \mathbf{e}\mathbf{x}^{RS} \tag{12}$$

where, $\mathbf{e}$ is the emission intensity row vector of the base year. If we define the input coefficient matrix of a hypothetical global economy $\mathbf{A}^{RS} = \mathbf{Z}^{RS}\widehat{\mathbf{x}^{RS}}^{-1}$ and the Leontief inverse $\mathbf{L}^{RS} = \left(\mathbf{I} - \mathbf{A}^{RS}\right)^{-1} = \left\{l_{ij}^{RS,rs}\right\}$, the CO_2 emission transfer from country s to country r within the global supply chain can be calculated based on the MRIO model (Peters, 2008; Peters et al., 2011) as follows:

$$E^{RS,sr} = \sum_{t,i,j} e_i^r l_{ij}^{RS,rt} y_j^{RS,ts} \tag{13}$$

4. Results

4.1. Changes in national wheat production

Table 1 presents the data on wheat production, value-added, and CO_2 emissions for each country during both favorable and unfavorable crop years. For instance, in a favorable crop year, wheat production increased in the four wheat-producing Northern Hemisphere countries: Canada (1.42), Russia (1.29), Ukraine (1.86), and the United States (1.22). Conversely, the cross-hemisphere production response decreased wheat production in the six wheat-producing Southern Hemisphere countries: Argentina (0.88), Australia (0.91), Brazil (0.77), Paraguay (0.69), South Africa (0.78), and Uruguay (0.69). The net increase in wheat production in the Northern Hemisphere was 71.39 Mt, whereas the net decrease in wheat production in the Southern Hemisphere was 6.11 Mt, thereby resulting in a global increase of 65.28 Mt.

Table 1
Changes in wheat production, value-added, and CO_2 emissions.

	Favorable harvest	Unfavorable harvest
Northern Hemisphere		
Canada	1.42	0.86
Russia	1.29	0.67
Ukraine	1.86	0.81
USA	1.22	0.99
Change in production (Mt)	71.39	−34.57
Southern Hemisphere		
Argentina	0.88	1.11
Australia	0.91	1.08
Brazil	0.77	1.22
Paraguay	0.69	1.34
South Africa	0.78	1.22
Uruguay	0.69	1.34
Change in production (Mt)	−6.11	5.71
Global change		
Wheat production (Mt)	65.28	−28.86
Value-added (billion USD)	10.80	−4.85
CO_2 emissions (Mt)	4.08	−1.72
Intensity		
CO_2 emissions (Mt-CO_2/Mt)	115	168

Note: The value for each country represents the percentage change in production using the production in the previous year as a baseline of 1. The CO_2 emission intensity represents the ratio of global CO_2 emissions to global wheat production.

Furthermore, this change in global wheat production generated an additional $10.80 billion in value-added and 4.08 Mt of CO_2 emissions compared with the base year. The CO_2 emission intensity of the wheat production associated with the global supply chain was 115 (Mt-CO_2/Mt) for favorable harvests and 168 (Mt-CO_2/Mt) for unfavorable harvests, with a base value of 147 (Mt-CO_2/Mt) in the base year (Table S1). This discrepancy arises from the fact that wheat production in Northern Hemisphere countries exhibited a lower CO_2 emission intensity than that in Southern Hemisphere countries (Table S2).

4.2. Impacts on the global wheat supply chain

In the wheat-producing Northern Hemisphere countries (Canada, Russia, Ukraine, and the United States), favorable harvests increased value-added and CO_2 emissions relative to the base year of 2019 (Table 2). For example, in Russia, Canada, and Ukraine, value-added increased by $2903 billion, $2488 billion, and $2476 billion, respectively, whereas CO_2 emissions increased by 2933 Kt, 2493 Kt, and 354 Kt, respectively. In addition, the supply chain associated with wheat production generated greater value-added and CO_2 emissions in Egypt, Bangladesh, Turkey, and Middle Eastern countries than in Mexico, Europe, and China, despite the latter group being geographically closer to the aforementioned wheat-producing Northern Hemisphere countries. Conversely, the wheat-producing Southern Hemisphere countries (Argentina, Brazil, Paraguay, South Africa, and Uruguay) experienced decreases in value-added and CO_2 emissions relative to the base year.

