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Response of the Northeast China grain market to climate change based on the gravity model approach

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ABSTRACT

Scientific evidence has revealed that climate change negatively affects agricultural crop production both regionally and globally. Previous studies have indicated that the role of climate change is significant in some parts of China. Thus, assessing the impact of the future climate on the grain market is vital for ensuring regional and national food security. In this study, regional climate model (RCM 4.5 and 8.5) simulations were employed to investigate the role of future climate change on a major grain-producing market in China (Northeast China). For this purpose, historical (2004–2017) and future (2020–2076) data were applied in the gravity model to examine the effects of climate change on the Northeast China grain market. The results revealed that the maximum temperature is a crucial climate factor that significantly affects the grain market. The analysis revealed that precipitation was positively related and that the temperature was significantly negatively related to domestic consumption and exports of rice, maize, and soybean. Moreover, the analysis of the RCM (4.5 and 8.5) simulations revealed a negative contribution of the maximum temperature to domestic consumption and export levels. Overall, the analysis enhances our understanding of the impacts of climate change on the Northeast China grain market.

1. Introduction

Growing evidence has revealed that climatic conditions such as precipitation, solar radiation, and temperature strongly influence agriculture worldwide [1–3]. Researchers have agreed that future climatic conditions may adversely affect agricultural production, which may lead to vulnerability of food supplies [4,5]. Moderate-level warming may be beneficial for agriculture in high-altitude countries, but in topical areas, minimal climate change may cause a decline in yield [6,7]. Northeast China is situated in a temperate continental zone at high altitudes. Therefore, future climate change may benefit grain production in the region.

Climate vulnerability and economic significance have encouraged researchers to study how climate change affects grain production/yield levels in different parts of the world. Previous studies have shown that precipitation and temperature play key roles in the total production of crops in Asia as well as in many regions of the world. For example, Furuya and Jun Koyama (2005) [8] used a global econometric model to study the effects of climate change on rice production by considering precipitation and temperature as key climate variables and reported that the increase in rice production is due to the increase in the future temperature. However, these climate variables are highly sensitive to weather conditions at different geographical locations within a country. Welch et al. (2010) [9] used rice data from different countries and concluded that increased daytime temperatures are beneficial for yields, whereas

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decreased nighttime temperatures could decrease yields. Similarly, a similar regional study was conducted by Erda et al. (2005) [10], and the authors reported an increase in wheat (28 %) and maize (18 %) yields. Xiong et al. (2008) used IPCC scenarios (A2 and B2) and reported an increase in grain production relative to the base period (1961–1990) in most provinces of southeastern, northwestern, and northeastern China. Piao et al. (2010) [11] reported that regional warming imposes a significant effect on the crop growing season (planting and harvesting), allowing farmers to plant earlier. Other researchers have reported that climate change can exert both negative and positive effects on grain production on the basis of county-level household data from 28 provinces in China [12]. Similarly, many studies have indicated a decrease in the grain yield due to a decrease or increase in the temperature during the growing season in different parts of Asia, such as Vietnam, Malaysia, Indonesia, the Philippines, Laos, and the Mekong Delta [13–16]. This mixed state of research findings has driven the further investigation of the impact of climate change on yields because previous researchers used different types of data in their studies. While several studies have focused on examining the impacts of climate change on grain production, few studies have been conducted to assess the impact of climate change on the grain market. For example, J. Furuya, Kobayashi, and Yamauchi (2014) [17] performed a study to assess the response of the rice market to climate change. The authors used evapotranspiration instead of precipitation and temperature as the key research variable. The reason behind the selection of evapotranspiration instead of temperature and precipitation was that climate change affects evapotranspiration, which leads to variations in farming areas and crop yields. The study results revealed that climate change affects the grain market and that production decreased by 1.76 %–2.19 % during the wet and dry seasons. Kunimitsu, (2015) [18] used a computable general equilibrium model to assess the long-term response of agricultural production to climate change and reported that climate change is not beneficial for farmers and that consumer surplus may increase. Le (2016) [19] reported that the production of rice may decrease by up to 18 % in 2030, and farmers may experience a sales loss of up to 16.02 % in Vietnam's rice market.

In this study, we first used a cointegration framework to calculate the long-term impacts of climate change and then adopted a gravity model to simulate the impact of climate change on the Northeast China grain market. For this purpose, we considered the most important climate variables (precipitation (P) and temperature (T)) to estimate the effects of climate change on grain yields.

The remainder of this manuscript includes descriptions of the datasets and the gravity model approach (Sections 2 and 3, respectively). The model and simulation results are presented in Section 4. Finally, in Section 5, the key findings and conclusions are outlined.

2. Datasets

Northeast Chinese farmers traditionally cultivate one crop per year due to the unique geographical location of the area, which exhibits a long winter and short summer. This area is the most prominent grain base in China, with a farmland area of approximately 1.82×10^5 km^2. In this analysis, yield data (metric tons) for rice, maize, soybean, and wheat were obtained from China Statistical Yearbooks (2004–2018) (Yearbooks, 2004–2018) [20]. Regional average meteorological data (P and T: maximum and minimum) from 106 stations were extracted from the China Meteorological Administration (CMA) (www.cma.gov.cn) for Northeast China provinces.

