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Climate shocks and price dynamics: the role of Shinano River in transmitting ENSO effects to Japanese rice markets

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Objective: Since 2024, Japan has experienced a rapid surge in rice prices. This study aims to explore the underlying climatic drivers of this price increase, with a particular focus on the potential impact of the El Niño–Southern Oscillation (ENSO).

Methods: High-frequency climate and market data are integrated, and regression models are constructed in distinct stages along with spatial econometric models to systematically assess the impact of ENSO on Japan's rice market. The NINO index serves as the primary explanatory variable representing ENSO intensity.

Results: The findings reveal that ENSO events indirectly affect rice prices in Niigata by altering hydrological conditions in the middle reaches of the Shinano River. These disruptions trigger price co-movement and spatial spillover effects across different regions, resulting in heterogeneous impacts on rice price volatility throughout Japan. Moreover, climate shocks are amplified through hydrological systems in rice-producing areas, ultimately influencing the national grain market.

Contributions: This study provides a natural explanation for recent fluctuations in Japanese rice prices and presents new empirical evidence on the climatic determinants of food price volatility. It also offers actionable policy recommendations to mitigate climate-related risks and enhance food security through climate-responsive agricultural strategies.

KEYWORDS

El Niño-Southern Oscillation (ENSO), rice prices, Japanese agriculture, hydrological resources, climate change

1 Introduction

In recent years, global climate change has become increasingly evident, characterized by a rise in both the intensity and frequency of extreme weather events. In Europe, the number of extreme weather incidents—including hydrometeorological phenomena—has increased by 60% over the past three decades (Furtak and Wolińska, 2023). In the United States, more than 90 weather-related disasters have occurred during the same period, each causing losses exceeding $1 billion (Motha, 2011). These developments have emerged as critical factors disrupting the stability of agricultural activities and posing significant threats to global food security. For example, in Germany, summer droughts between 1995 and 2019 led to substantial winter wheat yield reductions, resulting in estimated losses of €23 million (Schmitt et al., 2022). Climate-related anomalies—such as heatwaves, torrential rains, and severe droughts—have become more frequent, affecting all stages of agricultural production. In the U.S. alone, over 70% of the decline in grain yields in 2011 was attributed to droughts and floods (Furtak and Wolińska, 2023).

The El Niño–Southern Oscillation (ENSO), a major ocean-atmosphere coupling phenomenon originating in the equatorial Pacific, exerts broad and far-reaching effects on global climate systems. By altering precipitation patterns and temperature distributions, ENSO intensifies climatic anomalies and frequently triggers large-scale environmental disruptions, which have significant implications for agricultural productivity. In Thailand, another key rice-producing country, ENSO phases—particularly El Niño and La Niña—affect rice yields by modulating local temperature and rainfall patterns. During El Niño events, drought conditions induced by ENSO are strongly associated with significant reductions in rice production. Conversely, La Niña-related excessive rainfall may benefit some regions but also brings challenges such as flooding and pest outbreaks (Wannasingha, 2025). On the island of Java, approximately two-thirds of the interannual variability in rice planting and 40% of the variability in rice production can be explained by fluctuations in ENSO indices measured four and eight months in advance, respectively (Naylor et al., 2001).

As an island nation surrounded by oceans, Japan is particularly susceptible to climate change, with its agricultural sector being heavily dependent on natural conditions. Japan's unique topography, characterized by mountainous terrain and numerous short, fast-flowing rivers, makes its hydrological systems highly responsive to climatic variability (Kurihara et al., 2024). This environmental sensitivity introduces substantial risks to agricultural production.

Rice cultivation is particularly vulnerable to climate fluctuations, as it is highly sensitive to changes in both water availability and temperature. According to the *Key Points of Rice Cultivation* published by Japan's Ministry of Agriculture, Forestry and Fisheries (Ministry of Agriculture, Forestry and Fisheries, 2017), prolonged high temperatures during the ripening phase can reduce grain maturity and quality. Moreover, under high-temperature conditions during the late ripening stage, rice loses moisture rapidly, potentially leading to kernel cracking and further complicating harvest and post-harvest processes. Under conditions of climatic variability, rice production frequently faces challenges such as shortened grain-filling periods, increased incidence of pests and diseases, and flooding of paddy fields—all contributing to reduced yields and, in severe cases, complete crop failure. Irregular climatic patterns may also disrupt the timing of planting, growth, and harvest cycles, further exacerbating the fragility of agricultural systems. Rice cultivation, one of Japan's most important agricultural activities, is especially affected by climate-related factors. Changes in temperature, precipitation, and sunlight duration can directly or indirectly influence key growth stages such as sowing, seedling development, heading, and harvesting. These climatic shifts, in turn, affect rice yields and market prices, generating supply-side volatility. Against this backdrop, the vulnerability of Japanese agriculture to climate fluctuations is becoming increasingly pronounced. Following the conclusion of the El Niño event in the first half of 2024, Japan experienced a sharp spike in rice prices. Although human and policy-related factors also played a role, this phenomenon underscores the significant impact of natural forces—particularly climatic variability—on market dynamics.

Niigata Prefecture, located on the northwestern coast of Honshu Island along the Sea of Japan, is a renowned center of rice production. According to the statistics of MAFF, the largest rice production top 3 prefectures are Niigata (7.7%), Hokkaido (7.3%), and Akita (6.1%) in the year of 2013 in Japan (Ministry of Agriculture, Forestry and Fisheries, 2021). Benefiting from favorable natural conditions and a long-standing tradition of rice farming, Niigata has become widely recognized for its high-quality rice, particularly the "Koshihikari" variety, which enjoys national popularity. In 2024, Niigata's rice output reached 622,800 tons, representing 8.48% of Japan's total production—highlighting the region's critical role in the country's agricultural landscape (Ministry of Agriculture, Forestry and Fisheries, 2025). Analyzing fluctuations in Niigata's rice production offers valuable insights into regional agricultural trends and helps enhance understanding of Japan's local responses to climate change. Although Niigata is situated in a temperate zone and is not typically considered a core area for ENSO-related research, it remains influenced by the Pacific circulation system and ENSO-driven climate changes—an area that has received limited scholarly attention. Incorporating ENSO indices and associated meteorological and hydrological data into agricultural analysis is thus essential for uncovering the mechanisms behind fluctuations in rice production and for developing adaptive strategies to improve food security at both regional and national levels.

As Niigata rice holds symbolic and economic importance in the Japanese grain market, price fluctuations originating from ENSO-related climate shifts may influence national rice pricing structures and, in turn, affect food security at both domestic and international levels. In view of the current insufficient research on the influence of ENSO in mid-latitude agricultural production areas. Therefore, investigating the transmission mechanisms by which ENSO affects Niigata rice production and pricing—particularly through its influence on the Shinano River system—is not only vital for improving climate risk management in Japan's agricultural sector but also contributes to a deeper understanding of the global implications of climate-induced agricultural volatility.

2 Literature review

Agricultural production is inherently sensitive to climatic conditions, making it particularly vulnerable to climate anomalies. Consequently, numerous scholars have investigated the impacts of such anomalies on crop productivity across various geographic contexts. Among these climate phenomena, the El Niño–Southern Oscillation (ENSO), originating in the equatorial Pacific, has been identified as a major driver influencing agricultural outputs worldwide.