In years when the wheat-producing Northern Hemisphere countries experienced unfavorable harvests, production in the wheat-producing Southern Hemisphere countries increased compared with the base year, resulting in increases in value-added and CO_2 emissions (Table 3). In Australia, the changes in wheat production attributed to remote sensing in the Northern Hemisphere were minimal; consequently, the effects on value-added and CO_2 emissions were also marginal. Furthermore, certain countries such as China, the United Arab Emirates, and Turkey played important roles in the global wheat supply chain. Although they were not directly affected by production shocks (e.g., favorable or unfavorable harvests), significant emissions were still generated by their supply chains. Consequently, they should be included within the scope of supply chain management.

Table 2
Effects of favorable harvests in the Northern Hemisphere.

Rank	Country	Value-added (billion USD)	Rank	Country	CO_2 emissions (Kt-CO_2)
1	Russia	2903	1	Russia	2933
2	Canada	2488	2	Ukraine	2493
3	Ukraine	2476	3	Canada	354
4	USA	1528	4	USA	281
5	Egypt	242	5	China	239
6	Bangladesh	199	6	Indonesia	89
7	China	181	7	Pakistan	76
8	Philippines	165	8	UAE	63
9	Turkey	149	9	Bangladesh	54
10	Japan	142	10	Egypt	47
155	DR Yemen	0.E+00	155	Namibia	−1.E−02
156	Sierra Leone	−1.E−02	156	Sierra Leone	−5.E−02
157	Zambia	−3.E−02	157	Zambia	−8.E−02
158	Namibia	−4.E−02	158	Bolivia	−2.E−01
159	Bolivia	−1	159	Australia	−16
160	Uruguay	−23	160	Uruguay	−19
161	Paraguay	−43	161	South Africa	−71
162	South Africa	−67	162	Paraguay	−86
163	Brazil	−206	163	Brazil	−893
164	Argentina	−355	164	Argentina	−1869

Note: Top 10 countries with increased or decreased value-added and CO_2 emissions, respectively. Data for other countries are available in Table S3.

Table 3
Effects of unfavorable harvests in the Northern Hemisphere.

Rank	Country	Value-added (billion USD)	Rank	Country	CO_2 emissions (Kt-CO_2)
1	Argentina	308	1	Argentina	1615
2	Brazil	193	2	Brazil	830
3	South Africa	65	3	Paraguay	96
4	Paraguay	47	4	South Africa	68
5	Uruguay	25	5	Uruguay	21
6	Chile	3	6	Australia	16
7	Bolivia	1	7	Chile	1
8	Uganda	1	8	Kenya	1
9	Zambia	0	9	Zambia	0
10	Kenya	0	10	Uganda	0
155	Japan	−2.E+01	155	Egypt	−13
156	Philippines	−3.E+01	156	Libya	−16
157	Bangladesh	−5.E+01	157	Pakistan	−17
158	USA	−5.E+01	158	Indonesia	−19
159	China	−57	159	Turkey	−31
160	Egypt	−76	160	UAE	−56
161	Turkey	−129	161	Canada	−113
162	Ukraine	−592	162	China	−114
163	Canada	−871	163	Ukraine	−564
164	Russia	−3285	164	Russia	−3294

Note: Top 10 countries with increased or decreased value-added and CO_2 emissions, respectively. Data for other countries are available in Table S3.

Changes in wheat production within the Southern Hemisphere, influenced by remote sensing information on wheat production in the Northern Hemisphere, also affected the global supply chain. Favorable harvests in the wheat-producing Northern Hemisphere countries yielded value-added benefits not only for the wheat sectors in those countries but also for the cereal products ($76 billion) and fruit products ($67 billion) sectors in Egypt as well as the food and feed n. e.c. products sector in Japan and Bangladesh ($61 billion and $54 billion, respectively) (Table 4). Regarding CO_2 emissions, these favorable harvests generated substantial emissions in the energy sector, including electricity and gas in China, as well as in the vegetable sector in Russia and Indonesia. In the Southern Hemisphere, value-added and CO_2 emissions from the growing wheat product sector decreased, particularly in Argentina, Brazil, and Paraguay (Table S4).

