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The effects of weather extremes on wheat prices in Russia: The role of inputs and Russia's war in Ukraine

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Abstract

Utilizing the normalized difference vegetation index (NDVI) in the error correction model, we examine the effects of weather anomalies on wheat prices in six wheat-producing regions in Russia. Our analysis reveals that weather-induced price effects are most pronounced in regions most distant from the world market, particularly those primarily producing spring wheat for domestic consumption. These findings are corroborated by a model that incorporates precipitation data and partially supported by a model that uses maximum temperature as an alternative measure for weather extremes. The absence of significant weather impacts on wheat prices in the exporting North Caucasus region likely reflects the region's advanced production systems and modern management practices. Since Russia's invasion of Ukraine, the profitability of wheat production for Russian farmers has declined substantially, leading to reduced use of agricultural inputs. If this trend of low input application continues, weather fluctuations could have a more pronounced impact on wheat prices.

Keywords NDVI · Weather anomalies · Wheat prices · Russia · Food security · Inputs · War in Ukraine

1 Introduction

Over the last three decades, Russia has achieved tremendous growth in wheat production, transforming from a wheat importer to the largest exporter globally. However, the productivity of growing wheat in Russia remains more than twice as low as in France and Germany (FAOSTAT, 2023; Figure A1). The existing literature highlights the critical importance of climate conditions for wheat production in Russia (Belyaeva & Bokusheva, 2018; Schierhorn et al., 2014a), which is characterized by high yield variability and frequent harvest failures (Götz et al., 2016; Araujo-Enciso & Fellmann, 2020) due to extreme weather events linked to

climate change (Coumou & Rahmstorf, 2012; Schierhorn et al., 2014b).

Extreme weather anomalies decrease domestic yields and can exacerbate domestic price volatility, prompting the government to impose export restrictions. Notably, Russia experienced a severe drought in the summer of 2010, which drastically reduced the country's wheat harvest. As a result, in the 2010–11 marketing year, wheat production was more than 50% below average¹. In response, the Russian government imposed a wheat export ban to stabilize domestic food prices, which had a price dampening effect of between 35 and 67% (Götz et al., 2016). In contrast, in the 2012–13 marketing year, the Russian government did not restrict wheat exports, despite experiencing another drought that caused widespread harvest shortfalls and domestic wheat prices to rise above world price levels. This nevertheless resulted in a significant reduction in wheat exports. These weather-induced harvest shortfalls and potential export restrictions decrease Russia's export supply and further exacerbate the volatility in international markets.

The effects of adverse weather on agriculture can be mitigated by the increased use of fertilizers, crop protection, high-yielding seeds, modern machinery and

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¹ Wheat production as a % of the average of the three previous years.

advanced agricultural management practices. Historically, Russia has been highly dependent on Western countries, particularly the EU, for most of its agricultural inputs. For instance, in 2021, over 30% of Russia's agricultural machinery imports came from Germany (UN Comtrade, 2024). Since Russia's invasion of Ukraine, the Russian government has intensified its efforts to promote domestic production of input products through import substitution policies. This raises concerns about whether the availability of such inputs in Russia has been adversely affected by the war in Ukraine.

Against this backdrop, we investigate the effects of weather anomalies on domestic wheat prices in Russia's six main wheat-producing regions: North Caucasus, Black Earth, Central, Volga, Urals and West Siberia. Building on the price transmission framework developed by Baffes et al. (2019), we specify an error correction model that incorporates the likely impact of the 2010–11 export ban and the exchange rate as additional variables. We operationalize extreme weather events using the normalized difference vegetation index (NDVI), a widely used indicator capturing variations of crop growing conditions. To complement this analysis, we also use precipitation and maximum temperature as alternative climate variables, recognizing their importance in the wheat growing process in Russia. Furthermore, we analyze secondary data on Russia's imports of inputs, which could be used to mitigate the impact of weather anomalies on wheat production. This allows us to assess whether the adverse effects of extreme weather on harvests can be expected to intensify in the near future.

This research aims to bridge the gap in the literature on the relationship between weather fluctuations and agricultural prices. Moreover, there is a paucity of empirical research examining the impact of shocks on agricultural supply chains, which is essential for formulating and implementing policies to enhance resilience (FAO, 2023). Understanding price formation on Russia's domestic wheat market is particularly critical for global food security, as Russia accounts for approximately 20% of global wheat exports. Following the onset of the war in Ukraine, imports from Russia to the Middle East and North Africa (MENA) region doubled between the last quarter of 2022 and the first quarter of 2023. In the last quarter of 2023, Russia was the largest exporter of wheat to the MENA region, exporting more than one million metric tons, compared to 184,000 metric tons from France, the EU's largest wheat exporter (Ulybina & Rastogi, 2024).

Several studies use NDVI to explore the influence of weather conditions on food prices. Brown and Kshirsagar (2015) investigate the effects of weather variability in 554 domestic commodity markets in more than 50 developing countries, finding that about 20% of domestic prices are

impacted by weather anomalies on average. Furthermore, Baffes et al. (2019) utilize NDVI to highlight the importance of weather anomalies in examining the drivers of maize and rice prices in Tanzania. Hatzembuehler et al. (2020) also demonstrate that weather anomalies significantly influence both long- and short-run price transmission in maize and millet markets in Niger. Additionally, NDVI has proven useful for examining crop losses due to non-weather issues such as military conflict. For example, Deininger et al. (2023) use NDVI within a panel approach to show that Russia's invasion led to a decline of up to 17% in Ukraine's winter wheat crop output.

Letta et al. (2021) use the standardized precipitation evapotranspiration index (SPEI) to investigate the impact of harvest shortfalls on the dynamics of maize, rice and wheat prices in Indian local markets and find substantial price adjustments in response to anticipated harvest shortfalls. Similarly, Ubilava (2017) explores the influence of sea surface temperature (SST) anomalies, a proxy for El Niño Southern Oscillation (ENSO), on 43 commodity prices. The study reveals that SST anomalies affect the price dynamics of several commodities, including some agricultural products, but not cereal grains. Furthermore, Kan et al. (2023) utilize a structural econometric framework to examine the impacts of climate change on cropland allocation, crop production, output prices, and social welfare in Israel. Their findings indicate that forecast climate changes are expected to positively impact the farm sector, leading to the higher production of vegetables and field crops, although fruit production is expected to decline, leading to increased fruit prices.