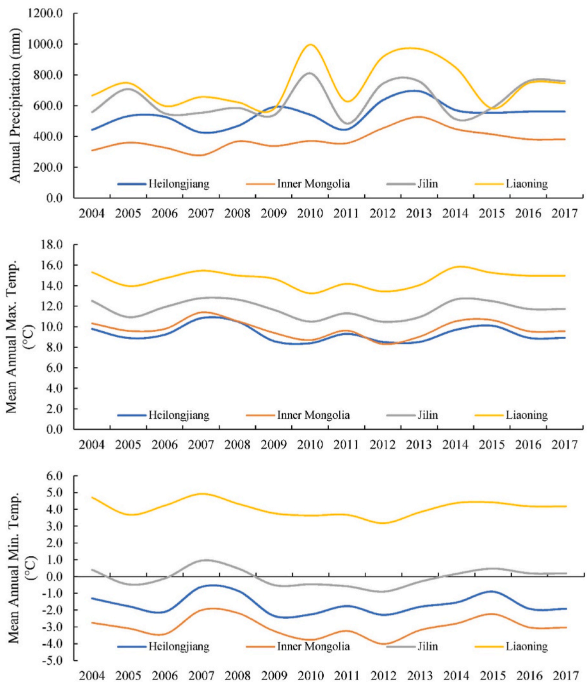

Fig. 1. Mean annual temperatures and precipitation in the provinces of Northeast China.

The highest temperature in July ranges from 22 °C to 35 °C, while the annual mean maximum temperature varies between 8 and 17 °C; the lowest temperature in January ranges from −15.5 °C to 25 °C, while the annual mean minimum temperature varies between −4 and 5 °C; the annual precipitation from May to September varies between 400 and 1062 mm, whereas the annual mean total precipitation varies between 200 and 1200 mm in Northeast China (Fig. 1) [21,22].

In the empirical analysis, the climate variables and yield were subjected to logarithmic form. Downscaled regional climate model (RCM) projections for three climate variables (precipitation and temperatures (maximum and minimum values)) and two representative concentration pathways (RCPs) (RCP4.5 and RCP8.5) were obtained from http://chinaccdp.org/for the 2020 to 2079 period. The performance of the RCM, namely, the Providing REgional Climate Impacts for Studies (PRECIS)–Hadley Centre Global Environment Model version 2 (HadGEM2)–Earth Systems (ES) model, has already been examined and assessed by Ref. [23] Zhu et al. (2018). The HadGEM2-ES simulations are restricted to the PRECIS model domain lateral boundary conditions [24]. Compared with eleven other Earth system models, this model provides high-resolution and significant vegetation dynamics information [25,26].

3. Model

A regression equation was used to study the effects of climate change on the Northeast China grain market. Before the calculation of regression results, the unit root test was adopted to avoid specious analysis. The base estimation models can be written as follows:

Precipitation model:

$$\ln p_{rt} = \alpha_{rt} + \beta_1(\ln E_{rt}) + \beta_2(\ln C_{rt}) + \beta_3(\ln BS_{rt}) + \beta_4(ES_{rt}) + \beta 5(\ln FOB) + \beta_6(\ln PR_{rt}) + \varepsilon_{it} \tag{1}$$

Maximum temperature model:

$$\ln T\ \max_{rt} = \alpha_{rt} + \beta_1(\ln E_{rt}) + \beta_2(\ln C_{rt}) + \beta_3(BS_{rt}) + \beta_4(\ln ES_{rt}) + \beta 5(\ln FOB) + \beta_6(\ln PR_{rt}) + \varepsilon_{it} \tag{2}$$

Minimum temperature model:

$$\ln T\ \min_{rt} = \alpha_{rt} + \beta_1(\ln E_{rt}) + \beta_2(\ln C_{rt}) + \beta_3(\ln BS_{rt}) + \beta_4(\ln ES_{rt}) + \beta 5(\ln FOB) + \beta_6(\ln PR_{rt}) + \varepsilon_{it} \tag{3}$$

where the coefficients and error terms of the explanatory variables are denoted as $\alpha, \beta, and\varepsilon$. In Eqs. (1)–(3), E denotes the export of a specific crop (rice, maize, and soybean), and C denotes the domestic consumption of rice, maize, or soybean. Moreover, BS and ES are the beginning and ending stock amounts, respectively, and FOB and PR denote the wholesale price linkage and export price, respectively.

$$\Delta m_t = \alpha m_{t-1} + n_t\delta + \sum_{p=1}^{p} \Delta m_{t-p} + \varepsilon_t \tag{4}$$

where Δm_{t-p} and m_t denote the high-order correlations and exogenous regressors, respectively. Moreover, the dynamic ordinary least square was used for the regression analysis ($m_t = n_t'\delta + \varepsilon_t$) to calculate the cointegration vector between the considered variables that may describe the long-run association.

$$m_t = \beta_{0+} + \vec{\beta} O + \sum_{j=-q}^{L} \vec{d} m_{t-j} + \mu_t \tag{5}$$

where O and y_t denote the matrix of the dependent variables and the dependent variable, respectively. The effect of a change in

Table 1
Descriptive statistics based on regional data.