Extensive empirical evidence consistently demonstrates that El Niño events are often accompanied by decreased precipitation and drought conditions, which negatively affect crop yields and frequently result in significant reductions in staple food production (Peethani et al., 2024; Limsakul, 2019; Izumi et al., 2014). For instance, Izumi et al. (2014) showed that both El Niño and La Niña phases significantly affect rice production in Japan. Complementing this, Limsakul (2019) found that in Thailand, El Niño-related rainfall deficits lead to rice yield declines, while La Niña tends to increase rainfall, occasionally causing flooding and pest outbreaks. This evidence collectively highlights that ENSO's agricultural impacts are highly context-dependent, shaped by local climatic and environmental conditions.

Furthermore, regional modeling studies provide additional insights into ENSO's differential effects. For example, Tan Yen et al. (2019) employed the ORYZA crop model to simulate substantial ENSO impacts on rice production in the Mekong Delta. Similarly, Zhang et al. (2008) revealed heterogeneous responses of rice yields to ENSO in southern China, primarily driven by spatial variation in water availability. Likewise, Zubair's analysis of Sri Lanka revealed contrasting regional patterns, with some areas experiencing yield increases correlated with higher NINO 3.4 index values, while others suffered declines (Zubair, 2002). These spatially variable outcomes underscore the geographic specificity of ENSO influences on crop productivity. Consistent with these findings, Barrios-Perez et al. (2021) documented that in Central America, El Niño events increase irrigation water demand and reduce rice yields, whereas La Niña phases tend to enhance yields. Such patterns emphasize the need for regionally tailored adaptive management strategies to mitigate ENSO-induced agricultural risks.

In addition to Asian and Central American contexts, North African agriculture also exhibits pronounced sensitivity to ENSO fluctuations. For example, in Morocco, wheat yields decline on average by 35%–45% during El Niño years compared to neutral years, while La Niña years are associated with smaller reductions of 4%–7% (Peethani et al., 2024). Importantly, these yield losses stem not only from drought but also from excess precipitation, indicating that both extremes of moisture availability can impair crop production. Similarly, studies in Thailand reaffirm the dual role of ENSO phases—El Niño correlates with drought-induced yield reductions, whereas La Niña's excessive rainfall benefits some areas but also introduces challenges such as flooding and pest outbreaks (Wannasingha, 2025).

Examining localized irrigation systems further elucidates how ENSO-driven climate variability affects production. In Niigata, Japan, rice cultivation relies heavily on irrigation from open channels, with drainage flowing into the Shinano River, a vital regional water source (Takada et al., 2024). This production system's dependence on precipitation, temperature, and snowfall makes it especially susceptible to ENSO-related climate fluctuations (Yoshida et al., 2016). Specifically, El Niño events tend to increase snowfall and rainfall (Ohba and Sugimoto, 2022), whereas La Niña events lead to reduced snowfall. Studies show that the seasonal flow of the Shinano River is linearly correlated with temperature (Whitaker, 2025). These hydrological changes directly affect irrigation availability and thus rice yields (Takada et al., 2024).

Finally, fluctuations in production conditions triggered by ENSO are closely linked to price dynamics within agricultural markets. Empirical studies substantiate this transmission mechanism. For instance, Onumah et al. (2022) employed an ARDL-ECM approach to demonstrate that rice imports significantly influence domestic rice prices in Ghana. Similarly, Ahmed et al. (2024) identified that wheat prices across various Indian regions adjust in response to price changes in Delhi. These findings collectively indicate that climatic variability influencing crop production forms a fundamental basis for regional price formation and transmission.

3 Theoretical framework and research hypotheses

3.1 Theoretical framework

ENSO, as a major climate variability phenomenon, exerts significant influence on agricultural production and price formation through its effects on regional hydrological conditions. In this study, NINO 3 and NINO West indices are used to measure the phases and intensity of ENSO. NINO 3 refers to the sea surface temperature anomalies in the central-eastern Pacific (typically 5°S–5°N, 150°W–90°W), while NINO West refers to those in the western Pacific warm pool (typically 0°–10°N, 125°E–140°E) (for further details, see Section 4.2).

Fluctuations in these indices reflect variation in Pacific climate patterns, which, in turn, affect precipitation and subsequently influence the hydrological conditions of the Shinano River. This process further impacts agricultural yields and markets, ultimately causing fluctuations in rice prices. Furthermore, price signals originating from major production centers, such as Niigata, may spill over to other markets due to their role in price discovery and transmission mechanisms.

Therefore, this study constructs a transmission framework linking ENSO (NINO 3 and NINO West) → Hydrological Conditions → Regional Rice Prices → National Market Volatility (see Figure 1). This framework forms the theoretical basis for formulating the hypotheses presented in the subsequent section.

3.2 Research hypotheses

The ENSO phenomenon, by regulating ocean–atmosphere interactions in the tropical Pacific, triggers a series of global climate anomalies, primarily manifesting in temperature and precipitation variation across different regions (Tsonis et al., 2003). In mid-latitude countries such as Japan, ENSO may influence the East Asian summer monsoon, thereby affecting local climate and causing severe floods or droughts (Wang et al., 2000; Wu and Wang, 2002; Sakashita et al., 2016). In Niigata, these climate anomalies are particularly reflected in fluctuations in temperature and precipitation, which in turn influence the hydrological conditions of the Shinano River (Akiyama, 1981). ENSO is also associated with a significant reduction in snowfall in the Niigata region (Ueda et al., 2017), further affecting the flow and water level of the Shinano River and causing deviations from their normal patterns.

The timing and intensity of irrigation water supply are crucial for rice agriculture. Even small deviations may disrupt large-scale agricultural operations, including sowing density, fertilization schedules, and pest control, ultimately affecting both yields and production costs (Alfassassi, 2023; Bouman et al., 2007). Therefore, by influencing precipitation and snowmelt pathways in Niigata,