Several studies investigate the impacts of climate change on Russian agricultural productivity (Alcama et al., 2007; Belyaeva & Bokusheva, 2018; Lobell et al., 2011; Pavlova et al., 2014; Sirotenko et al., 1997). Wheat yields in Russia have been investigated as well (Schierhorn et al., 2014a and 2014b). However, to the best of the authors' knowledge this is the first study to examine the effect of weather anomalies on wheat prices in Russia's main grain-producing regions. One exception is a study by Götz et al. (2016), which considers harvest shortfalls and investigates the price effects of export controls on the relationship between world and regional Russian wheat prices.

The remainder of this article is structured as follows: Section 2 characterizes Russia's wheat market and weather extremes and examines the import of input products for wheat cultivation following Russia's invasion of Ukraine. Section 3 introduces the modeling framework, and Section 4 discusses the data, including a detailed description of the weather proxies. Section 5 presents the results, and Section 6 offers concluding remarks.

Fig. 1 Map of wheat-producing regions in Russia. Source: Authors' illustration



2 Russian wheat production and import substitution policy

In Russia, wheat production is concentrated in six major regions: North Caucasus, Black Earth, Central, Volga, Urals, and West Siberia (Fig. 1). The North Caucasus region, the country's largest wheat producer, is closest to the Black Sea ports and primarily supplies wheat to the international market. In contrast, West Siberia, located over 4,000 km from the Black Sea, mainly supplies the domestic market. The Urals, the second most distant region from the Black Sea ports, also primarily serves the domestic market. The Black Earth and Volga regions are significant wheat producers as well, contributing both to the domestic market and to international exports through the Black Sea ports. The Central region, which includes Moscow, the most populous economic area in Russia with over 32 million residents, receives wheat primarily from the Black Earth and Volga regions.

Russia produces both winter and spring crops (USDA, 2021). Winter wheat (sown at the end of summer and in early autumn and harvested in summer) is predominantly grown in European Russia, particularly in the North Caucasus, Black Earth, Central, and Volga regions (Figure A2), and accounts for about half of the total wheat area and around 70% of total wheat production. Spring wheat, with a shorter growing period (planted in May and harvested in August–September), is mainly grown in the regions bordering Kazakhstan, including Volga, Urals and West Siberia (Figure A3). Winter wheat accounts for about half of Russia's wheat and is categorized into three classes: 3, 4 and 5. Class 3 wheat is mostly traded domestically for human consumption, class 4 wheat is primarily exported, and class 5 wheat is mainly used for animal feed in Russia.

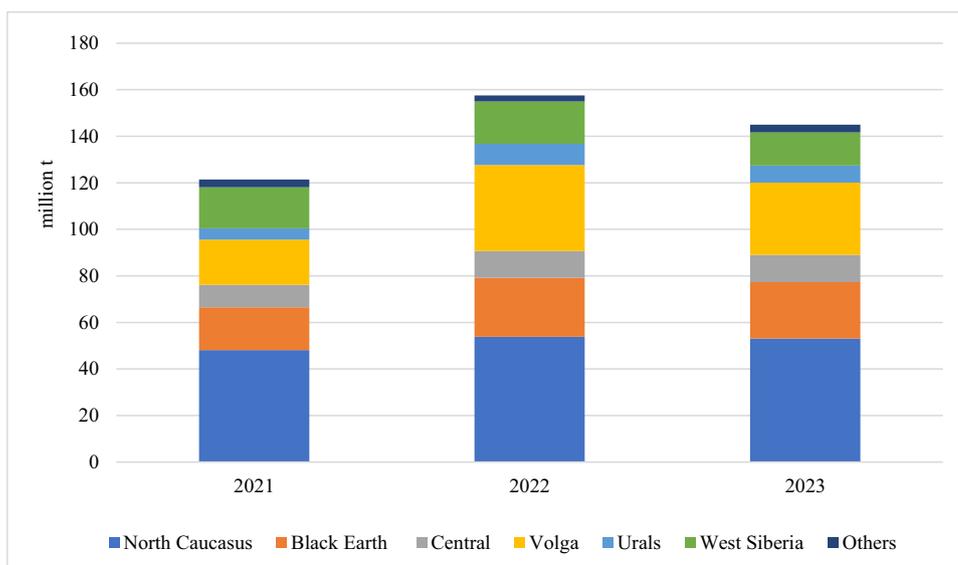
Weather anomalies and climate conditions play a significant role in influencing wheat yields in Russia, especially

temperature and precipitation. High temperatures can severely damage wheat crops, leading to harvest failures. Belyaeva and Bokusheva (2018) find that daily temperatures exceeding 25 °C can result in significant yield losses, with spring wheat being more sensitive to higher temperatures than winter wheat. Additionally, large variations in precipitation are a major constraint on wheat production in Russia (Schierhorn et al., 2014a and b; Belyaeva & Bokusheva, 2018). A lack of precipitation can lead to reduced yields, even with high fertilizer use (Schierhorn et al., 2014b). The vast territory of Russia means that regions can simultaneously experience both high and low yields (Fig. 2). For example, during the 2010 drought, grain production in the Volga, Urals and Black Earth regions dropped by 66%, 62%, and 54%, respectively, compared to the average production of the previous three years, while production in North Caucasus increased by 4%² (Götz et al., 2016). In contrast, in 2012–13, extreme weather events led to wheat production decreases of 32%, 39% and 54% below the three-year average in North Caucasus, Urals and West Siberia, respectively. The Black Earth region, however, experienced only a 4% decline in production.

Since February 2021, the Russian government has implemented an export tax on wheat, which has been adjusted several times in response to market conditions. The highest export tax, at USD 146, was imposed in July 2022, corresponding to about half the domestic wheat price. To

² To prevent domestic supply shortages and price increases, the Russian government imposed a wheat export ban on August 15, 2010. This lasted until July 2011 and substantially affected grain trade across Russia's wheat-producing regions.

Fig. 2 Grain production in Russia by region. Source: Rosstat; authors' illustration



boost the competitiveness of wheat exports amid the ruble's appreciation and high global wheat prices, the government reduced the tax in July 2022 and June 2023 (Götz et al., 2023).

Wheat production costs vary across regions and are highest in the north and east of Russia, while the lowest-cost production areas are found in the south and the west. This disparity reflects the better soil quality and more developed infrastructure in North Caucasus compared to West Siberia. Additionally, in regions where winter wheat is predominantly grown, farmers can replant crops in the spring if extreme weather damages them in autumn or winter.