Definition	Variables	Hadri LM test (unit root)	Mean	Maximum	Minimum	Std. dev.	Jarque–Bera	Probability
Rice Export	*RE*	8.1353	11	67	0	16	81.6	0.3
Soybean Export	*SE*	8.9733	6	28	0	7	31.9	0.6
Maize Export	*ME*	7.2342	34	491	0	82	743.3	0.56
Rice Ending Stock	*ESR*	14.3375	753	2819	51	755	17.1	0.3
Rice Consumption	*CR*	6.3321	55	170	2	52	9	0.089
Maize Ending Stock	*ESM*	14.388	2131	4280	977	843	5.7	0.061
Maize Consumption	*CM*	6.8672	161	327	49	65	2.5	0.28
Soybean Ending Stock	*ESS*	5.969	205	769	17	227	14.2	0.07
Soybean Consumption	*CS*	8.568	31	144	3	35	25.3	0.12
Free-on-Board	*FOB*	14.3775	1639469	2343222	593647	594285	5.2	0.065
Precipitation	*P*	1.4675	574	998	279	167	2.1	0.34
Maximum Temperature	*Tmax*	−0.311	11	16	8	2	4.7	0.09
Minimum Temperature	*Tmin*	−0.5524	0	5	−4	3	5.7	0.06
Rice Price	*PR*	14.8579	2307	3100	1500	683	7.3	0.07
Maize Price	*PM*	12.0351	1813	2240	1500	293	6.2	0.05
Soybean Price	*PS*	12.2404	3628	4710	1433	1220	8.5	0.17

The obtained test results revealed that the variables were normally distributed and stationary and could be used for regression analysis.

variable O on m is represented by the cointegration vector $\overrightarrow{\beta}$. Moreover, P and q are the lag and lead lengths, respectively.

4. Results

4.1. Descriptive statistics

Nonstationarity in data leads to specious econometric results. Thus, the identification of stationary or nonstationary data is necessary to obtain a robust regression. A panel unit root test was employed to examine the data properties, whether they were stationary or nonstationary. The null hypothesis was set to Ha (there is no unit root), and the alternative hypothesis was set to Ho (there is a unit root, which indicates that the data are not stationary). The Hadri LM test revealed that the properties of the data were stationary at a given level ($p < 0.05$). Table 1 provides a summary of the descriptive statistics, panel unit root test results, and Jarque–Bera test results for the normality distributions of all the variables.

4.2. Cointegration analysis

Engle and Granger (1987) proposed the cointegration method to assess the long-term associations between regression variables [27]. Therefore, we used Eview version 10 software and the Dickey−Fuller method to analyze the associations between the studied variables. This method is appropriate for more than two variables. Thus, the Dickey−Fuller method was finally used for evaluating the association among the variables. The Dickey−Fuller statistics for precipitation, maximum temperature, and minimum temperature are presented in Table 2. The results revealed that the variables exhibit long-term associations on the basis of the p value (<0.01).

4.3. Dynamic ordinary least square and fully modified ordinary least square estimation

The effects of the climate variables on consumption and exports were obvious (Table 3). For example, a 1 % increase in precipitation may lead to an increase of 0.13 % in rice consumption while causing a reduction in exports of 0.49 %. An increase in the maximum temperature was also beneficial for the rice market. For example, an increase in the maximum temperature of up to 1 % could decrease wholesale prices by up to 0.45 %. The reason is that Northeast China is situated in the Northern Hemisphere, where the winters are long and the summers are very short. Therefore, an increase in the temperature may help growers achieve early sowing in the largest area typically covered with snow and ice until the end of March, which could increase yields and lead to maximum consumption, lower export (Fig. 2) and low prices. The positive sign of the temperature for the export of rice revealed that the increase in exports caused a reduction in wholesale prices (Table 3). Similarly, for maize consumption and export, both the maximum temperature and precipitation functioned in similar ways in regard to rice consumption and export.

4.4. Long- and short-run causality tests

Long- and short-term causality tests were performed to assess the long-or short-term effects, respectively, among the variables (Table 4). The Granger causality test was used to assess causality among the variables. The negative coefficients suggested long-and short-term causality characteristics from the independent to the dependent variables. The consumption variables for maize and soybeans showed significant long- and short-term causality characteristics. The climate variables did not affect rice consumption, whereas the maximum temperature and minimum temperature affected maize consumption in the long run. Regarding the exports of rice, maize, and soybean, long-term causality was found between the dependent and independent variables (Table 5).

4.5. Impacts of climate change on the consumption and export of rice, maize, and soybean

The possible impacts of climate change on domestic consumption and export levels were examined on the basis of precipitation and

Table 2
Long-term associations among the variables based on the cointegration test.

	Statistic	P value
P vs. RE, SE, ME, CR, CS, CM		
Modified Dickey–Fuller t	−3.3424	0.0004
Dickey–Fuller t	−5.2347	0.000
Augmented Dickey–Fuller t	−3.1291	0.0009
Tmax vs. RE, SE, ME, CR, CS, CM		
Modified Dickey–Fuller t	−2.7609	0.0029
Dickey–Fuller t	−2.77	0.0028
Augmented Dickey–Fuller t	−3.3308	0.0004
Tmin vs. RE, SE, ME, CR, CS, CM		
Modified Dickey–Fuller t	−3.087	0.001
Dickey–Fuller t	−3.1012	0.001
Augmented Dickey–Fuller t	−3.4846	0.0002

Table 3
Panel dynamic least square and fully modified least square estimation results.