Table 4
Top 10 sectors affected by favorable harvests in the Northern Hemisphere.

Value-added (billion USD)		
Rank	Sector	
1	Russia: Growing wheat product	2871
2	Ukraine: Growing wheat product	2474
3	Canada: Growing wheat product	2446
4	United States of America: Growing wheat product	1277
5	Egypt: Cereal products product	76
6	Egypt: Fruit products product	67
7	Philippines: Alcoholic and other beverages product	63
8	Bangladesh: Hospitality product	63
9	Japan: Food products and feed n.e.c. products	61
10	Bangladesh: Food products and feed n.e.c. products	54
CO_2 emissions (Kt-CO_2)		
Rank	Sector	
1	Russia: Growing wheat product	2862
2	Ukraine: Growing wheat product	2486
3	Canada: Growing wheat product	339
4	United States of America: Growing wheat product	238
5	China: Distribution of gaseous fuels through mains product	142
6	Russia: Vegetable products product	33
7	Indonesia: Growing wheat product	27
8	China: Electric power generation, transmission and distribution product	23
9	United Arab Emirates: Cereal products product	22
10	Indonesia: Vegetable products product	20

Conversely, when countries in the Northern Hemisphere experienced unfavorable harvests, the wheat sector in the major wheat-producing Southern Hemisphere countries, along with the sheep and poultry farming sectors that use wheat as raw material, generated increased value-added from remote sensing information (Table 5). This also resulted in CO_2 emissions in the vegetable products and fruit products sectors in Brazil and the energy sector in South Africa.

4.3. CO_2 emissions associated with hypothetical wheat trade

Fig. 3 illustrates the changes in value-added and CO_2 emissions for

Table 5
Top 10 sectors affected by unfavorable harvests in the Northern Hemisphere.

Value-added (million USD)		
Rank	Sector	
1	Argentina: Growing wheat product	296
2	Brazil: Growing wheat product	165
3	South Africa: Growing wheat product	52
4	Paraguay: Growing wheat product	45
5	Uruguay: Growing wheat product	20
6	Brazil: Raising of sheep product	5
7	Uruguay: Cereal products product	4
8	Brazil: Cereal products product	3
9	Brazil: Raising of poultry product	3
10	Argentina: Alcoholic and other beverages product	2
CO_2 emissions (Kt-CO_2)		
Rank	Sector	
1	Argentina: Growing wheat product	1610
2	Brazil: Growing wheat product	776
3	Paraguay: Growing wheat product	95
4	South Africa: Growing wheat product	44
5	Uruguay: Growing wheat product	18
6	Brazil: Vegetable products product	18
7	Australia: Growing wheat product	17
8	South Africa: Electric power generation, transmission and distribution product	9
9	Brazil: Fruit products product	8
10	South Africa: Distribution of gaseous fuels through mains product	8