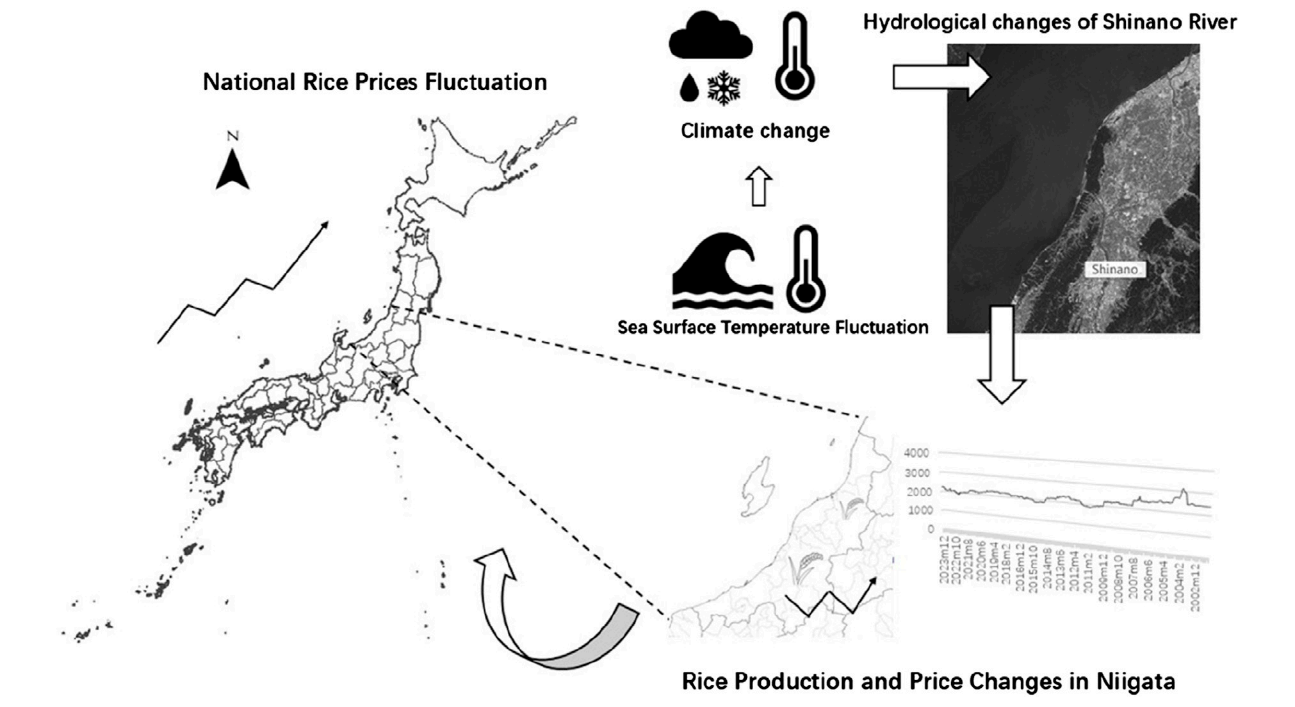

FIGURE 1
Schematic diagram of the core transmission mechanism.

ENSO modifies the hydrological conditions of the Shinano River, thereby affecting agricultural production in the region, particularly rice cultivation.

Based on the above analysis, the following hypothesis is proposed:

H1: There is a significant positive correlation between ENSO indices and hydrological conditions in the Niigata region.

Agricultural responses to climate change are highly regional and seasonal. Hydrological conditions, as a mediating variable linking climate to agricultural output, are particularly critical in rice cultivation systems. Within a water resource allocation framework, both excessively high and low water levels can disrupt farming schedules and raise marginal and risk assessment costs in agricultural operations. At the same time, hydrological anomalies may be transmitted through price expectation mechanisms in agricultural markets. This is especially evident in premium rice markets, where price formation is strongly influenced by supply-demand expectations and quality indicators. For instance, in the Mekong Delta, irrigation conditions are closely related to rice price formations (Johnson and Kurosaki, 2024). A similar phenomenon is likely to be present in major rice-producing areas such as Niigata. Therefore, even in the absence of actual yield losses, market prices may increase due to heightened risk expectations when irrigation systems face uncertainty.

Based on this mechanism, the following hypothesis is proposed:

H2: Fluctuations in hydrological conditions in the Niigata region significantly affect the direction and magnitude of rice price changes.

Furthermore, if ENSO significantly affects hydrological conditions, and hydrological conditions in turn influence rice prices, then it can be inferred that ENSO has an impact on rice prices.

Accordingly, the following hypothesis is proposed:

H3: ENSO events indirectly influence rice prices in Niigata through changes in hydrological conditions, forming a significant transmission pathway.

As one of Japan's major rice-producing regions, Niigata's rice prices reflect not only local agricultural supply and demand dynamics but also exert a broader influence on the national rice market due to the region's strong reputation for quality, brand value, and premium positioning. In particular, prices for high-end varieties such as Koshihikari from Niigata are frequently regarded as a benchmark, shaping consumer expectations, guiding wholesaler procurement strategies, and influencing pricing decisions in other production areas (Kobayashi et al., 2018). According to data from the Statistics Bureau of Japan, Ministry of Internal Affairs and Communications, Koshihikari produced in Niigata serves as a baseline variety against which other rice prices are measured. This price leadership emerges not only from Niigata's renowned branding but also from its central role within the interconnected national rice supply chain.

From a spatial economics perspective, price fluctuations in leading production areas tend to exhibit both transmissibility and spillover effects (von Cramon-Taubadel and Goodwin, 2021). These effects are propagated through mechanisms such as market information diffusion, the radius of trade flows, and policy interventions, thereby influencing rice prices in other regions. For instance, in Indonesia, COVID-19 disrupted price transmission mechanisms, significantly affecting the time required for price adjustments to reach a new equilibrium Ariga and Asmarantaka

(2022). At the same time, the degree to which regional markets respond to such price signals varies, depending on factors including geographical proximity, structural differences in supply and demand, and the extent of their integration into the rice value chain. Thus, price fluctuations in Niigata not only reflect local market conditions but also generate strong spillover effects across related markets.

Based on this, the following hypothesis is proposed:

H4: Fluctuations in rice prices in Niigata exert significant spatial transmission effects on rice prices in other Japanese cities.

Furthermore, Japan's regional differences in rice cultivation area and production volume lead to varied market responses to price fluctuations. Regions such as Kanto and Kansai have relatively small rice-growing areas and produce limited quantities, making them more reliant on rice supplies from major production regions like Niigata and thus more sensitive to its price changes. In contrast, agricultural powerhouses like Tohoku and Hokkaido cultivate extensive rice paddies and generate substantial rice output, which grants these regions greater market self-sufficiency and resilience, resulting in weaker sensitivity and stronger buffering against price shocks from other areas (Ministry of Agriculture, Forestry and Fisheries, 2025). Therefore, the spatial impact of Niigata's rice prices exhibits significant heterogeneity across Japan, shaped largely by regional disparities in rice production scale and market dependency.

Accordingly, the following hypothesis is further proposed:

H5: The spatial impact of Niigata's rice prices exhibits significant heterogeneity across different agricultural regions in Japan, with notable regional variation effects.

4 Data sources and variable descriptions

4.1 Data sources and research period

The selected research period spans from January 2000 to February 2025, comprising a total of 302 monthly data points. This time range ensures good continuity and representativeness. The primary data sources include the Statistics Bureau of Japan, the Japan Meteorological Agency, the Ministry of Land, Infrastructure, Transport and Tourism of Japan, and the National Oceanic and Atmospheric Administration (NOAA) of the United States. All relevant data are obtained from official statistical platforms, ensuring their authority and verifiability.

4.2 Variable descriptions

This study covers key variables including climate indicators reflecting the ENSO status, meteorological and hydrological variables that describe the agricultural ecological environment, and rice price indicators that measure market performance. Table 1 presents the variables used in this analysis. Data processing and analysis were conducted using Excel and Stata 18.

4.3 Definition criteria for ENSO events

To systematically identify ENSO event periods and improve model accuracy, this study adopts the definitions provided by NOAA and the Japan Meteorological Agency. An El Niño period is defined when the sea surface temperature anomaly (SST anomaly) in the NINO3 region (5°N–5°S, 150°W–90°W) is equal to or greater than +0.5°C and persists for at least six consecutive months. Conversely, a La Niña period is defined when the SST anomaly is equal to or less than −0.5°C for a duration of six months or more.