Method: Panel Dynamic Least Squares (DOLS)							Method: Panel Fully Modified Least Squares (FMOLS)					
Rice	P		Tmax		Tmin		P		Tmax		Tmin	
Variable	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic
lnCR	0.1331	1.9437	−0.0027	0.9902	0.3581	0.2605	0.1111	1.0529	−0.2996	−6.7081	−2.6932	−7.9318
lnBSR	0.5185	0.5963	−1.0840	0.0559	−6.8037	−2.1697	−22.6979	−1.0416	4.0538	0.4797	67.5858	1.0173
lnESR	−0.5416	−0.6615	0.3144	1.6059	2.2191	1.6484	22.3031	1.0108	−4.0760	−0.4772	−68.2773	−1.0162
lnER	−0.4993	−7.7962	0.5226	9.3722	2.8159	12.3898	−0.1610	−1.2207	0.0450	0.6647	0.8240	1.5669
lnFOB	1.5726	2.4862	0.3340	0.4147	0.9837	0.5128	0.2862	2.1075	0.2074	3.8689	2.2418	5.3758
lnPR	2.4395	1.9948	−0.2526	−0.6668	1.5241	0.5496	0.1949	1.1172	−0.4567	−6.1934	−4.3841	−7.7942
SE of regression	14.1023		1.2591		3.3295		9.5800		1.6287		19.6390	
Long-run variance	0.0151		0.0021		0.0496		0.0060		0.0011		0.0611	
Maize												
lnCM	1.4592	4.9744	−0.9037	−5.1527	−6.0360	−5.3425	0.0666	1.0099	−0.1341	−4.8284	−0.6988	−4.2488
lnBSM	2.2555	4.4466	−0.9186	−4.8290	−6.2102	−4.7740	25.3398	1.2144	−11.1309	−1.0278	−123.5325	−1.7482
lnESM	−0.8667	−1.7059	0.3937	2.5546	2.4523	3.0431	−25.0911	−1.2034	10.9180	1.0100	122.8157	1.7413
lnEM	0.0159	1.2068	−0.0038	−0.4836	−0.0023	−0.0660	0.0166	1.1277	0.0069	0.8893	0.0782	1.5591
lnFOB	−1.2297	−3.2839	0.6341	16.9861	5.2804	7.2685	−0.3014	−1.4025	0.2819	3.1617	2.1583	3.9654
lnPM	2.7272	4.1904	−1.4360	−22.1330	−10.2549	−8.1219	0.7896	3.1986	−0.3656	−3.5617	−3.2480	−5.1335
SE of regression	6.9864		1.3610		9.2234		5.5764		2.3956		16.6625	
Long-run variance	0.0116		0.0001		0.0435		0.0066		0.0011		0.0443	
Soybean												
lnCS	−0.2152	−0.3074	−0.5521	−2.5318	−4.1742	−2.7563	−0.5138	−2.7660	0.0770	0.9640	−0.3646	−0.6347
lnBSS	0.3668	0.5337	0.4558	1.8807	3.7096	2.2216	33.6912	1.0773	−10.3109	−0.6301	−48.1654	−0.4475
lnESS	0.2419	1.2784	−0.2929	−3.9196	−1.6300	−3.3431	−32.5618	−1.0385	9.9363	0.6056	46.7170	0.4330
lnES	0.0341	0.8117	−0.0321	−2.2082	−0.1200	−1.5408	0.1141	0.5304	−0.0654	−0.5859	−0.4014	−0.5444
lnFOB	2.4612	8.4098	−0.8067	−7.1317	−5.2612	−14.1200	0.0731	0.4341	−0.0312	−0.3792	−1.0962	−1.9679
lnPS	−2.5070	−6.3171	1.0049	6.5512	7.7961	15.4295	0.1415	1.0035	−0.0216	−0.3218	0.6668	1.4370
SE of regression	5.4946		1.9112		3.6735		10.9001		3.6330		17.6291	
Long-run variance	0.0057		0.0009		0.0093		0.0099		0.0022		0.1039	

Note: For variable definitions, please refer to Table 1.

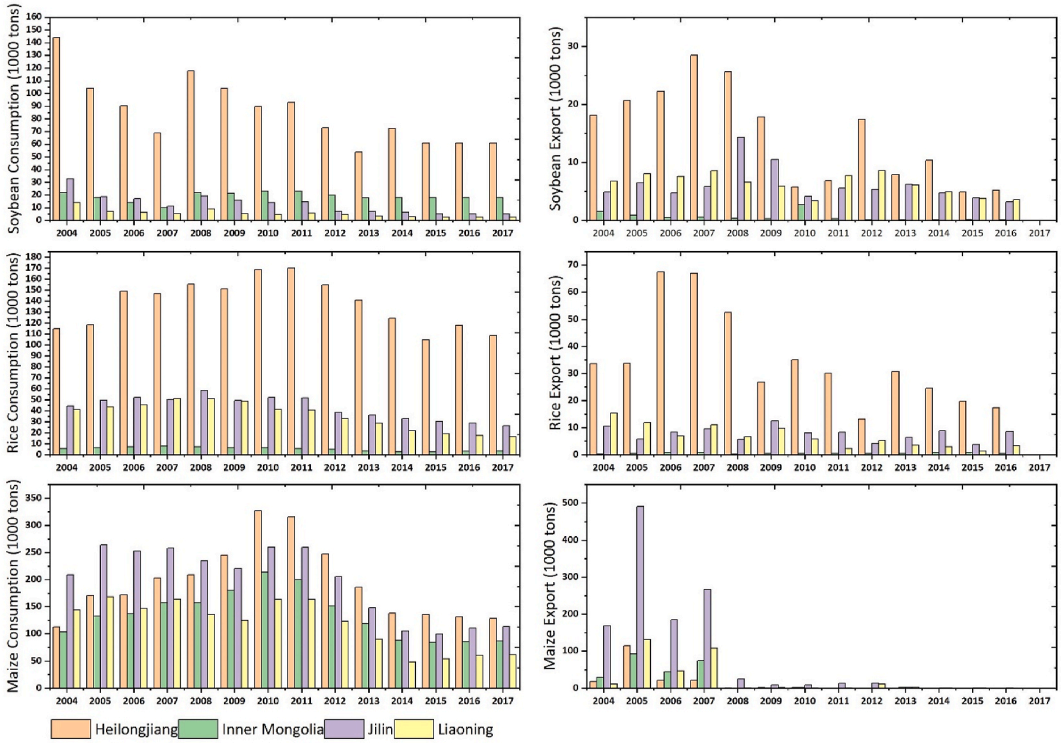

Fig. 2. Export and consumption of rice, maize, and soybean.