Apart from climatic conditions and soil quality, wheat yields in Russia also depend on the quality of seeds, fertilizer application rates and the use of modern agricultural technologies. The Russian government implemented a number of policies to help grain producers mitigate the negative impacts of weather extremes. For instance, wheat producers can receive subsidies to purchase seeds of better quality and cheaper fertilizers (20% below the export price) (Forbes.ru, 2023). While Russia is self-sufficient in the production of wheat seeds and fertilizers, crop protection materials and agricultural machinery are, to a large extent, imported.³

Traditionally, Germany has been the primary supplier of agricultural machinery to Russia, accounting for 31% of Russian imports of agricultural machinery in 2021 (Figure A4). Other significant suppliers have been China (10%), Belarus (9%), and the USA (8%). The composition of exporters significantly changed after the war in Ukraine

began, with Turkey supplying 87% of total imported agricultural machinery to the Russian market (Figure A5). Nonetheless, the Russian Association of Specialized Machinery and Equipment Manufacturers (Rosspetsmash) reported that Germany remained the top supplier of agricultural machinery to Russia in the first half of 2023 with a share of 32.2% of Russia's imports (The Global Tribune, 2023).

This is confirmed by data suggesting that Russia might have continued importing agricultural machinery from the EU through other "friendly" countries. For instance, exports of agricultural machinery from Germany to Kyrgyzstan and Turkey increased by 254.1% and 132.1%, respectively, in 2023 compared to 2021. Moreover, exports of agricultural machinery from Germany to China increased by 100% in 2023 compared to 2021 (UN Comtrade, 2024).

Since 2013, the government has provided subsidies for Russian-made agricultural machinery, increasing the share of domestically produced agricultural machinery from 24% in 2013 to 60% in 2022 (Agroinvestor, 2023). With Russia's invasion of Ukraine, subsidy programs to spur input import substitution were extended. Despite these governmental efforts, however, the share of domestically produced agricultural machinery fell to 53% in 2023 (Glavpahar, 2024).

The decreasing demand for agricultural machinery⁴, may be explained by the decline of Russian farmers' profitability due to export restrictions and low domestic wheat prices. In the first quarter of 2023, demand for imported and domestic agricultural combines and tractors on the Russian market decreased by around 10% and 27%,

³ To save space, we present information regarding the production of seeds and fertilizers in the [Appendix](#).

⁴ Usually, wheat producers allocate funds for agricultural machinery using the "residual principle", and buy it after purchasing fertilizers, fuel and seeds.

respectively (Agroinvestor, 2023).⁵ Moreover, worsening macroeconomic conditions in Russia due to the war in Ukraine might have contributed to a decline in farmers’ purchasing power for agricultural machinery and other inputs. For instance, the Russian inflation rate increased to 11.9% and 7.4% in 2022 and 2023, respectively (Interfax, 2024; Voice of America, 2024). To prevent further inflationary pressure on the Russian economy, the Central Bank increased the interest rate up to 16% (Reuters, 2023a). Moreover, the devaluation of the Russian ruble in 2023 led to higher prices in rubles for imported equipment from China that is used in the production of agricultural machinery. The ruble/US dollar exchange rate devaluated by about 40% in August 2023 compared to the same month in the previous year.

Since Russia’s invasion of Ukraine, Russia has had difficulty importing spare components for the production of agricultural machinery, partially as a result of Western sanctions (The Global Tribune, 2023). The EU partially restricted the supply of agricultural machinery to Russia due to the possibility of the dual usage of spare parts in the production of military weapons (Figure A6). Moreover, the largest agricultural machinery producers (Caterpillar, John Deere and CNH Industrial) left the Russian market following Russia’s invasion of Ukraine (Bloomberg, 2022; Reuters, 2023b).

Russia also heavily relies on imported crop protection chemicals. Before the war, the largest suppliers of crop protection materials to Russia were France (23%), China (21%) and Germany (15%) (Figure A7). However, after the war began, Turkey took over as the primary supplier, with 87% of the import share in 2023 (Figure A8). Despite this shift, EU exports of crop protection materials to Russia even increased for some months of 2023 compared to 2021 (Figure A9).

3 Modeling framework

Building on the price transmission framework applied by Baffes et al. (2019), we employ an error correction model (ECM) to analyze the behavior of domestic wheat prices. This approach enables us to identify a suitable benchmark for Russian domestic wheat prices among world wheat prices. The long-run relationship between the domestic price and the corresponding world wheat price is estimated with the following equation:

$$P_{ijt}^d = \alpha + \beta P_t^w + \varepsilon_t \tag{1}$$

where P_{ijt}^d represents the wheat price in production region i (North Caucasus, Black Earth, Central, Volga, Urals, West Siberia) for wheat of class j (class 3, 4 and 5); P_t^w denotes the corresponding world wheat price, α is the intercept, and ε_t is the error term. The parameter β represents the long-run price transmission elasticity—a value of one indicates complete price transmission.

Estimating the unbiased model parameters in Eq. (1) requires commodity prices to be either stationary or non-stationary and cointegrated, implying that the residual term $\varepsilon_t \sim I(0)$ is stationary (Engle & Granger, 1987). Note that even if the long-run price transmission elasticity (β) is not equal to one (e.g., due to high trade costs) price differentials can still grow despite the cointegration of the price series (Baffes, 1991, 2019; Barrett, 1996). In the context of a linear dynamic regression model, price differentials should be stationary to guarantee that non-stationary price series are not drifting too far apart. Stationary price differences imply that trade costs are also stationary, amounting to the constant proportion of prices (expressed in natural logarithm). Hence, stationary price differences guarantee market integration in the long run (Fackler & Goodwin, 2001). A price differential, which is obtained by adjusting Eq. (1) with $\alpha = 0$ and $\beta = 1$, can be tested for a unit root in Eq. (1’):

$$(P_{ijt}^d - P_t^w) \sim I(0) \tag{1’}$$

After establishing the validity of (1’), we employ the error correction model (Engle & Granger, 1987) with price differentials retrieved from Eq. (1’) that are included as the error correction term to assess the effects of weather anomalies and other factors on Russian domestic wheat prices.

