Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea

Muhammad Nasrullah, Muhammad Rizwanullah, Xiuyuan Yu, Hyeonsoo Jo, Muhammad Tayyab Sohail and Lizhi Liang

ABSTRACT

This study aims to explore the impact of climate change, technology, and agricultural policy on rice production in South Korea. In the presence of a long-run relationship among variables, the results show that an increase in CO_2 emissions increases rice production by 0.15%. The mean temperature raises rice production by 1.16%. The rainfall has an adverse impact on rice production which shows improper irrigation systems and weather forecasting reports. Similarly, for technical factors, the area under rice and fertilizer used in the study has a direct effect on rice production. The study suggests that the Korean government needs to implement new policies and acquire advanced technology for weather forecasting. The concerned authorities need to inform rice growers about future weather and climate changes. We recommend that Korea needs to provide virgin arable undivided land to deserving rice growers based on ownership and/or lease for future food security. Finally, the study recommends that legislators should recommend policies for sustainable food security with the introduction of new agricultural technologies and subsidies, along with the provision of new varieties of seeds that can absorb the adverse shock of climate change and ensure a suitable amount of food.

Key words | ADF, ARDL, climatic factors, cointegration, PP, technical factors

Muhammad Nasrullah
Muhammad Rizwanullah
Xiuyuan Yu
Muhammad Tayyab Sohail
Lizhi Liang (corresponding author)
College of Public Administration,
Xiangtan University,
Hunan 411105,
China
E-mail: *188793258@qq.com*

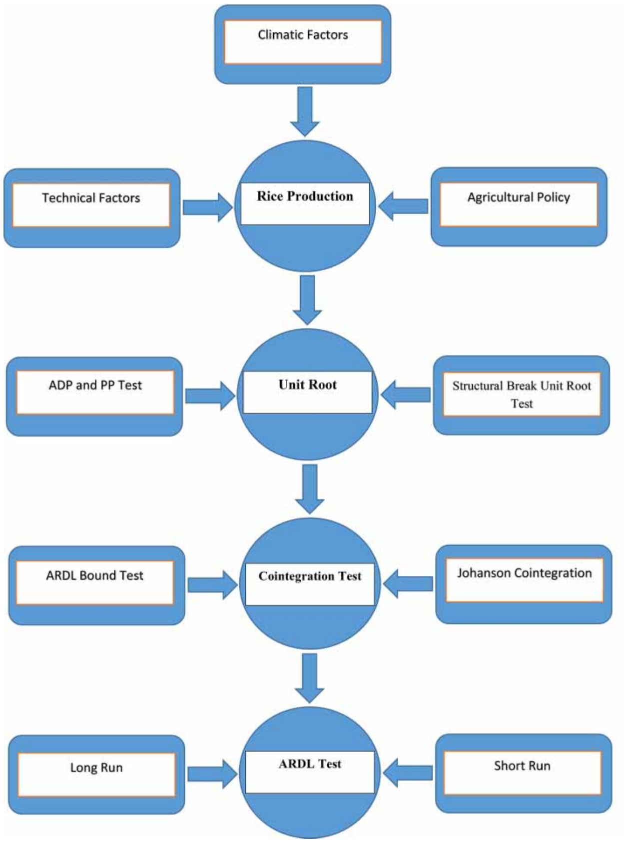
Hyeonsoo Jo
College of Animal Science and Technology,
Northeast Agricultural University,
Harbin 150030,
China

HIGHLIGHTS

- Carbon dioxide emission improves the process of photosynthesis due to which rice production increases in Korea.
- Rice production increases 1.16% with an increase in mean temperature in the long-run.
- Adverse shock of rainfall on rice production shows the improper irrigation system and weather forecasting reports.
- Cultivated area under rice has a noteworthy direct effect on rice production both in the short- and long-run.