Table 4
Long- and short-run causality test results for domestic consumption.

Rice		P			Tmax			Tmin		
		Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
Long run		−0.014903	−1.301824	0.1969	−0.028455	−1.385923	0.1698	−0.026364	−1.361193	0.1775
	Durbin-Watson stat	2.100311			2.258033			1.931438		
Short-run	Wald test	2.372996		0.3053	1.388815		0.4994	0.995365		0.6079
Maize										
Long run		−0.163402	−2.317883	0.0231	−0.162112	−3.977905	0.0416	−0.13587	−2.848355	0.0484
	Durbin-Watson stat	2.371374			2.52748			2.482218		
Short-run	Wald test	0.174113		0.9166	1.959957		0.3753	7.756456		0.0207
Soybean										
Long run		−0.093877	−4.91128	0.0397	−0.090751	−1.554329	0.1243	−0.063712	−1.272197	0.2072
	Durbin-Watson stat	2.215731			2.095935			1.977667		
Short-run	Wald test	0.182659		0.9127	3.144526		0.2076	9.147369		0.0103

Note: The highlighted values indicate the significance of the variables. For variable definitions, please refer to Table 1.

the maximum and minimum temperatures under the two representative concentration pathways (RCPs) obtained from the RCM simulations with different CO_2 concentrations. The results revealed that under RCP4.5 and RCP8.5, domestic consumption may be promoted by precipitation from 2020 to 2076, whereas ln_Tmax exhibited a significant negative sign for domestic consumption (Table 6). An earlier study revealed that the temperature might increase in the region [28]. The negative effect of precipitation under RCP8.5 may be due to uncertainties linked with the regional climate model. Moreover, the possibility of conforming with the availability of water might not be an important limiting factor in the region. The climate change scenario results also revealed that the exports of rice, maize, and soybean might decrease due to an increase in domestic consumption. A previous study revealed that a decrease in crop productivity is expected in Northeast China during future periods [28]. In this scenario, climate change adaptation strategies such as changing crop cultivation locations, planting dates, and crop management practices are necessary to mitigate climate change.

Table 5
Long- and short-run causality test results for exports.

RE		P			Tmax			Tmin		
		Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
Long run		−0.194	−3.159	0.0023	−0.195	−3.129	0.0025	−0.1950	−1.3612	0.0018
	Durbin-Watson stat	2.220			2.132			1.9274		
Short-run	Wald test	0.943		0.6242	0.329		0.8485	2.0296		0.3625
ME										
Long run		−0.498	−7.227	0.000	−0.500	−7.381	0.000	−0.4899	−7.1974	0.000
	Durbin-Watson stat	2.154			2.066			1.9867		
Short-run	Wald test	2.555		0.287	8.271		0.016	12.5264		0.0019
SE										
Long run		−0.200	−2.079	0.041	−0.200	−2.198	0.031	−0.1834	−2.1437	0.0353
	Durbin-Watson stat	2.197			2.237			1.8703		
Short-run	Wald test	0.562		0.7551	5.148		0.0762	9.6368		0.0081

Note: The highlighted values indicate the significance of the variables. For variable definitions, please refer to Table 1.

5. Discussion and conclusions

The statistical findings of this study indicated that climate change is a significant factor influencing domestic consumption and export levels of grains in Northeast China. Grain production exhibits great economic value in the region, and the significant impact of climate change could restrict the regional food security. Specifically, domestic production and exports exhibit a significant relationship with the temperature throughout the study period. The study results demonstrated that further models for climate change impact estimation at the local and global levels are needed. For example, our results revealed that precipitation generates a negative effect, which is a crucial element for agriculture [29]. Future studies could focus on investigating the impacts of management practices combined with climate change adaptation strategies on future food production and food security. Furthermore, this work may contribute to our understanding of how warmer climates impact the agricultural crop production market by addressing the positive and negative impacts of climate change on agriculture. In contrast, competitive behavior between grain-producing regions under climate change can support the creation of new models that can be used freely beyond the national level for developing future adaptation strategies.

Moreover, our findings emphasize the crucial effects of extreme temperatures on the export and domestic consumption of grain crops, guiding future research efforts to investigate the entire spectrum of climate change risks to agricultural production, particularly concerning the effects of high- and low-temperature differences. There is a growing need for adaptation due to the likelihood of climate change and its increasing severity. Farming practices still encompass many substantial opportunities for improvement in the future, even though research institutes have started to provide adaptation policies and methodologies on the basis of forecasts [30,31]. For example, research could include additional advanced techniques such as controlling climate vulnerability through early season forecasting, which could enable precise irrigation by knowing the starting dates for crop harvesting [32–34].