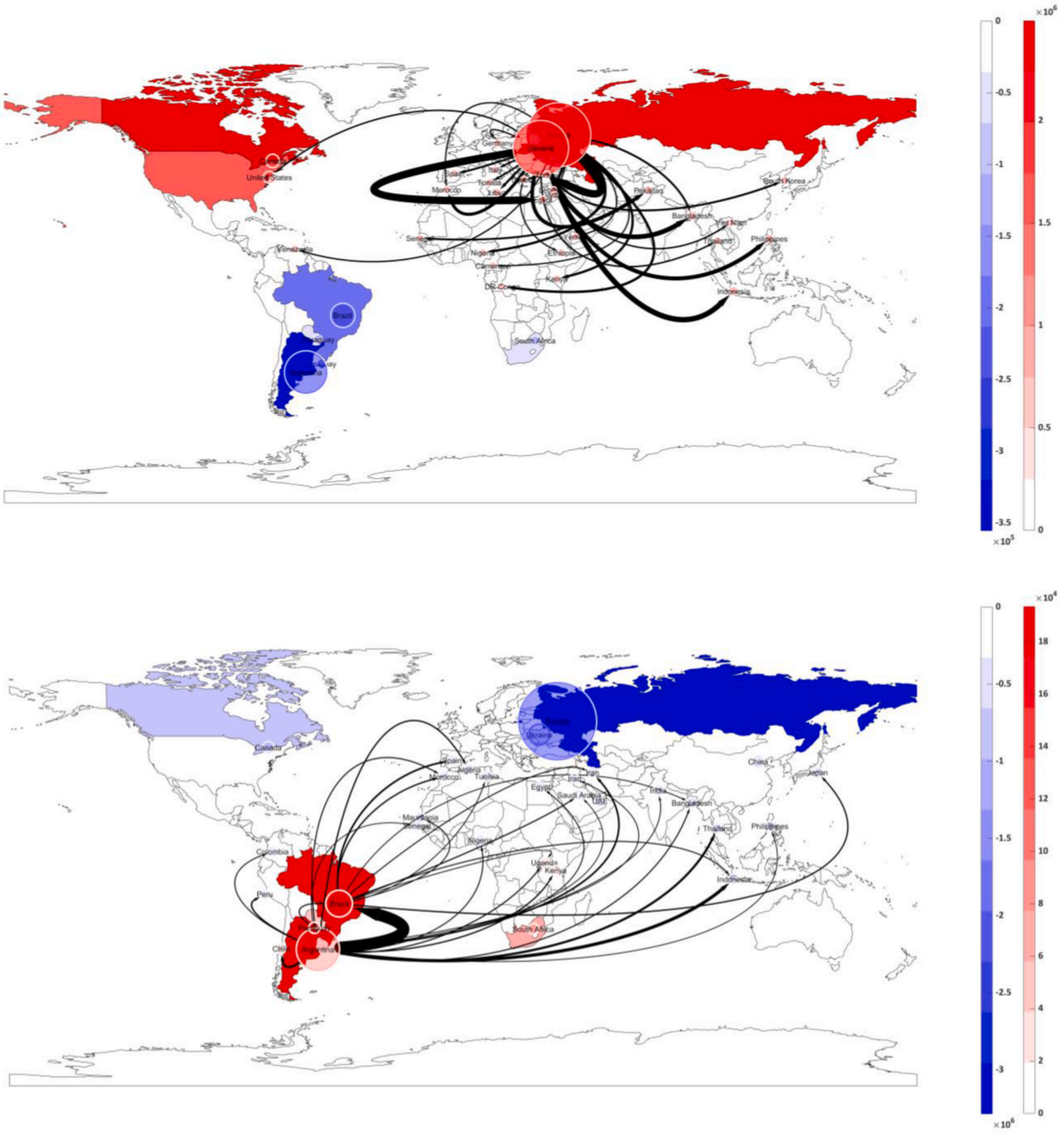

Fig. 3. Value-added and CO_2 emissions associated with wheat trade.
Note: Changes in value-added and CO_2 emissions for each country resulting from favorable (top) and unfavorable (bottom) harvests in the Northern Hemisphere are shown. The colors of the map indicate the changes in value-added from the base year (million USD) and the arrows represent the top 30 gross CO_2 emission transfers exhibiting the highest increase. The source and target of the arrows indicate the countries that emit and induce emissions, respectively. The size of the circle corresponds to the total change in CO_2 emissions, while its red (blue) color signifies positive (negative) change.

each country resulting from the cross-hemisphere production response induced by remote sensing of wheat production forecasts in the Northern Hemisphere, considering both favorable and unfavorable harvests. In the Northern Hemisphere, favorable harvests resulted in increased CO_2 emissions from wheat production in Russia and Ukraine, affecting neighboring countries (Turkey, Lebanon, and Egypt). The higher increases in emissions in Russia and Ukraine than in the United States and Canada, which also experienced favorable harvests, can be attributed to the comparatively high emission intensities linked to wheat production in these countries (Table S2). Conversely, unfavorable harvests in the Northern Hemisphere led to increased wheat production in the Southern Hemisphere, subsequently causing increased CO_2 emissions in other countries, notably in Argentina and Brazil. For example, Argentina induced transboundary emissions in Brazil (605 Kt), Indonesia (102 Kt),

Chile (99 Kt), Thailand (88 Kt), and Iran (50 Kt). Similarly, Brazil induced transboundary emissions in Spain (102 Kt), Japan (102 Kt), Morocco (102 Kt), Saudi Arabia (102 Kt), and China (102 Kt) (Table S5).