In addition, the NINO West index—which represents sea surface temperature changes in the region from the equator to 15°N and 130°E to 150°E—effectively captures the direct transmission pathway of ENSO events near Japanese coastal waters. This index offers practical relevance and geographic correlation for the region under study (Hirahara et al., 2014; Kurihara, 2006).

4.4 Hydrological variables and data completion method

The hydrological variables used in this study primarily include the water level (H) and runoff (R) of the midstream region of the Shinano River. Considering that climate change may initially affect agricultural production through river systems, variations in hydrological variables are of critical importance for rice cultivation.

The water level data were obtained from the "Ōkōzu Hydrological Station," located in the midstream of the Shinano River and operated by the Ministry of Land, Infrastructure, Transport and Tourism. This station has continuously monitored hydrological data since 1979 and is known for having the most complete and consistent records in the entire river basin.

Runoff data (R) became significantly incomplete after 2024, mainly due to the cessation of runoff observations at several hydrological stations in the Shinano River basin starting in 2023. To fill this gap, this study employed a prediction method based on paired water level and runoff data from the year 2023, referencing the modeling approach established by Zhiqiang (2025). A predictive model was fitted using the nonlinear least squares method, as shown below:

$$R = 137.92 \times H^2 - 3883.87 \times H + 27255.31$$

The model incorporates the water level variable H to parameterize factors such as cross-sectional flow velocity, flow inertia, and watershed area. According to validation tests, the model demonstrates a good fit with the observed runoff data from 2023. Based on this, it was used to predict the runoff data of the Shinano River from January 2024 to February 2025.

4.5 Agricultural regional classification

In conducting spatial econometric model analysis, to assess the impacts across different regions, the participating cities were

TABLE 1 Experimental variable.

Variable name	Symbol	Unit	Data source	Variable attribute	Description
Niigata rice price	*P*	JPY/kg	Statistics Bureau of Japan, Ministry of Internal Affairs and Communications	Dependent variable	Monthly average price of Koshihikari and non-Koshihikari rice
NINO3 index	*NINO3*	°C	National Oceanic and Atmospheric Administration (NOAA)	Primary explanatory variable	5-month running mean sea surface temperature (SST) anomaly in the east-central equatorial Pacific
NINO west index	*NINO_W*	°C	Japan Meteorological Agency (JMA)	Secondary explanatory variable	5-month running mean SST anomaly in the northwest Pacific coastal region
Water level	*H*	m	Ōkōzu Hydrological Station, Ministry of Land, Infrastructure, Transport and Tourism	Core control variable	Midstream water level of the Shinano River, reflecting its hydrological conditions. The water level data were obtained from the Ōkōzu Hydrological Station, located in the midstream of the Shinano River
Runoff	*R*	m^3/s	Nagaoka Hydrological Station, Ministry of Land, Infrastructure, Transport and Tourism	Non-core reference variable	River runoff, measured at Nagaoka Hydrological Station along the Shinano River. Missing values after 2024 were imputed but are excluded from regression analyses (see Section 4.4 for details)
Monthly mean temperature	*T*	°C	Japan Meteorological Agency (JMA)	Control variable	Represents thermal conditions for agriculture
Monthly precipitation	*Pre*	mm	Japan Meteorological Agency (JMA)	Control variable	Key indicator of water resource availability
Monthly mean wind speed	*WS*	m/s	Japan Meteorological Agency (JMA)	Control variable	Influences evaporation and snow accumulation dynamics
Monthly snowfall	*Snow*	cm	Japan Meteorological Agency (JMA)	Control variable	Reflects snow depth and delayed hydrological effects
Monthly sunshine duration	*Sun*	hours	Japan Meteorological Agency (JMA)	Control variable	Affects rice photosynthetic efficiency
City-level rice prices	*Price*	JPY/kg	Statistics Bureau of Japan, Ministry of Internal Affairs and Communications	Reference variable	Used for robustness checks and regional comparative analysis

TABLE 2 Japan agricultural regional classification.

Agricultural area	City name
Hokkaido	Sapporo, Hakodate, Asahikawa
Tōhoku	Aomori, Morioka, Sendai, Akita, Yamagata, Fukushima, Koriyama
Hokuriku	Nagaoka, Toyama, Kanazawa, Fukui
Kantō-Higashiyama	Mito, Utsunomiya, Maebashi, Kawaguchi, Tokorozawa, Chiba Kawasaki, Sakura, Tachikawa, Fuchū, Yokohama, Tokyo, Kofu, Nagano, Matsumoto
Tōkai	Gifu, Shizuoka, Hamamatsu, Nagoya
Kinki	Tsu, Otsu, Kyoto, Osaka, Kobe, Higashiōsaka, Hirakata, Himeji, Nishinomiya, Itamishi, Nara, Wakayama
Chūgoku	Tottori, Matsue, Okayama, Hiroshima, Fukuyama,Yamaguchi, Ube
Shikoku	Tokushima, Takamatsu, Matsuyama, Kochi
Kyūshū	Fukuoka, Kitakyushu, Saga, Nagasaki, Sasebo, Kumamoto, Oita, Miyazaki, Kagoshima, Naha

Note: Okinawa is counted within Kyushu.

categorized into distinct agricultural zones according to the classification criteria established by the Japanese Ministry of Agriculture, Forestry and Fisheries, as detailed in Table 2.

5 Empirical methodology and model specification

5.1 Identification strategy for the mediating role of hydrological conditions between ENSO and rice prices

To investigate how the ENSO phenomenon influences rice prices in Niigata, Japan, through its effects on local hydrological conditions, this study adopts a two-step mediation analysis framework inspired by Jiang (2022), which offers a well-established approach for modeling mediation and moderation effects in causal inference.

The first step aims to identify whether ENSO significantly disrupts the regional hydrological system. Specifically, we estimate a regression model where the ENSO index (measured by the NINO West Index) serves as the independent variable, and the hydrological condition is proxied by the water level of the Shinano River (denoted as H). The specification is as follows:

$$H_t = \alpha + \beta NINOW_t + \gamma_1 Pre_t + \gamma_2 WS_t + \gamma_3 Snow_t + \gamma_4 Sun_t + \varepsilon_t$$

Where H_t denotes the monthly average water level measured at the Okozu hydrological station in the midstream section of the Shinano River, $NINOW_t$ represents the NINO West index for the current month, and Pre_t, WS_t, $Snow_t$, Sun_t represent control variables for precipitation, wind speed, snowfall, and sunshine duration, respectively. ε_t denotes the error term.

To examine the direct impact of ENSO on rice prices in the Niigata region, the following regression model is specified:

$$P_t = \alpha + \beta NINOW_t + \gamma_1 R_t + \gamma_2 Pre_t + \gamma_3 WS_t + \gamma_4 Snow_t + \gamma_5 Sun_t + \varepsilon_t$$

In this specification, P_t denotes the monthly rice price in Niigata, $NINOW_t$ refers to the ENSO index for the corresponding month, and R_t, Pre_t, WS_t, $Snow_t$, Sun_t represent control variables for runoff volume, precipitation, wind speed, snowfall, and sunshine duration, respectively. ε_t denotes the error term.