As China has undergone rapid development, the conflicts between industrial land use and property development and between industrial land use and grain production land use have intensified. Since increasing agricultural land rapidly is challenging, the most feasible approach is to maximize the per capita limit. Currently, the government has considered grain-producing regions, while core grain areas (e.g., Northeast China) are receiving more attention from the Chinese government in terms of food policies [35,36]. Therefore, identifying the factors influencing the grain yield can be accomplished by concentrating on important aspects of grain production. This could be achieved by implementing the following measures. (1) Given the adverse impact of climate change on grain production, monitoring climatic conditions throughout the growing season is imperative. Thus, crop loss can be reduced if farmers receive accurate weather forecasts in advance and make the best possible decisions accordingly. (2) Adjusting the agricultural layout could also help minimize the effects of climate change. Even though the layout of Chinese grain-producing farmers has greatly improved over the last few decades, additional modifications are still necessary. For layout modification, China must focus on the implementation of water conservancy projects. Notably, precipitation exhibits a nonsignificant trend and does not reach the standard level. Some researchers also mentioned that water conservancy projects in the region are insufficient, which is why a major portion of grain production still depends on natural water resources. Therefore, it is highly advised that infrastructure and water conservation be amended and made more appropriate. Furthermore, the research results based on fully modified ordinary linear squares and dynamic least squares methods revealed that climate change and global warming significantly affect export and domestic consumption levels. The positive and negative coefficients attributed to precipitation and temperature, respectively, suggest that both variables are very important for yields because the study area is situated in a severely cold region of China, and an increase in the temperature may be beneficial for early sowing. Similarly, long- and short-term causality characteristics were observed from the independent variables to the dependent variables, suggesting that both variables are very important for consumption and exports. The results of two climate scenarios, namely, RCP4.5 and RCP8.5, revealed that domestic consumption may benefit from increased precipitation from 2020 to 2076.

Precipitation and temperature affect crop yields differently at different crop growth stages. Therefore, using month-based data on precipitation and temperature as explanatory variables is a potential extension of this study. This approach may provide insights into

Table 6
Impact of climate change on the selected variables.

RCP 4.5												
P	D1 (2020–2034)			D2 (2035–2048)			D3 (2049–2062)			D4 (2063–2076)		
Variable	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
lnCR	16.023	3.789	0.001	12.101	2.709	0.010	2.804	1.152	0.256	−6.317	−1.482	0.146
lnCM	1.456	3.864	0.000	0.874	1.813	0.077	1.005	2.991	0.005	0.524	0.915	0.365
lnCS	6.942	1.609	0.115	1.385	0.198	0.844	3.493	0.758	0.453	8.367	1.120	0.269
lnRE	33.245	2.848	0.007	−23.259	−1.860	0.070	−4.700	−0.774	0.443	−1.454	−0.130	0.898
lnME	−0.020	−0.086	0.932	0.618	1.749	0.088	0.192	0.734	0.467	0.319	0.696	0.490
lnSE	−15.855	−3.189	0.003	−11.366	−1.951	0.058	−4.007	−1.207	0.234	9.993	1.744	0.089
Tmax												
lnCR	−0.159	−8.661	0.000	−0.125	−3.232	0.002	−0.122	−2.948	0.005	0.061	2.369	0.023
lnCM	0.012	6.360	0.000	0.010	2.923	0.006	0.010	3.652	0.001	−0.004	−2.004	0.052
lnCS	−0.012	−0.443	0.660	−0.060	−1.418	0.164	−0.098	−3.136	0.003	−0.035	−1.611	0.115
lnRE	−0.194	−3.802	0.001	0.231	2.031	0.049	−0.027	−0.205	0.838	0.193	2.400	0.021
lnME	0.006	4.606	0.000	−0.001	−0.629	0.533	−0.008	−3.670	0.001	0.000	0.017	0.987
lnSE	−0.006	−0.256	0.799	0.033	0.701	0.487	−0.008	−0.158	0.875	0.055	1.770	0.084
Tmin												
lnCR	−0.103	−3.139	0.003	−0.070	−2.375	0.022	−0.095	−2.552	0.015	0.104	4.558	0.000
lnCM	0.006	3.325	0.002	0.008	3.654	0.001	0.005	2.170	0.036	−0.007	−4.049	0.000
lnCS	−0.011	−0.539	0.593	−0.067	−2.337	0.024	−0.069	−2.911	0.006	−0.025	−1.479	0.147
lnRE	−0.228	−2.077	0.044	0.049	0.529	0.600	−0.009	−0.077	0.939	0.046	0.659	0.513
lnME	0.004	2.523	0.016	−0.002	−1.422	0.162	−0.007	−4.081	0.000	−0.002	−1.323	0.193
lnSE	−0.063	−1.586	0.120	−0.008	−0.229	0.820	−0.006	−0.136	0.893	0.062	2.289	0.027
RCP 8.5												
P												
lnCR	6.366	1.363	0.180	5.031	1.242	0.221	4.771	1.127	0.266	1.516	0.434	0.666
lnCM	1.101	1.889	0.066	0.627	1.839	0.073	−2.132	−4.985	0.000	0.079	0.178	0.859
lnCS	−4.709	−0.557	0.581	−7.999	−1.950	0.058	−1.562	−0.284	0.778	−9.024	−1.833	0.074
lnRE	−30.355	−2.607	0.013	−33.565	−2.844	0.007	5.887	0.497	0.622	−35.671	−4.750	0.000
lnME	0.210	0.499	0.621	0.241	1.065	0.293	0.961	3.138	0.003	−0.162	−0.526	0.602
lnSE	−3.258	−0.524	0.603	−14.873	−3.064	0.004	−1.342	−0.255	0.800	−1.691	−0.408	0.686
Tmax												
lnCR	−0.047	−1.296	0.202	0.292	6.724	0.000	−0.191	−10.764	0.000	−0.102	−3.183	0.003
lnCM	−0.008	−2.453	0.018	−0.006	−2.348	0.024	0.007	4.204	0.000	0.004	0.996	0.325
lnCS	0.050	1.191	0.240	0.019	0.741	0.463	−0.062	−3.454	0.001	−0.047	−1.267	0.212
lnRE	0.003	0.030	0.976	0.188	1.342	0.187	−0.253	−6.296	0.000	−0.462	−7.454	0.000
lnME	0.005	2.383	0.022	−0.007	−3.372	0.002	−0.005	−5.189	0.000	−0.002	−1.244	0.221
lnSE	0.036	0.818	0.418	0.117	2.263	0.029	0.027	1.379	0.175	0.046	1.301	0.200
Tmin												
lnCR	−0.055	−1.928	0.061	0.044	1.678	0.101	−0.128	−8.477	0.000	−0.032	−1.432	0.160
lnCM	−0.005	−2.134	0.039	0.003	1.261	0.214	−0.004	−2.305	0.026	0.000	−0.149	0.882
lnCS	0.033	1.421	0.163	−0.027	−1.547	0.129	−0.027	−2.036	0.048	−0.056	−2.109	0.041
lnRE	−0.015	−0.176	0.861	0.021	0.257	0.798	−0.137	−3.634	0.001	−0.404	−7.520	0.000
lnME	0.002	1.081	0.286	−0.009	−5.611	0.000	−0.003	−1.770	0.084	−0.001	−0.690	0.494
lnSE	0.037	1.100	0.278	0.061	1.959	0.057	0.014	0.822	0.416	−0.040	−1.521	0.136