The ECM takes the following form:

$$\begin{aligned} \Delta P_{ijt}^d = & \delta_0 + \delta_1 (P_{ijt-1}^d - P_{t-1}^w) + \sum_{k=1}^K \delta_{2k} \Delta P_{ijt-k}^d \\ & - \sum_{k=1}^K \delta_{3k} \Delta P_{t-k}^w + \sum_{k=1}^K \gamma \Delta P_{t-k}^w * I_{BAN} \\ & + \sum_{k=1}^K \delta_{4k} \Delta ER_{t-k} + \sum_{k=1}^K \delta_{5k} \Delta WA_{t-k} + \omega_{ijt} \end{aligned} \tag{2}$$

Δ is a first difference operator while $\delta_0, \delta_1, \delta_{2k}, \delta_{3k}, \delta_{4k}, \delta_{5k}$ and γ are parameters to be estimated. The term ω_{ijt} represents the error term, and k is the optimal lag length, chosen to ensure that the residuals are not serially correlated. The expression $(P_{ijt-1}^d - P_{t-1}^w)$ is the lagged price difference obtained from Eq. (1’). The speed of adjustment parameter (δ_1), which ranges from 0 to 1 in absolute value, measures the speed at which price deviations are corrected. I_{BAN} is the dummy variable of the export ban in the 2010–11 marketing year, taking the value of 1 during the ban and 0

⁵ Moreover, the demand for used agricultural combines and tractors fell by 30.3% and 35.7%, respectively, in the first quarter of 2023 (Agroinvestor, 2024).

otherwise. ER_t represents the ruble/US dollar exchange rate, which influences price formation on the Russian wheat market (Yugay et al., 2024). WA_{t-k} is the weather anomaly variable and is proxied by three measures (NDVI, precipitation, and maximum temperature).

4 Data sources and data properties

Monthly Russian wheat prices (ruble/metric ton) for classes 3, 4, and 5 from the six main wheat-producing regions were taken from the Russian Grain Union (n.d.) (Table 1, Fig. 3 and A12). North Caucasus, Black Earth, Central and Volga

Table 1 Databases of the analyses

Variable	Specification	Source
Domestic wheat price	Producer prices for North Caucasus, Black Earth, Central, Volga, Urals, West Siberia for wheat of class 3, 4, 5; in RUB/t	Russian Grain Union (n.d.)
World wheat price	US export price (FOB), hard red winter, in USD/t US export price (FOB), soft red winter, in USD/t EU (France) export price (FOB), wheat grade 1, in USD/t	FAO
Climate data	Normalized difference vegetation index (NDVI) winter wheat – 35 provinces spring wheat – 19 provinces Precipitation, in millimeters Maximum temperature, in degrees Celsius	GEOGLAM (n.d.)
Exchange rate	In ruble/US dollar	The Federal State Statistics Service (Rosstat)

Source: Authors' elaboration

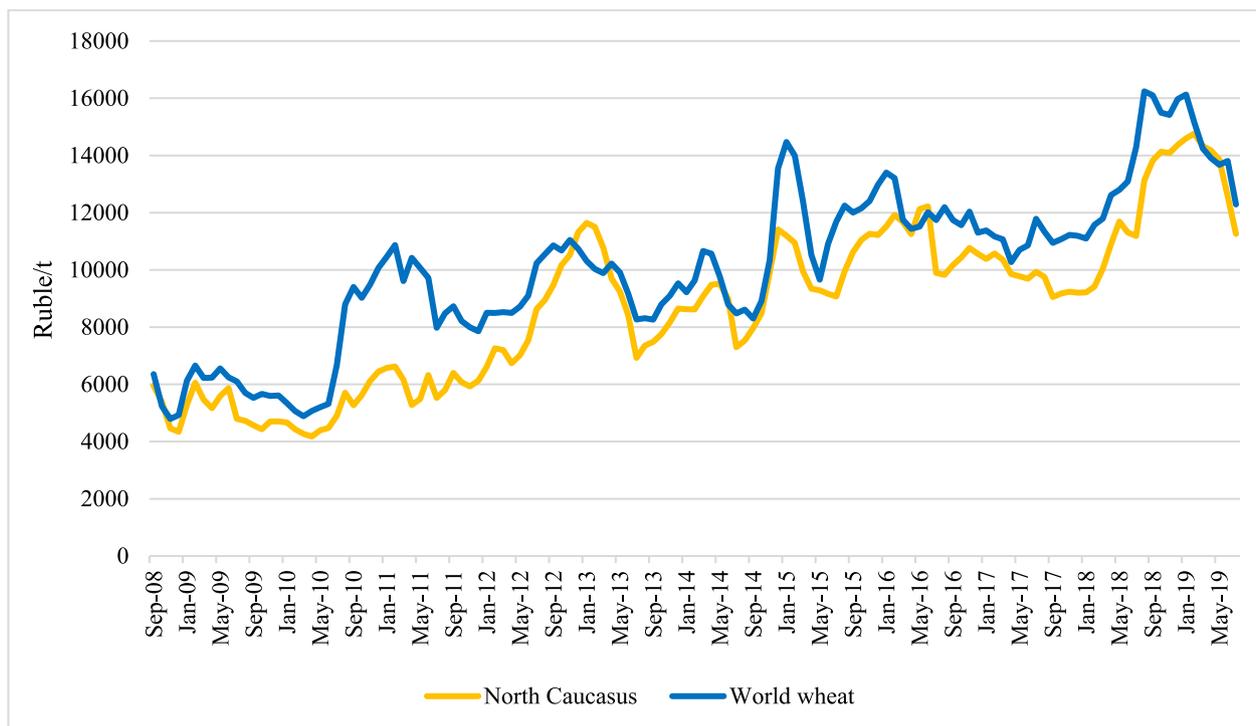


Fig. 3 Russian wheat prices of class 3 in North Caucasus and world wheat prices. Source: Russian Grain Union (n.d.), FAO. Authors' illustration