Importantly, the two regression models presented share a similar structural form but serve different analytical purposes. The first equation focuses on estimating the effects of the NINO West Index on the water level of the Shinano River, while the second assesses its direct impact on rice prices in Niigata. Although both models include a set of control variables and employ a linear specification, their dependent variables and coefficients of interest differ. Specifically, the parameter β in the first equation measures the transmission from ENSO to water level, whereas in the second it captures the direct influence of ENSO on agricultural prices.

Regarding the "hydrology-to-price" transmission pathway, in order to address potential endogeneity issues and avoid undermining the credibility of the study's results, this paper does not employ a mediating effects test (Igartua and Hayes, 2021). Instead, it draws upon existing literature that offers theoretical explanations and empirical evidence on the transmission mechanisms linking hydrological variability to agricultural product prices, thereby strengthening the logical coherence and robustness of the argumentation.

5.2 Spatial econometric model specification and empirical strategy

To further examine the spatial effects of rice prices in Niigata on other regions in Japan, this study employs spatial econometric models. An inverse distance weight matrix is constructed to capture these spillover mechanisms, reflecting the notion that geographically closer regions are more likely to be influenced by price signals originating from Niigata.

The selection of inverse distance weights over alternative schemes, such as inverse squared distance, is motivated by two primary considerations. First, the inverse distance matrix exhibits a gradual attenuation of spatial influence with increasing distance, in contrast to the steep decline characteristic of inverse squared distance specifications. This property enables the incorporation of moderate spillover effects that may persist across larger spatial scales. Second, this weighting approach enhances the robustness and stability of parameter estimates by mitigating potential multicollinearity and numerical instability issues (Lu and Wong, 2008).

Considering the potential price interdependence and spatial autocorrelation among regions, and following the approach frequently used in environmental economics and agricultural economics (Liu et al., 2021; Bai et al., 2024; Cerqueti, et al., 2025), this paper adopts the Spatial Durbin Model (SDM) and the Spatial Autoregressive Model (SAR) to systematically assess the mechanisms through which rice prices originating in Niigata are transmitted across space.

First, a SDM is constructed using panel data from 67 Japanese cities with a resident population exceeding 150,000. The main objective is to evaluate the extent to which rice prices in Niigata influence rice prices in other urban markets. An inverse distance weight matrix is used to account for geographic proximity and market connectivity, thereby capturing the underlying spatial dependency structure. In this framework, the rice price of each city is used as the dependent variable, while the contemporaneously determined rice price in Niigata serves as the key explanatory variable. Control variables are intentionally excluded to highlight the pure spillover effects of the main variable.

To account for potential dynamic effects, two additional models are further specified. The first augments the SDM by including the lag of the main explanatory variable (P_{t-1}) alongside its current counterpart (P_t). The second further extends this specification by employing both the lag of the main explanatory variable and its current value, while employing robust standard errors to account for possible heteroskedasticity and serial correlation in the residuals.

A Hausman test is performed to determine the appropriateness of a fixed effects specification (with p-value = 0.000), strongly rejecting the null hypothesis and validating the use of fixed effects. The respective models are presented as follows:

5.2.1 Original model

$$price_{it} = \alpha_i + \rho W price_{it} + \beta P_t + \theta W P_t + \varepsilon_{it}$$

Among them, $price_{it}$ represents the rice price of City i in the year t, P_t represents the rice price in the Niigata area during the same period, W is the inverse distance spatial weight matrix, and α_i is the fixed effect of the city. ε_{it} is the perturbation term. In the model, ρ represents the spatial lag term coefficient of the explained variable, and θ represents the spatial lag term coefficient of the explanatory variable.

5.2.2 Model with lag of main explanatory variable

$$price_{it} = \alpha_i + \rho W price_{it} + \beta_1 P_t + \beta_2 P_{t-1} + \theta W P_t + \varepsilon_{it}$$

In this specification, we include a lag of the main explanatory variable—namely, the lag of Niigata's rice price (P_{t-1}) — to account for potential delayed effects on rice prices in other cities or regions. All other control variables and fixed effects remain the same as in the baseline SDM. This lag term allows us to capture the temporal dependency and assesses whether past price signals from Niigata continue to influence current price formations elsewhere. This consideration is particularly important in agricultural markets, where price transmission mechanisms may manifest with a delay due to information processing, storage, and transportation.

5.2.3 Model with lag of main explanatory variable and robust standard errors

$$price_{it} = \alpha_i + \rho W\,price_{it} + \beta_1 P_t + \beta_2 P_{t-1} + \theta W P_t + \varepsilon_{it}$$

In this specification, robust standard errors are used to account for potential heteroskedasticity and serial correlation in the error term. This approach helps mitigate the risk of internal endogeneity and improves the credibility and robustness of the estimated coefficients, thereby strengthening the reliability of the empirical results.

5.2.4 SAR-Based Analysis of Regional Rice Price Spillovers from Niigata

To further investigate the spatial effects of rice prices in Niigata at the regional scale, the SAR is employed. This approach focuses on the transmission mechanisms through which price signals propagate across agricultural regions in Japan. The average regional rice price serves as the dependent variable, while the rice price in Niigata is the main explanatory variable. All control variables are omitted to highlight pure spatial spillover effects.

$$price_{rt} = \alpha_r + \rho W\,price_{rt} + \beta P_t + \varepsilon_{rt}$$

Among them, $price_{rt}$ represents the average rice price of the agricultural regional r in year t, P_t is the rice price of the Niigata region, and α_r is the regional fixed effect.

Through the above two models, this paper explores the spatial diffusion path and mechanism of Niigata rice prices from the two levels of urban scale and regional scale respectively, providing empirical support for revealing its guiding and influencing role in the national rice market.

6 Results

6.1 Impact of ENSO indices on rice prices via hydrological transmission

6.1.1 Effects of ENSO events on rice prices

To investigate the potential mechanisms through which ENSO events influence rice prices in the Niigata region, this study constructs a multivariate regression model incorporating meteorological and hydrological variables. The dependent variable is the monthly rice price (*P*) in Niigata, with the core explanatory variable being the tropical Pacific ENSO index (specifically, the NINO West index, which exhibits stronger impacts on Japan). Control variables include monthly average precipitation (*Pre*), temperature (*T*), wind speed (*WS*), snow accumulation (*Snow*), and sunshine duration (*Sun*). Robust standard errors (Robust SE) were applied to mitigate potential heteroskedasticity.

TABLE 3 Results of regression model of NINO WEST index on rice price.

Variable	Coefficient
NINOW	1188.558***
	(209.9815)
T	−10.36799
	(8.79737)
Pre	−0.1350587
	(0.3017031)
WS	−403.4057**
	(162.5307)
Snow	0.4681011
	(0.8417134)
Sun	−0.5294133
	(0.9320977)
cons	3490.809***
	(410.4975)
R^2	0.1663
Observations	302

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

With reference to the methodological framework of Brakat et al. (2024) and Sun (2010) in their analyses of agricultural economic benefits, this study applies variance inflation factor (VIF) tests to address potential multicollinearity concerns. All variables exhibit VIF values well below 10, with a mean VIF of 2.13, thereby indicating the absence of severe multicollinearity and ensuring the stability of the model estimates. Furthermore, the significance of the variable is robust to the inclusion of a one-period lag, which further confirms its credibility and robustness.