For variable definitions, please refer to Table 1.

the effects of precipitation and temperature on crop yields, which could facilitate optimizing their consumption and export. Moreover, this study provides sufficient results that may help policy-makers develop the regional agricultural economy.

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Ethical approval

This study does not require ethical approval, as no human participants or animal subjects were involved.

Data availability

RCP data are available at http://chinaccdp.org/. Regional averaged meteorological data are available at www.cma.gov.cn, and yield consumption and export data can be obtained from http://tongji.cnki.net and the Statistical Yearbook of 2018.

Consent for publication

Is not applicable.

CRediT authorship contribution statement

Trinh Thi Viet Ha: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Wenqi Zhou:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

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

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References

[1] S. Asseng, F. Ewert, P. Martre, R.P. Rötter, D.B. Lobell, D. Cammarano, B.A. Kimball, M.J. Ottman, G.W. Wall, J.W. White, Rising temperatures reduce global wheat production, Nat. Clim. Change 5 (2015) 143–147.
[2] M. Burke, S.M. Hsiang, E. Miguel, Global non-linear effect of temperature on economic production, Nature 527 (2015) 235–239.
[3] B.C. O'neill, M. Oppenheimer, R. Warren, S. Hallegatte, R.E. Kopp, H.O. Pörtner, R. Scholes, J. Birkmann, W. Foden, R. Licker, IPCC reasons for concern regarding climate change risks, Nat. Clim. Change 7 (2017) 28–37.
[4] M.A. Hanjra, M.E. Qureshi, Global water crisis and future food security in an era of climate change, Food Pol. 35 (2010) 365–377.
[5] R. Wassmann, S.V.K. Jagadish, K. Sumfleth, H. Pathak, G. Howell, A. Ismail, R. Serraj, E. Redona, R.K. Singh, S. Heuer, Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation, Adv. Agron. 102 (2009) 91–133.
[6] N. Stern, The economics of climate change, Am. Econ. Rev. 98 (2008) 1–37, https://doi.org/10.1257/aer.98.2.1.
[7] N. Stern, The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models, J. Econ. Lit. 51 (2013) 838–859.
[8] J. Furuya, O. Koyama, Impacts of climatic change on world agricultural product markets: estimation of macro yield functions, Jpn. Agric. Res. Q.: Jpn. Agric. Res. Q. 39 (2005) 121–134.
[9] J.R. Welch, J.R. Vincent, M. Auffhammer, P.F. Moya, A. Dobermann, D. Dawe, Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures, Proc. Natl. Acad. Sci. U.S.A. 107 (2010) 14562–14567, https://doi.org/10.1073/pnas.1001222107.
[10] L. Erda, X. Wei, J. Hui, X. Yinlong, L. Yue, B. Liping, X. Liyong, Climate change impacts on crop yield and quality with CO_2 fertilization in China, Phil. Trans. R. Soc. B 360 (2005) 2149–2154, https://doi.org/10.1098/rstb.2005.1743.
[11] S. Piao, P. Ciais, Y. Huang, Z. Shen, S. Peng, J. Li, L. Zhou, H. Liu, Y. Ma, Y. Ding, The impacts of climate change on water resources and agriculture in China, Nature 467 (2010) 43–51.
[12] H. Liu, X. Li, G. Fischer, L. Sun, Study on the impacts of climate change on China's agriculture, Climatic Change 65 (2004) 125–148, https://doi.org/10.1023/B:CLIM.0000037490.17099.97.
[13] M.M. Alam, B. Talib, C. Siwar, M.E. Toriman, The impacts of climate change on paddy production in Malaysia: case of paddy farming in North-West Selangor, in: Proceedings of the International Conference of the 4th International Malaysia-Thailand Conference on South Asian Studies, National University of Malaysia, Malaysia, Mar, 2010, pp. 25–26.
[14] R.L. Naylor, D.S. Battisti, D.J. Vimont, W.P. Falcon, M.B. Burke, Assessing risks of climate variability and climate change for Indonesian rice agriculture, Proc. Natl. Acad. Sci. U.S.A. 104 (2007) 7752–7757, https://doi.org/10.1073/pnas.0701825104.
[15] D.K. Nhan, N.H. Trung, N. Van Sanh, The impact of weather variability on rice and aquaculture production in the Mekong Delta, in: M.A. Stewart, P.A. Coclanis (Eds.), Environmental Change and Agricultural Sustainability in the Mekong Delta, Springer Netherlands, Dordrecht, 2011, pp. 437–451, https://doi.org/10.1007/978-94-007-0934-8_24.
[16] M. Shean, Southeast Asia: historical el nino-related crop yield impact, Washington DC: US department of agriculture/foreign agricultural service, Commodity Intelligence Reports (2014). https://fas.usda.gov/data/southeast-asia-historical-el-ni-o-related-crop-yield-impact.