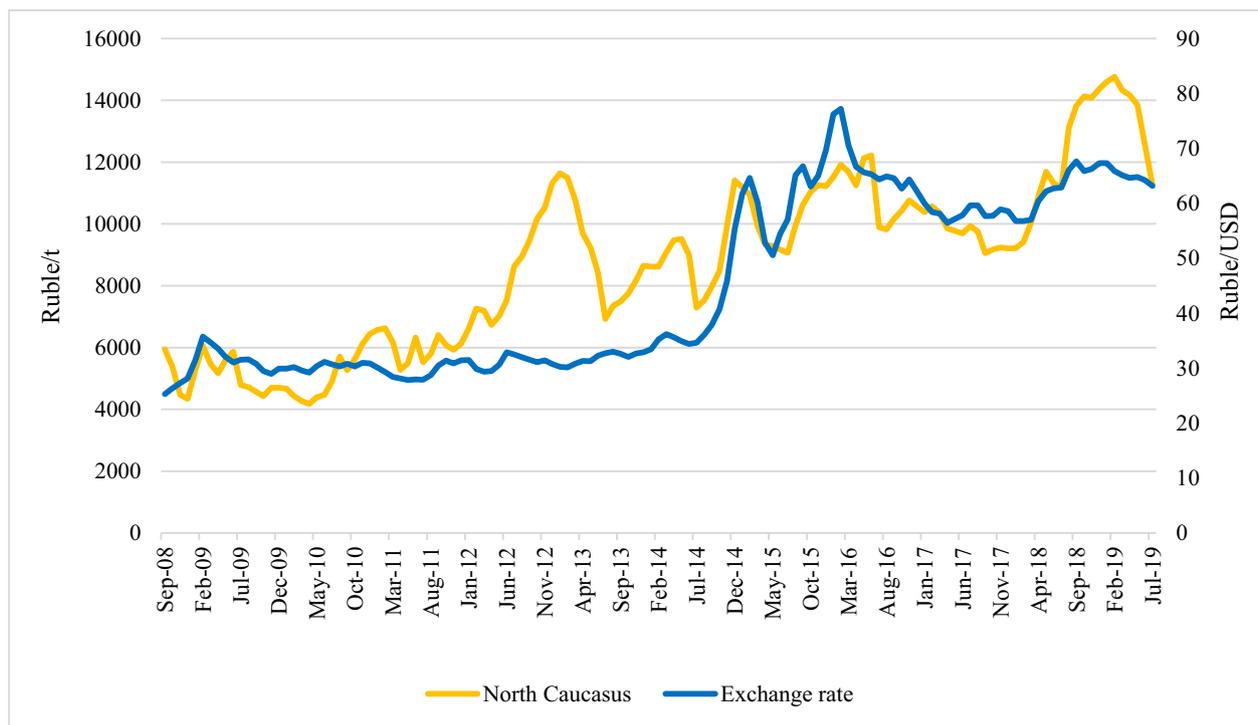


Fig. 4 Russian wheat prices of class 3 in North Caucasus and RUB/USD exchange rate. Source: Russian Grain Union, Rosstat. Authors' illustration

represent winter wheat while Volga, Urals and West Siberia represent spring wheat.

The data set comprises 131 monthly observations for each of the 18 Russian regional wheat price series for the period of September 12, 2008 to July 26, 2019. Wheat export prices for US hard red winter and US soft red winter and the EU wheat export price (France, grade 1, Rouen), sourced from the Food and Agriculture Organization (FAO), were world market barometers considered in our analysis. The ruble/US dollar exchange rate was obtained from the Federal State Statistics Service of Russia (Rosstat [n.d.](#)) (Fig. 4).

The climate proxies employed in this study include NDVI, precipitation, and maximum temperature. NDVI, an indicator of plant growth, is derived from satellite sensor data that measure the light waves reflected from the earth's surface (Peters et al., 2002). It is monitored during the peak growing season to assess plant productivity (Becker-Reshef et al., 2010; Brown, 2014; Johnson, 2014). Notably, NDVI values below the mean value are associated with lower yields and vice versa (Baffes et al., 2019).

Monthly data for NDVI, precipitation (in millimeters) and maximum temperature (in degrees Celsius) were utilized, with values representing the mean of daily averages by province.⁶ These data were aggregated by region and weighted

according to production share across the provinces in each region (Table A1 lists the provinces).

To calculate weather anomalies, the percent deviation of the actual monthly value from the mean of each month from September 2008 to July 2019 was computed separately for NDVI, precipitation, and maximum temperature. The rescaled NDVI values range from -1 to $+1$ and were measured at 5-km grid cell resolution.⁷ The analysis was confined to the wheat growing season in Russia, encompassing the vegetative, ripening and harvest periods. Specifically, the periods from March to August for winter wheat and June to September for spring wheat were included (see Table A2). Values of the remaining months were set to zero.

To test for time series properties of the price data, we used the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979) with the null hypothesis that the price series are non-stationary and the Phillips–Perron (PP) test (Phillips & Perron, 1988) with the null hypothesis that the price series are stationary (Table A3). Both tests with constant and without trend show that all Russian and world wheat prices are non-stationary at the 5% significance level. Furthermore, the results for prices in first difference indicate the stationarity of all Russian and world wheat prices, implying that all price

⁶ Provinces in Russia can be classified as autonomous republics, krais or oblasts.

⁷ In order to rescale NDVI values, we transformed original NDVI values (x) using the following formula: $(x-50)/200$.

series contain unit root and are integrated of order one. We present descriptive statistics on wheat prices, the exchange rate and the world wheat price in Table A4.

5 Empirical results

In the following subsection, we present the results of the price transmission analysis, which identifies the appropriate external benchmark. The subsequent section discusses key results from the ECM specification.

5.1 Choice of the external benchmark

The three external benchmarks used in the analysis are wheat export prices for US hard red winter (HRW) wheat, US soft red winter (SRW) wheat, and EU (France) wheat of grade 1. We estimated the long-run price equilibrium between these benchmarks and wheat prices (Tables A5 to A7). We tested for cointegration by examining the stationarity of the residuals and price differentials based on the Engle-Granger approach.

The estimation results for Eq. (1) suggest that R^2 is significantly higher for models based on the EU benchmark. While the 2-step procedure shows that domestic wheat prices are cointegrated with each of the corresponding world wheat prices, stationarity statistics based on the price differentials gave mixed evidence. For instance, the ADF test finds price differentials stationary for 17 out of all 18 price pairs investigated in this analysis at the 5% significance level for all world wheat prices. In contrast, the PP test suggests

stationarity of price differentials only for the US SRW wheat price at the 1% significance level (Table 2).

These findings are corroborated by the literature. For example, Heigermoser et al. (2021) show that the Russian export price is endogenous and that French and US export prices are weakly exogenous in the wheat tender market of Egypt's state procurement agency for food commodities (GASC). Furthermore, Janzen and Adjemian (2017) find the French futures market better reflects the fundamentals in the Black Sea wheat market. They also highlight the increasing importance of the EURONEXT wheat futures market for price discovery in the international wheat market compared to the Chicago Board of Trade. Therefore, considering the results of the goodness-of-fit measure and the stationarity tests and the empirical evidence from the existing literature, we select the EU export price of France as our external benchmark.