As shown in Table 3, the NINO West index exerts a statistically significant positive effect on rice prices ($p < 0.01$), with a coefficient of 1485.15. This indicates that during warm-phase ENSO events, rice prices rise substantially. This phenomenon is likely linked to agriculturally adverse climatic conditions triggered by ENSO, such as elevated temperatures, droughts, and erratic precipitation. Among other variables, wind speed (*WS*) demonstrates a significant negative correlation with rice prices, suggesting that increased wind speeds may suppress rice growth—potentially by accelerating soil moisture evaporation—thereby reducing yields and driving price increases.

6.1.2 Impact of ENSO events on hydrological conditions in the Shinano River

As shown in Table 4, the regression results indicate that *NINOW* exerts a statistically significant positive effect on water levels, with a coefficient of 0.1206 ($p = 0.003$), significant at the 1% level. This suggests that during intensified El Niño events, the average water

TABLE 4 Regression results for the impact of the NINO west index on water levels in the Shinano River.

Variable	Coefficient
NINOW	0.1205933***
	(0.0400656)
R	0.0017827***
	(0.0000458)
T	0.0024463
	(0.0022363)
Pre	0.0000579
	(0.0000987)
WS	0.0510257
	(0.0382712)
Snow	−0.000426**
	(0.0002024)
Sun	0.0002078
	(0.0002718)
cons	41.33675***
	(0.0933843)
R^2	0.8710
Observations	302

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

level in the region rises significantly. This mechanism is likely mediated through ENSO-induced alterations in precipitation patterns, snowmelt timing, and regional hydrological cycles, which indirectly affect agricultural irrigation and yields, thereby establishing a potential hydrological transmission channel for rice price fluctuations.

Among control variables, runoff (*R*) exhibits a significant positive coefficient of 0.00178 ($p < 0.01$), confirming its direct and substantial influence on river water levels. Conversely, snow accumulation (*Snow*) shows a negative coefficient of −0.00043 ($p = 0.004$), implying that increased snowpack reduces average water levels—a phenomenon potentially tied to seasonal water storage and release dynamics. Other meteorological variables (*T*, *WS*, *Pre*, *Sun*) lack statistical significance in this model, indicating that water level variations in the Shinano River are primarily driven by *NINOW*, precipitation, and snow-related factors. The model's mean VIF of 2.14, well below the multicollinearity threshold, confirms the absence of severe collinearity and underscores the robustness of the results.

6.1.3 The influence mechanism of Shinokawa hydrological conditions on rice price in Niigata region

Extensive studies have demonstrated a bidirectional interaction between river hydrological conditions and rice cultivation. Wilber et al. (1996), through an empirical analysis of the Cache River's discharge and surrounding rice cultivation areas in the Mississippi Valley, found that agricultural irrigation significantly influences observed river water level fluctuations, confirming the feedback effect of farming activities on hydrological processes. Similarly, Li et al. (2021), in a study of the Yangtze River Basin, highlighted that climatic factors such as precipitation and temperature alter runoff patterns, thereby affecting rice planting schedules and yields. In Bangladesh, Masahiro Tokumura et al. (2019) examined the relationship between river water quality and irrigation practices in rice cultivation, assessing potential public health risks associated with irrigation methods. Parallel findings were reported by Bandurin et al. (2021), who analyzed the impact of the Kuban River's runoff and water quality on local rice production, underscoring the critical role of favorable hydrological conditions in ensuring stable and high yields. Additionally, Patle et al. (2023) investigated seasonal precipitation effects on runoff variability and rice yields in the Dhuti Dam and Wainganga River basin in India, further reinforcing these dynamics.

The literature collectively confirms that hydrological variables—including water level, runoff, and water quality—exert significant positive effects on rice yield and quality. In this study, water level is selected as the primary hydrological variable, and the preceding regression analysis has already established a positive correlation between the ENSO index and both the Shinano River's water levels and Niigata's rice prices. Building on this empirical foundation and supported by existing research, we infer that ENSO events indirectly elevate rice prices in Niigata by increasing the Shinano River's water levels, with both variables exhibiting a co-movement relationship.

TABLE 5 Moran's I Test result.

Variable	Moran's I	Z-score	p-value
P	0.177	3.848	0.000***

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

6.2 Spatial spillover effects of Niigata rice prices on other Japanese cities

6.2.1 Diagnostic tests

Before estimating the SDM, by referring to other findings, a series of diagnostic tests are performed to determine its appropriateness (Kelejian and Prucha, 2001).

As results in Table 5, Preliminary Moran's I tests confirm significant spatial autocorrelation in price variables. The computed Moran's I index is 0.177, with a standardized *Z*-score of 3.848 ($p = 0.000$). This robustly rejects the null hypothesis ($p < 0.01$), validating the necessity of spatial econometric modeling.

As results in Table 6, The Hausman test yields a χ^2 statistic of 12.08 (p = 0.005), strongly rejecting the null hypothesis. This indicates that the fixed effects SDM, is preferred over the random effects model.

As results in Table 7, The results of the Likelihood Ratio (LR) test confirm the statistical necessity of employing a spatial econometric model, as it decisively rejects the null hypothesis of no spatial effects ($\chi^2 = 1519.57$, p < 0.001). This provides robust

TABLE 6 Hausman test result.

χ^2	p-value
12.08	0.005***

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

TABLE 7 LR test result.

χ^2	p-value
1519.57	0.000***

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

empirical justification for incorporating spatial dependence structures in the analytical framework.

To account for potential endogeneity, we included lagged terms of the main explanatory variable and used robust standard errors in the estimation process. This combination helps to ease the effects of endogeneity and produce more reliable and accurate estimates of the spillover effects of Niigata's rice prices on other agricultural markets in Japan.

6.2.2 Price transmission mechanism from Niigata to national markets

Table 8 presents the estimation results for the Space Durbin Model with robust standard errors (Model 3). The main explanatory variable rice price in Niigata (P) shows a significantly positive and large coefficient (1.013408) at the 1% significance level ($p < 0.01$), indicating that an increase in Niigata's rice price is strongly and positively transmitted to neighboring agricultural regions. Furthermore, the lag of the main variable (Pt-1) also displays a significantly positive effect (0.100852) at the 1% significance level ($p < 0.01$), reflecting the persistence of spillover effects over time.

The interaction term (WxP) is significantly and negatively related to the dependent variable (−1.174845) at the 1% significance level, implying that the spillover effects diminish with increasing geographical distance. This phenomenon resonates with the view that closer regions are more influenced by price signals from Niigata, while farther ones are less affected. Furthermore, the lag of the interaction term (WxPt-1) maintains its significantly negative coefficient (−0.128375) at the 5% significance level ($p < 0.05$), suggesting the temporal persistence of this attenuation.

Lastly, the estimated spatial autoregressive coefficient (ρ) is positively significant (1.164314) at the 1% significance level, which underscores the strong and significant spillover effects stemming from neighboring regions' price formations. The robustness of these results is further supported by high R^2 (0.9232) and a large number of observations (20,167), reflecting a strong fit to the data.