Despite the lower rate of change in wheat production in Argentina (1.11) and Brazil (1.22) than in Paraguay (1.34) and Uruguay (1.34) following crop failures in the Northern Hemisphere (Table 1), the larger increases in emissions in Argentina and Brazil can be attributed to the larger scales of production and higher emission intensities—driven by weather conditions and other factors—in both countries (FAO, 2023). By contrast, the smaller changes in emissions in Australia, a major wheat producer in the Southern Hemisphere, were caused by the relatively low carbon footprints associated with wheat production in the country. For example, emissions from wheat production in Australia were 0.19 kg CO_2/kg compared with those of Argentina (0.63 kg CO_2/kg) and Brazil (0.46 kg CO_2/kg) (Table S2). Similar results have been reported in carbon footprint analyses of wheat production in Brazil (Veiga et al., 2024) and Australia (Wang and Dalal, 2015).

5. Discussion

5.1. Reducing the environmental impact of global wheat production

Gan et al. (2014) observed that several factors influence the carbon footprint of crops, including the production system, production yield, and inputs (e.g., water and fertilizer), which differ based on regional climate and land conditions (Zhang et al., 2017). Therefore, as Simmons et al. (2020) suggested, increasing crop production in regions with minimal environmental impacts owing to favorable climatic and geographic conditions may reduce the global emissions associated with production. Designing these incentives is essential for promoting sustainable crop trade.

Recent anomalous changes in wheat production in Russia and Ukraine (FAO, 2023) may be analogous to the unfavorable Northern Hemisphere harvest in our study. If so, the wheat production sector in Southern Hemisphere countries (e.g., Argentina, Brazil, Paraguay, South Africa, and Uruguay) has generated considerable value-added with substantial CO_2 emissions. Given the higher emission intensity of the wheat production sector in these Southern Hemisphere countries than in their Northern Hemisphere counterparts, emission reductions in this sector must be prioritized to achieve sustainable wheat production (Deng et al., 2021). Key strategies include enhanced productivity (Masuda, 2016), supply chain management (Gholamian and Taghanzadeh, 2017; Hosseini-Motlagh et al., 2021), and technological innovation (Atinafu et al., 2022).

5.2. Sustainable wheat production through remote sensing

Tanaka et al. (2024) demonstrated that satellite yield forecasts can stabilize global crop prices. However, this may also lead to increased wheat production in Southern Hemisphere countries with high emission intensities, such as Argentina and Brazil, thereby resulting in higher emissions throughout the global wheat supply chain. Therefore, for the sustainable use of satellite yield forecasts, a mechanism (e.g., a carbon border adjustment mechanism) is required to explicitly incorporate carbon prices into crop pricing and supply/demand adjustment systems (European Commission, 2021b). Implementing such a mechanism would lead to increased trade from low-emission regions in the short term and an increase from regions actively reducing emissions in the medium to long term, allowing regions with currently high emissions to re-enter the crop market. Accounting for carbon leakage in production forecasts for trading agricultural commodities across hemispheres may stabilize prices, reduce emissions, and improve global food security.

Implementing such a carbon border adjustment mechanism into wheat trade would be expected to lead the responses of countries to satellite-based harvest forecasts to diverge based on their respective carbon intensities. Specifically, nations with low-emission production systems would face a smaller burden from carbon-related tariff costs, allowing them to maintain strong price competitiveness in a market in which carbon pricing is internalized. Consequently, when an unfavorable harvest for the Northern Hemisphere is forecasted, countries with high carbon efficiency such as Australia would have a stronger incentive to proactively raise their production compared with high-emission countries such as Argentina and Brazil. Such carbon efficiency-based supply optimization could ensure that supply from low-emission regions is prioritized in the short term. In the medium to long term, this mechanism could encourage regional emission reductions, ultimately helping improve global food security while minimizing the environmental footprint of the entire global wheat supply chain.