5.2 Error correction model results

Table 3 presents parameter estimates of the error correction model (Eq. 2). All explanatory variables are lagged by one period, and we ensure that residuals are not serially correlated by increasing the number of lags of the dependent variable until the autocorrelation is eliminated. For class 4 wheat, the results show that the short-term effect of world wheat price is the lowest in the most distant regions, such as Urals (0.39) and West Siberia (0.43). The estimates for the North Caucasus, Black Earth and Central regions, which are closer to the Black Sea ports, are much higher (0.48, 0.49 and 0.49, respectively). These results suggest that the

Table 2 Summary indicators of the relationship between domestic Russian wheat prices and international wheat prices

	France, wheat grade 1	US, hard red winter (HRW)	US, soft red winter (SRW)
Conventional goodness-of-fit measure			
Lowest R^2	0.70	0.68	0.66
Median R^2	0.83	0.78	0.81
Highest R^2	0.87	0.84	0.84
Stationary ECT, count out of 18			
ADF < 5%	18	18	18
PP < 5%	18	18	18
ADF < 1%	18	18	18
PP < 1%	18	18	18
Stationary price spreads, count out of 18			
ADF < 5%	17	17	17
PP < 5%	7	11	16
ADF < 1%	1	7	6
PP < 1%	0	0	5

The statistics underlying the numbers reported in this table are available in supplementary Tables A5 to A7. Source: Authors' estimations

Table 3 Results of the error correction model estimations with NDVI as weather anomaly variable

	<i>Winter wheat</i>				<i>Spring wheat</i>			
<i>Wheat of class 3</i>								
	North Caucasus	Black Earth	Central	Volga	Volga	Urals	West Siberia	
Intercept	-0.00	-0.02**	-0.02*	-0.02**	-0.02*	0.02**	-0.02**	
(t-1)	(-0.94)	(-1.99)	(-2.05)	(-2.10)	(-1.89)	(-2.12)	(-2.16)	
Price differential	-0.10**	-0.13***	-0.13***	-0.12***	-0.12***	-0.09***	-0.09***	
(t-1)	(-2.19)	(-2.68)	(-2.76)	(-2.78)	(-2.76)	(-2.92)	(-2.80)	
Δ World wheat	0.42***	0.45***	0.38***	0.41***	0.42***	0.44***	0.42***	
(t-1)	(3.02)	(3.23)	(2.83)	(3.10)	(3.27)	(3.59)	(3.22)	
Δ World wheat*ban	-0.36*	-0.31	-0.24	-0.37*	-0.61***	-0.36*	-0.29	
(t-1)	(-1.72)	(-1.33)	(-1.07)	(-1.74)	(-2.79)	(-1.87)	(-1.39)	
Δ Exchange rate	0.34**	0.18	0.17	0.18	0.18	0.26*	0.26*	
(t-1)	(2.32)	(1.24)	(1.18)	(1.24)	(1.32)	(1.95)	(1.85)	
R-squared	0.23	0.26	0.34	0.35	0.40	0.55	0.46	
<i>Wheat of class 4</i>								
Intercept	-0.02	-0.03**	0.07	-0.03**	-0.02*	-0.02*	-0.02	
(t-1)	(-1.56)	(-2.14)	(0.32)	(-2.01)	(-1.91)	(-1.87)	(-1.65)	
Price differential	-0.12**	-0.12***	-0.09	-0.10**	-0.10***	-0.08**	-0.07**	
(t-1)	(-2.54)	(-2.73)	(-1.59)	(-2.55)	(-2.62)	(-2.51)	(-2.23)	
Δ World wheat	0.48***	0.49***	0.49***	0.50***	0.50***	0.39***	0.43***	
(t-1)	(2.99)	(3.33)	(3.40)	(3.67)	(3.84)	(3.00)	(2.94)	
Δ World wheat*ban	-0.45*	-0.36	-0.27	-0.41*	-0.64***	-0.33	-0.31	
(t-1)	(-1.89)	(-1.46)	(1.25)	(-1.91)	(-2.93)	(-1.62)	(-1.26)	
Δ Exchange rate	0.34*	0.24	0.25	0.22	0.23	0.26	0.29*	
(t-1)	(2.03)	(1.53)	(1.65)	(1.55)	(1.65)	(1.89)	(1.80)	
R-squared	0.25	0.37	0.37	0.41	0.45	0.51	0.45	
<i>Wheat of class 5</i>								
Intercept	-0.03*	-0.03*	-0.02*	-0.03**	-0.03*	-0.03**	-0.03*	
(t-1)	(-1.88)	(-1.95)	(-1.78)	(-2.05)	(-1.91)	(-2.05)	(-1.77)	
Price differential	-0.11***	-0.09***	-0.09**	-0.09***	-0.09***	-0.08***	-0.08**	
(t-1)	(-2.64)	(-2.68)	(-2.50)	(-2.63)	(-2.70)	(-2.62)	(-2.34)	
Δ World wheat	0.48***	0.47***	0.51***	0.50***	0.51***	0.48***	0.47***	
(t-1)	(2.94)	(3.01)	(3.26)	(3.23)	(3.48)	(3.72)	(2.78)	
Δ World wheat*ban	-0.34	-0.32	-0.32	-0.38	-0.69***	-0.54**	-0.29	
(t-1)	(-1.43)	(-1.22)	(1.22)	(-1.58)	(-2.80)	(-2.59)	(-1.04)	
Δ Exchange rate	0.26	0.24	0.22	0.27*	0.27*	0.24*	0.31*	
(t-1)	(1.57)	(1.43)	(1.33)	(1.66)	(1.74)	(1.75)	(1.71)	
R-squared	0.26	0.39	0.39	0.41	0.46	0.57	0.41	

NDVI parameters are presented in Table 4 in comparison with the parameters for precipitation and maximum temperature. Δ is the difference operator. Significance level: * = 10%, ** = 5%, *** = 1%; t-statistics are in parentheses. The dependent variable is the change in the Russian wheat price for the corresponding region and class (in natural logarithm, nominal value)

Source: own estimations

distance from the Black Sea ports decreases the size of the parameter for the price for wheat of class 4, which is predominantly exported. One exception is the Volga region, where the parameter estimate is 0.50, indicating a comparable size despite being at a greater distance from the Black Sea ports. However, this relationship between distance and the strength of the short-term effect of the world wheat price is not evident for wheat of class 3 and class 5.