6.2.3 Impact of Niigata rice prices on rice prices in other agricultural regions of Japan

As the results in Table 9, the analysis reveals a significant spatial spillover effect of rice prices ($\rho = 0.366$, $p < 0.01$), indicating a strong spatial correlation of rice prices among cities. The coefficient for the main variable P is 1.027 ($p < 0.01$), suggesting that in other agricultural regions, a 1-yen increase in the rice price in Niigata leads to an average increase of 1.027 yen in the rice prices of other cities.

The coefficients for the respective agricultural regions show significant variation in their responses to price signals originating in Niigata. Specifically, Hokkaido ($\beta = 0.15896$, $p < 0.01$) and

TABLE 8 Influence of rice price in Niigata on rice price in other cities in Japan.

Variable	(1)	(2)	(3)
	Coefficient	Coefficient	Coefficient
P	1.114611***	1.013408***	1.013408***
	−0.0031396	0.80155201	0.0281179
Pt-1		0.1008516***	0.1008516***
		0.153529	0.0284665
WxP	−1.316997***	−1.174845***	−1.174845***
	−0.0282125	0.0477714	0.0722466
WxPt-1		−0.1283751***	−0.1283751**
		0.0400273	0.0616308
ρ	1.176553***	1.164314***	1.164314***
	−0.024039	0.0244127	0.0480649
R^2	0.9249	0.9232	0.9232
Observations	20,234	20,167	20,167
Estimation method	SDM	SDM	SDM with robust standard errors

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

TABLE 9 Impact of Niigata rice prices on price fluctuations in other agricultural regions of Japan.

Variable	Coefficient
P	1.02714***
	(0.013359)
Hokkaido	0.1589571***
	(0.0151269)
Tōhoku	0.0731683***
	(0.0139046)
Hokuriku	−0.1326859***
	(0.0144956)
Kantō-Higashiyama	−0.1783233***
	(0.0136346)
Tōkai	0.0759946***
	(0.0144944)
Kinki	−0.1066996***
	(0.0137437)
Chūgoku	−0.1025329***
	(0.0138672)
Shikoku	−0.0571372***
	(0.0144929)
Kyūshū	0.0843284***
	(0.0136477)
ρ	0.3660657***
	(0.0103329)
R^2	0.9592
Observations	20,234

Note: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

Tōhoku (β = 0.07317, p < 0.01) exhibit significantly positive spillover effects, reflecting a strong price transmission in these nearby and closely connected markets. The Tōkai (β = 0.07599, p < 0.01) and Kyūshū (β = 0.08433, p < 0.01) regions also show significantly positive responses, although with somewhat lower magnitudes.

In contrast, several other major agricultural areas exhibit significant and unfavorable spillover effects. The coefficients for Hokuriku (β = −0.13269, p < 0.01), Kantō-Higashiyama (β = −0.17832, p < 0.01), Kinki (β = −0.1067, p < 0.01), Chūgoku (β = −0.10253, p < 0.01), and Shikoku (β = −0.05714, p < 0.01) are all significantly negative, implying a dampening or reverse spillover from Niigata's price signals in these markets.

Furthermore, the spatial autoregressive coefficient (ρ) is positively significant (β = 0.36607, p < 0.01), indicating strong spillover effects stemming from the price formations in neighboring agricultural markets. The high R^2 (0.9592) further confirms a strong fit of the model to the data.

This study utilizes ArcGIS software to visualize the spillover effects of rice prices in Niigata on other agricultural regions in Japan. The resulting schematic map (see Figure 2) clearly illustrates how price fluctuations in Niigata propagate and influence rice markets across different areas, highlighting the spatial extent and intensity of these economic interactions.

7 Discussion

7.1 The impact of ENSO on Niigata rice prices through hydrological conditions of the Shinano River

According to the results of the empirical analysis, the NINO West index exerts a significant positive influence on rice prices in Niigata (coefficient = 1188.558, $p < 0.01$), as well as on the water level of the midstream Shinano River (coefficient = 0.1206, $p < 0.01$). These findings indicate that ENSO events affect regional agricultural prices indirectly through hydrological variables. This transmission mechanism confirms the coupled relationship between ENSO and the hydrological system of the Shinano River, which in turn affects rice production and price formation in the Niigata region via changes in irrigation availability and agricultural scheduling.

From a logical perspective, fluctuations in the NINO index reflect the intensity of ENSO events, which subsequently influence local climatic conditions and hydrology in Niigata. Such environmental changes increase uncertainties in agricultural production—particularly rice farming—thereby triggering anticipatory responses in the market and amplifying price volatility. This establishes a multi-tiered interaction chain of climate–hydrology–price.

The empirical results provide robust support for the research hypotheses: H1 (ENSO significantly affects hydrological conditions), H2 (hydrological conditions significantly influence rice prices), and H3 (ENSO indirectly affects rice prices through hydrological variables). These findings not only enrich the research framework concerning the economic impacts of ENSO climate events on agriculture in mid-latitude regions, but also offer theoretical and empirical foundations for regional agricultural risk management and food price forecasting.

7.2 Spatial transmission of Niigata rice price fluctuations

The empirical results presented in Table 8 indicate that price fluctuations in Niigata exhibit significant and robust spillover effects on agricultural prices in other Japanese regions. The robust SDM (Model 3) was employed to further investigate the mechanisms through which price signals originating in Niigata influence price formation elsewhere.

The coefficient for P is positively significant (1.0134, p < 0.01), suggesting that a one-unit increase in the price of Niigata rice is associated with a 1.0134-unit increase in nearby agricultural prices. This highlights the key role of Niigata in transmitting price signals across the Japanese agricultural market. Furthermore, the significantly positive and large spatial autoregressive parameter (ρ = 1.1643, p < 0.01) confirms the strong spillover effects stemming from price formations in Niigata. The lag term is also

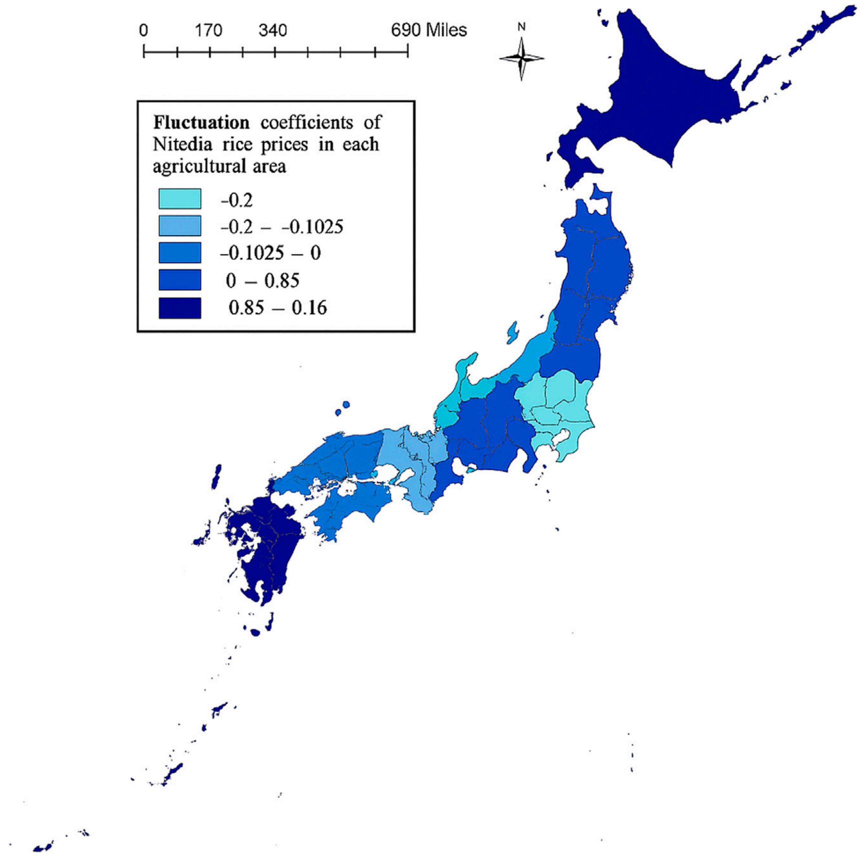

FIGURE 2
Fluctuation coefficients of Niigata rice prices in Japan.