5.3. Limitations and future research directions

A limitation of this study was positing that wheat from Northern or Southern Hemisphere countries was not substitutable for wheat-consuming countries. Countries that originally imported wheat solely from one hemisphere would refrain from importing it from the opposite hemisphere, even with production changes from remote sensing. This assumption focuses on the spillover effects of remote sensing-induced production changes. This issue could be resolved by modeling the effects of remote sensing production shocks on wheat import and export structures using a computable general equilibrium model (Tanaka et al., 2024) or similar approaches.

In this study, the emission coefficients are assumed to be identical to those of the base year. Consequently, changes in production structures and variations in output are not reflected in emission intensities. A detailed assessment of the impacts would require a technology-based analysis using more disaggregated, micro-level data to estimate emissions in accordance with the actual changes in production induced throughout the supply chain clarified in this study.

While direct empirical validation of farmers' behavioral responses to satellite-derived information remains a challenge, the plausibility of the cross-hemispheric response assumed in this study is grounded in the mechanism of global price discovery. Information on potential crop failures in the Northern Hemisphere—whether from official sources or real-time remote sensing data—is rapidly incorporated into global futures prices such as those on the Chicago Board of Trade (CBOT). Economic producers in the Southern Hemisphere, particularly large-scale commercial farmers in Australia and Argentina, do not necessarily need to monitor satellite imagery directly; instead, they respond to these shifting international price signals. As demonstrated by Haile et al. (2015), global supply for major staples such as wheat is significantly elastic relative to international price expectations. Higher futures prices during the Southern Hemisphere's planting or early growth window provide a clear economic incentive to optimize acreage or input applications such as fertilizers to maximize expected returns. This temporal alignment ensures that the information shock from the Northern Hemisphere becomes an actionable economic signal for Southern Hemisphere production.

6. Conclusions

The cross-hemisphere production response informed by remote sensing helps stabilize crop supply and pricing. This study quantified the economic and environmental impacts (i.e., value-added and CO_2 emissions) of production changes using remotely sensed Northern Hemisphere wheat forecasts for Southern Hemisphere countries. The results indicate that satellite yield forecasts generate substantial value-added and increase CO_2 emissions in the global wheat supply chain. These impacts are particularly pronounced in Argentina and Brazil, which are the major wheat-producing Southern Hemisphere countries with higher emission intensities. To ensure the sustainable use of satellite yield forecasts, mechanisms that incorporate carbon pricing into crop pricing and supply/demand adjustment systems are required. Such policies

could help balance economic gains with environmental responsibilities, promoting a more sustainable global food system.

CRediT authorship contribution statement

Yuya Nakamoto: Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Tetsuji Tanaka:** Conceptualization, Data curation, Funding acquisition, Methodology, Resources, Validation, Writing – original draft. **Shohei Tokito:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Software, Visualization, Writing – original draft. **Laixiang Sun:** Methodology, Resources, Validation. **Xiao-Peng Song:** Methodology, Resources, Writing – review & editing. **Inbal Becker-Reshef:** Data curation, Methodology, Resources. **Jin Guo:** Methodology, Writing – review & editing. **Ken'ichi Matsumoto:** Conceptualization, Methodology, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supporting information

The following files are available free of charge:

Changes in wheat production, value-added, and CO_2 emissions (Table S1); Emission intensity of the wheat production sector (Table S2); Effects of favorable and unfavorable harvests (Table S3); Top 10 sectors affected by favorable harvests in the Northern Hemisphere (Table S4); and Value-added and CO_2 emissions associated with wheat trade (Table S5).

Abbreviations

FAO	Food and Agriculture Organization
GDD	growing degree day
GHG	greenhouse gas
GLORIA	Global Resource Input-Output Assessment
LCA	life cycle assessment
MRIO	multi-regional input-output
NDVI	normalized difference vegetation index
WASDE	World Agricultural Supply and Demand Estimates

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clrc.2026.100421.

Data availability

Data will be made available on request.

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