[17] J. Furuya, S. Kobayashi, K. Yamauchi, Impacts of climate change on rice market and production capacity in the Lower Mekong Basin, Paddy Water Environ. 12 (2014) 255–274, https://doi.org/10.1007/s10333-013-0394-y.

[18] Y. Kunimitsu, Regional impacts of long-term climate change on rice production and agricultural income: evidence from computable general equilibrium analysis, Jpn. Agric. Res. Q.: Jpn. Agric. Res. Q. 49 (2015) 173–185.

[19] T.T. Le, Effects of climate change on rice yield and rice market in Vietnam, J. Agric. Appl. Econ. 48 (2016) 366–382.

[20] C.S. Yearbook, National bureau of statistics of the People's Republic of China (2004). URL: Http://Www. Stats. Gov. Cn/Tjsj/Ndsj/. (Accessed 31 July 2021).

[21] M.A. Faiz, D. Liu, Q. Fu, F. Naz, N. Hristova, T. Li, M.A. Niaz, Y.N. Khan, Assessment of dryness conditions according to transitional ecosystem patterns in an extremely cold region of China, J. Clean. Prod. 255 (2020) 120348.

[22] M.A. Faiz, D. Liu, Q. Fu, Q. Sun, M. Li, F. Baig, T. Li, S. Cui, How accurate are the performances of gridded precipitation data products over Northeast China? Atmos. Res. 211 (2018) 12–20.

[23] J. Zhu, G. Huang, X. Wang, G. Cheng, Y. Wu, High-resolution projections of mean and extreme precipitations over China through PRECIS under RCPs, Clim. Dynam. 50 (2018) 4037–4060, https://doi.org/10.1007/s00382-017-3860-1.

[24] W.J. Collins, N. Bellouin, M. Doutriaux-Boucher, N. Gedney, T. Hinton, C.D. Jones, S. Liddicoat, G. Martin, F. O'Connor, J. Rae, Evaluation of the HadGEM2 Model, Met Office Exeter, UK, 2008. https://www.inscc.utah.edu/~reichler/publications/papers/Collins_08_MetOffice_74.pdf. (Accessed 16 July 2024).

[25] K.C. Hegewisch, J.T. Abatzoglou, An Improved Multivariate Adaptive Constructed Analogs (MACA) Statistical Downscaling Method, 2016.

[26] N. Bellouin, W.J. Collins, I.D. Culverwell, P.R. Halloran, S.C. Hardiman, T.J. Hinton, C.D. Jones, R.E. McDonald, A.J. McLaren, F.M. O'Connor, The HadGEM2 family of met office unified model climate configurations, Geosci. Model Dev. (GMD) 4 (2011) 723–757.

[27] R.F. Engle, C.W. Granger, Co-integration and error correction: representation, estimation, and testing, Econometrica: J. Econom. Soc. (1987) 251–276.

[28] Q. Xu, H. Liang, Z. Wei, Y. Zhang, X. Lu, F. Li, N. Wei, S. Zhang, H. Yuan, S. Liu, Y. Dai, Assessing climate change impacts on crop yields and exploring adaptation strategies in NortheastNortheast China, Earth's Future 12 (2024) e2023EF004063, https://doi.org/10.1029/2023EF004063.

[29] D.B. Lobell, M.B. Burke, C. Tebaldi, M.D. Mastrandrea, W.P. Falcon, R.L. Naylor, Prioritizing climate change adaptation needs for food security in 2030, Science 319 (2008) 607–610, https://doi.org/10.1126/science.1152339.

[30] S. Sacchelli, S. Fabbrizzi, M. Bertocci, E. Marone, S. Menghini, I. Bernetti, A mix-method model for adaptation to climate change in the agricultural sector: a case study for Italian wine farms, J. Clean. Prod. 166 (2017) 891–900.

[31] M.K. Linnenluecke, J. Han, Z. Pan, T. Smith, How markets will drive the transition to a low carbon economy, Econ. Modell. 77 (2019) 42–54.

[32] T.M. Osborne, D.M. Lawrence, A.J. Challinor, J.M. Slingo, T.R. Wheeler, Development and assessment of a coupled crop–climate model, Global Change Biol. 13 (2007) 169–183, https://doi.org/10.1111/j.1365-2486.2006.01274.x.

[33] W.J. Sacks, D. Deryng, J.A. Foley, N. Ramankutty, Crop planting dates: an analysis of global patterns, Global Ecol. Biogeogr. 19 (2010) 607–620, https://doi.org/10.1111/j.1466-8238.2010.00551.x.

[34] R.P. Rötter, T. Palosuo, K.C. Kersebaum, C. Angulo, M. Bindi, F. Ewert, R. Ferrise, P. Hlavinka, M. Moriondo, C. Nendel, Simulation of spring barley yield in different climatic zones of Northern and Central Europe: a comparison of nine crop models, Field Crops Res. 133 (2012) 23–36.

[35] K. Xie, M. Ding, J. Zhang, L. Chen, Trends towards coordination between grain production and economic development in China, Agriculture 11 (2021) 975.

[36] X. Jiao, G. He, Z. Cui, J. Shen, F. Zhang, Agri-environment policy for grain production in China: toward sustainable intensification, China Agric. Econ. Rev. 10 (2018) 78–92.