positively significant, implying that the transmission process operates with a temporal delay, reflecting the influence of transportation, information diffusion, and other market frictions.

The interaction term WxP is significantly and negatively related (−1.1748, $p < 0.01$). This indicates a dampening or competitive spillover effect: although a price increase in Niigata directly pushes up prices in nearby markets, indirect effects may be suppressed by their own pricing mechanisms and market structures. This phenomenon likely reflects competition and structural differences in production and consumption across regions. Some neighboring prefectures, for instance, produce the same varieties of rice and form a competitive market with Niigata, thereby dampening its price transmission. Additionally, variation in growing conditions, as well as in production outcomes—with poor yields in Niigata in 2024 and strong production in Iwate and Miyagi—further contributes to these effects (Ministry of Agriculture, Forestry and Fisheries, 2025).

From the above, it can be judged that fluctuations in rice prices in Niigata exert significant spatial transmission effects on rice prices in others Japanese cities. In this way, Hypothesis 4 (H4) is correct.

This transmission pattern varies considerably across different agricultural regions in Japan. The coefficients for Hokkaido (0.1590, $p < 0.01$), Tōhoku (0.07317, $p < 0.01$), Tōkai (0.07599, $p < 0.01$), and Kyūshū (0.08433, $p < 0.01$) are significantly positive, reflecting strong spillover effects from Niigata's price signals. These neighboring areas typically grow analogous varieties of rice and operate within a competitive market structure, which collectively foster high price transmission. Furthermore, geographical proximity may facilitate faster information flow and reduce transaction costs, thereby strengthening transmission mechanisms.

In contrast, the coefficients for Kantō-Higashiyama (−0.17832, $p < 0.01$), Kinki (−0.1067, $p < 0.01$), Chūgoku (−0.10253, $p < 0.01$), and Shikoku (−0.05714, $p < 0.01$) are significantly negative. This may be due to differing production conditions, varieties, and market structures, which dampen or even reverse transmission effects. These agricultural areas have their own production regimes, making them less vulnerable to price signals stemming from Niigata. Shikoku, in particular, is relatively isolated and less influenced by price signals from the Niigata market, reflecting greater market self-sufficiency and reduced reliance on external price formations. This further emphasizes the role of market preferences and policy mechanisms in mitigating spillover effects.

Overall, the transmission mechanisms of price signals originating in Niigata are influenced by both market structures and production conditions across different agricultural regions. The transmission effect varies in different agricultural regions, and Hypothesis 5 (H5) holds true. This highlights the necessity for policy interventions that account for these mechanisms in order to stabilize the Japanese rice market.

7.3 Research deficiencies and prospects

This study focuses primarily on the effects of ENSO events on hydrological conditions and rice prices. The linear regression framework was adopted to quantify these relationships, under the main assumption that the effects of different explanatory variables are additively linear. While this approach is frequently used in agricultural economics, it may not fully account for potential non-linear interactions or synergistic effects that can arise under real-world conditions—for instance, when precipitation and temperature anomalies combine in a non-additive manner.

Nevertheless, the main effects of ENSO, as measured by NINO 3 and NINO West indices, have a well-established and significant influence on both agricultural production and prices, as documented by previous empirical study, which shows a significant negative impact of El Niño events on rainfed rice production in the Philippines (Boer and Surmaini, 2020). Thus, the linear framework is appropriate for capturing these principal relationships in the context of this study.

At the same time, we acknowledge that this approach cannot fully reflect the complexity of climate–agriculture interactions, particularly the potential non-linear effects stemming from interactions among climate variables. This limitation should be kept in mind when interpreting the results. Future research employing non-linear models, threshold regressions, or machine-learning methods may help uncover these additional mechanisms, thereby strengthening the robustness of policy recommendations related to climate risk management and agricultural production.

While this study reveals significant and heterogeneous spillover effects of Niigata's rice prices on other agricultural regions, there are several limitations that should be addressed in future research.

One limitation is that this study does not sufficiently uncover the underlying mechanisms through which these spillover effects are transmitted. Whether this transmission is driven by differences in production conditions, consumer preferences, logistics infrastructure, policy restrictions, or other factors related to production chains is a matter that warrants further investigation. A more in-depth understanding of these mechanisms would aid in interpreting the formation of spillover effects and provide a scientific basis for policy design.

Additionally, the study falls short in conducting a sufficiently granular and in-depth analysis of the variation in spillover effects across agricultural regions. Each region is influenced by its own production conditions, geographical location, consumer preferences, infrastructure, and policy regimes—all of which may contribute to the heterogeneous spillover effects. Without a more disaggregated empirical analysis, it is difficult to fully account for the mechanisms underlying these differences. Future research should collect data at the regional level—including production volumes, price elasticities of demand, logistics conditions, and import and export flows—and apply disaggregated models to enable a more exhaustive and rigorous understanding of spillover mechanisms, thereby offering policy guidance tailored to the specific conditions of each region.

8 Conclusion

This study contributes to understanding the mechanisms through which climate signals influence agricultural prices and how these effects propagate across space. The empirical results indicate that ENSO events, as represented by the NINO West Index, affect water levels in the Shinano River, thereby influencing rice prices in Niigata. An increase in the NINO West Index typically corresponds to a rise in water levels, which, in turn, exerts upward pressure on the price of rice in this region. This process underscores the vulnerability of agricultural markets to climate-related disturbances and highlights the role of water conditions in shaping price formations.

Furthermore, price increases originating in Niigata do not remain isolated; instead, they spill over to other agricultural markets across Japan. This transmission occurs with a short-lived lag, reflecting the temporal mechanisms through which price signals move through space. The effects are particularly pronounced in nearby agricultural areas, including Hokkaido and Tohoku, demonstrating a strong and persistent pattern of price contagion.

These findings reveal the significance of climate signals and spillover mechanisms in understanding price volatility and market interconnectedness. The results suggest that policymakers and stakeholders should account for both climate variability and the transmission of price effects across space when designing strategies to stabilize agricultural markets and enable greater resilience to climate-related shocks.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

HZ: Funding acquisition, Validation, Resources, Writing – review and editing, Formal Analysis, Project administration, Writing – original draft, Software, Methodology, Conceptualization, Investigation, Visualization, Data curation, Supervision.

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