The export ban negatively impacted the relationship between the world price and the domestic price, leading to

a substantial price dampening effect in the North Caucasus (classes 3 and 4), Volga (all classes)⁸ and Urals (classes 3 and 5) regions. The estimated parameters vary from -0.36 in North Caucasus and Urals (class 3) to -0.69 in Volga (class 5). Additionally, the results indicate that the exchange rate has a moderate impact on wheat prices compared to the effect of the global benchmark. For example, the influence

⁸ In the case of wheat of class 5, it is only for spring wheat in Volga.

of the exchange rate on the price of class 3 wheat in North Caucasus is estimated at 0.34.

The estimated parameters of the price differentials vary from -0.07 in West Siberia (class 4) to -0.13 in the Black Earth and Central regions (class 3). For example, the estimated parameter of -0.12 for the price of class 4 wheat in North Caucasus suggests that the wheat prices in this region adjust by 12% in each month to restore long-run price parity.

The estimation results for NDVI are presented in Table 4 (model 1). NDVI parameters that are significant at the 10% level and have a negative sign, as expected, implying that prices decline under favorable growing conditions. However, there is heterogeneity of the influence of NDVI deviations. The effect of NDVI on spring wheat prices is most pronounced in West Siberia, the region farthest from the

Black Sea ports. Specifically, the NDVI parameter of -0.60 for class 4 wheat in West Siberia suggests that a 10% positive deviation in the NDVI value from its expected mean leads to a 6% decrease in spring wheat prices in this region.

Furthermore, the impact of weather extremes on spring wheat prices is lower in the Volga and Urals regions compared to West Siberia. The estimated NDVI parameter in West Siberia is more than twice as high as in Urals (-0.56 and -0.22 , respectively).

In contrast, the empirical results do not indicate that weather extremes have significant effects on wheat prices in North Caucasus, which primarily exports wheat via direct access to the Black Sea ports. Similarly, weather extremes do not appear to influence wheat prices in the Black Earth region, which also has relatively close world market access

Table 4 Parameter estimates of weather anomaly variables

	NDVI (model 1)	Precipitation (model 2)	Max. temperature (model 3)
<i>Wheat of class 3</i>			
<i>Winter wheat</i>			
North Caucasus	0.05 (0.64)	0.01 (0.74)	0.08 (1.18)
Black Earth	-0.00 (-0.06)	0.03* (1.81)	0.00 (0.51)
Central	0.02 (0.22)	0.02 (1.32)	0.00 (0.44)
Volga	-0.05 (-0.79)	0.00 (0.43)	0.01 (1.23)
<i>Spring wheat</i>			
Volga	-0.31 *** (-3.08)	-0.00 (0.03)	0.23** (2.10)
Urals	-0.16 (-1.33)	-0.06 *** (-2.80)	0.28** (2.35)
West Siberia	-0.39 ** (-2.37)	-0.05 * (-1.74)	-0.10 (-0.80)
<i>Wheat of class 4</i>			
<i>Winter wheat</i>			
North Caucasus	0.07 (0.72)	0.00 (0.48)	0.10 (1.25)
Black Earth	-0.02 (-0.17)	0.02 (1.56)	0.00 (0.29)
Central	-0.01 (-0.46)	0.01 (0.70)	0.00 (0.15)
Volga	-0.09 (-1.21)	0.00 (0.00)	0.01 (1.09)
<i>Spring wheat</i>			
Volga	-0.34 *** (-3.27)	-0.00 (-0.40)	0.25** (2.29)
Urals	-0.19 (-1.50)	-0.06 *** (-2.70)	0.33*** (2.69)
West Siberia	-0.60 *** (-3.13)	-0.08 ** (-2.32)	-0.10 (-0.73)
<i>Wheat of class 5</i>			
<i>Winter wheat</i>			
North Caucasus	0.07 (0.68)	0.00 (0.31)	0.07 (0.85)
Black Earth	-0.05 (-0.39)	0.02 (1.47)	0.00 (0.01)
Central	-0.08 (-0.55)	0.00 (0.11)	-0.00 (-0.06)
Volga	-0.11 (-1.36)	0.00 (0.06)	0.01 (0.94)
<i>Spring wheat</i>			
Volga	-0.43 *** (-3.68)	0.00 (0.21)	0.21* (1.67)
Urals	-0.22 * (-1.76)	-0.06 *** (-2.62)	0.32*** (2.66)
West Siberia	-0.56 ** (-2.53)	-0.10 ** (-2.34)	-0.01 (-0.09)

Significance level: * = 10%, ** = 5%, *** = 1%; t-statistics are in parentheses. Deviations from the mean of NDVI, precipitation and maximum temperature are included from March to August for winter wheat and June to September for spring wheat

Source: Authors' estimations

via the Black Sea ports. The lack of weather-related price impacts in Black Earth might be explained by its close proximity to North Caucasus, as wheat prices in this region might adjust to those in North Caucasus, reflecting the flow of exports through this corridor (see Svanidze & Götz, 2019).

Additionally, our results do not indicate that weather extremes have significant effects on prices in Central for all wheat classes. This could be due to Central's dependence on wheat supplies from other regions, making weather extremes in these supplier regions more relevant for price formation in Central than local weather conditions. Consequently, we estimate the error correction model for the Central region using the NDVI variable for the Volga region, a primary wheat supplier to Central. The empirical results (available upon request) indicate that weather extremes in Volga have effect on wheat prices in Central for all wheat classes, with NDVI parameters of -0.24 , -0.31 , and -0.41 for classes 3, 4, and 5, respectively.

Table 4 compares the estimated parameters for NDVI with those of the precipitation (model 2) and maximum temperature (model 3) variables. The complete estimation results of the error correction models with precipitation and maximum temperature are presented in Table A8 and Table A9, respectively.

The empirical results retrieved from model 2, which uses the percentage deviation from the mean for precipitation, indicate a significant influence on spring wheat prices across all classes in the most remote regions, specifically Urals and West Siberia. These negative parameter estimates suggest that positive deviations from the mean precipitation, which improve growing conditions, have reverse effects on wheat prices. Conversely, below-average precipitation has the opposite effect, similar to drought conditions. The estimated parameters for the precipitation variable are highest for West Siberia (-0.08 and -0.10 for class 4 and 5 wheat, respectively) and Urals (-0.06 for all classes). Unlike the results from model 1, model 2 does not show significant effects of weather extremes on spring wheat prices in the Volga region. However, consistent with model 1, the effects of weather anomalies were not significant at the 5% level for winter wheat in the North Caucasus, Black Earth, and Central regions, which are closer to the Black Sea export ports. The exception is the parameter for class 3 wheat in Black Earth (0.03), which is significant at the 10% level and has a positive sign. Thus, model 2 partially confirms the results from model 1, which used NDVI as the climate variable.

Model 3, which uses the deviation from the mean of maximum temperature, indicates that weather extremes affect spring wheat of all classes in the Volga and Urals regions, with estimates varying between 0.23 in Volga (class 3) and 0.33 in Urals (class 4). All statistically significant parameters are positive, indicating that a substantial increase in maximum temperature reduces wheat yields.

Additionally, we tested for the effect of non-linear weather anomalies on crop yields, which may occur with extremely high levels of precipitation or temperature. To do this, we included quadratic terms of the weighted average values of precipitation and temperature. However, we did not find any effect due to nonlinearities (results are available upon request).

6 Conclusions

We investigated the effects of weather extremes on domestic wheat prices in Russia's main wheat-producing regions using an error correction model that considers NDVI as a climate variable. Our study compares NDVI with precipitation and maximum temperature as alternative measures for weather anomalies, contributing to the understanding of the relationship between weather extremes and agricultural prices. Moreover, we complement our empirical study with a qualitative analysis using comparative data for imported input materials from before and after the beginning of the war in Ukraine. These input materials, by affecting wheat production levels, could play an important role in mitigating the effects of weather extremes on prices, especially during the war period. However, we acknowledge that not including input data explicitly in error correction model estimations is one of the limitations of our study.

Our empirical results indicate that weather extremes have more substantial price effects in Urals and West Siberia, regions distant from the Black Sea ports where significant amounts of spring wheat are grown. For example, a 10% negative deviation in NDVI in West Siberia results in regional wheat price increases ranging from 3.9% (class 3) to 6% (class 4).

In contrast, we did not observe significant effects caused by weather anomalies on wheat prices in regions closer to the Black Sea ports, such as the North Caucasus, Black Earth, and Central regions. Wheat prices in these regions are more influenced by world market price, particularly for class 4 wheat, which is primarily exported. The lack of weather anomalies effects in these regions may be due to advanced agricultural technologies.

These results confirm findings by Svanidze and Götz (2019) and Svanidze et al. (2021) that suggest that spatial market efficiency and transport infrastructure, which are weaker in Russia's distant regions, play an important role for interregional grain trade from surplus to deficit regions within Russia, especially in periods of harvest shortfalls. Moreover, our results are in line with the findings of other studies that suggest that weather variations more strongly affect the yield (and, hence, the price) of spring wheat rather than of winter wheat (Belyaeva & Bokusheva, 2018; Meza et al., 2003), which is explained by the different vegetative periods for these crops (see Table A2).

Moreover, we attribute the absence of extreme weather effects on wheat prices in the closest regions to the Black

Sea ports to a higher share of agricultural enterprises in total wheat production in these regions compared to the most distant regions (compare Figure A11). Agricultural enterprises might use more advanced agricultural technologies, which are an important determinant of mitigating the effects of weather anomalies. Therefore, advanced agricultural technologies and up-to-date management practices (Prishchepov et al., 2019) could mitigate weather-induced fluctuations of wheat yields and prices in Russia.

The existing literature shows that areas located in the northern part of the Black Earth region are expected to benefit from global warming conditions, and wheat yields there might substantially increase (Schierhorn, 2021). Vast cropland has been abandoned in this region, so it will be important to expand agricultural land under cultivation. Climate change will also be favorable for wheat production in the northern part of Russia. However, it is important to take into account various agroclimatic and socioeconomic factors which will substantially limit crop cultivation in northern Russia.

Given the vast availability of data suitable to serve as climate variables (e. g. minimum, average and maximum temperature, the standardized precipitation evapotranspiration index (SPEI), growing degree days (GDD), extreme degree days (EDD), heatwaves with precipitation and heatwaves without precipitation), our model might be further developed by using machine learning methods such as random forest to identify most relevant climate variables (Schierhorn et al., 2021). Including these variables in the time series model with agricultural prices could improve mapping of the price effects of weather anomalies, particularly given the limitations of NDVI when it comes to efficient vegetation assessment (Huang et al., 2021). In addition, a more flexible model could be used to distinguish between the size of price changes and the duration of the price effect caused by weather anomalies.

Our qualitative analysis shows that Russia's wheat production relies heavily on imported agricultural machinery, which has shifted in origin due to geopolitical events. The current import substitution policy and changing macroeconomic conditions have reduced farmers' demand for agricultural inputs, potentially increasing the future influence of weather extremes on wheat production.

Moreover, war-related macroeconomic conditions have increased inflation, which has led to higher production costs. This might pose further challenges for farmers seeking to obtain agricultural insurance, which is an important means of protection in case of weather extremes. Even before the war started, agricultural insurance programs were not common among Russian agricultural producers. As of August 15, 2024, only 49 out of 89 Russian regions participated in insurance with state support for agricultural crops and perennial plantings. One of the main reasons for the low level of insured crops is farmers' lack of trust in insurance policies (Forbes.ru, 2024).

Export restrictions may dampen the effect of weather anomalies on domestic wheat prices, warranting further investigation. Given Russia's significant contribution to the global wheat supply, our findings have implications for global food security. The ongoing war in Ukraine adds uncertainty to the wheat market, affecting both investments in Russia's wheat sector and the global grain trade.

Due to the war, the structure of the export market had changed substantially by the end of the 2022–23 trade year, as international trading companies Louis Dreyfus, Cargill and Viterra left the Russian grain export market. This decreased competition and increased concentration in the domestic wheat market (Reuters, 2023c, d, e). This development might lead to lower producer wheat prices in various production regions, leading to disintegration of the Russian market from the world market and impacting the efficiency and profitability of grain production.

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Data Availability Russian wheat prices, which were used in this study, are not publicly available.

Declarations

Conflict of interest The authors have no conflicts of interest to declare.

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