doi: 10.2166/wcc.2021.030

GRAPHICAL ABSTRACT



INTRODUCTION

Agricultural researchers pay great attention to crop production due to variations in climate from the past to the present and from the present to the future (Lobell *et al.* 2011; Butler & Huyber 2012; Urban *et al.* 2012; Asseng *et al.* 2013; Wheeler & von Braun 2013). These variations in climate have an impact on agricultural production, but the variation in production over time has received less attention (Chen *et al.* 2013; Osborne & Wheeler 2013). The variations in agricultural production destabilize farmers' income (Reidsma *et al.* 2010; Li *et al.* 2013; Mottaleb *et al.* 2013), food supply (Slingo *et al.* 2005; Lobell & Burke 2010), and increase the price, which are negative effects of climate change (Ray *et al.* 2012, 2013). Climate change easily influences agricultural production due to meteorological variables that control the basic process in crop development and growth (Meza & Silva 2009). Climate has a positive or negative impact on agricultural production worldwide (Reilly *et al.* 2003; Tao *et al.* 2006, 2008; li *et al.* 2009; Lobell & Burke 2010; Özdoğan 2011; Siddiqui *et al.* 2012; Licker *et al.* 2013; Mishra *et al.* 2013; Janjua *et al.* 2014; Saadi *et al.* 2015; Ben-Ari *et al.* 2016), although these effects are unclear and their spatial pattern, driving mechanism, and severity are unidentified (Tao & Zhang 2013; Tao *et al.* 2014).

The Republic of Korea is situated in East Asia at 37° north, 127° 30 east with a total area of 96,920 square kilometers with 17,360 square kilometers of agricultural land. The share of agriculture in the GDP of South Korea fell from 27% to 3.3% from 1970 to 1999 (CIA 2007). In 2017, the total contribution of agriculture to GDP was

1.9%, and the contribution of rice in agriculture to GDP was 13.1% (KOSTAT 2017). The most grown crops in Korea are rice, barley, millet, corn, sorghum, buckwheat, etc. The production of rice in Korea decreased by 2.6% from the last year's production reported by KOSTAT (2019). Korea mostly depends on imports of agricultural products but these can be affected by various factors (Nasrullah *et al.* 2020). The most important Korean crop is rice, and is 90% of the country's total grain. Korean farmers cannot be competitive rice producers in the international market, but produce enough rice to fulfill domestic demand. The Korean agricultural policy in 1990 hugely disturbed farming communities due to removal of subsidies from agricultural inputs (fertilizer, pesticides, farm equipment, machinery, etc.). This policy not only caused a declines in agricultural production but also increased the demand for international agri-products (OECD 1999).

Mostly, two methods are used in natural science to work out the impact of climate changes on agriculture. In the first approach, there are crop simulation models (Chami & Daccache 2015; Li *et al.* 2015; Rotich & Mulungu 2017) (CERES, C-CAM, EPIC, and others) and climate change scenario (Özdoğan 2011; Jalota *et al.* 2014; Wilcox & Makowski 2014), while the second approach is climate chamber experiments or field experiments (Leadley & Drake 1992). The most used approach in natural science is the crop simulation model with a climate change scenario. However, this model is difficult and laborious because of its dependency on many inputs such as rainfall, temperature, nutrition, atmospheric circulation, carbon circulation, economics factors, etc. Researchers are trying to find the uncertainties in parameter values because of a lack of understanding during model projection, which misleads the required predicted results (Lobell & Burke 2010). For field experiments, enough time and funds are required to get more sample results (Guo 2015).

In the field of socioeconomics, researchers mostly use empirical models (regression model, panel data model) (Huang *et al.* 2010; Conradt *et al.* 2016; Gornott & Wechsung 2016) and economic models (Ricardian model, yield function) (Yang 2007; Zhou 2012) to cover the impact of climate variation based on statistical data. These approaches are used to diagnose the uncertainty in the model and decrease the dependency on field data (Lobell & Burke 2010). The statistical approach depends on historical data which are collected from different experimental stations (Siddiqui *et al.* 2012; Gornott & Wechsung 2016), or advanced technology (Tian & Wan 2000), but there is less evidence of empirical analysis related to climate changes and technology used in agricultural production (Zhang & Huang 2012; Tao & Zhang 2013).

The autoregressive distributed lag (ARDL) bound test, proposed by Pesaran *et al.* (2001), allows determination of the long-run relation existing in series. The ARDL approach has recently become more known in some empirical studies for exploring the relation of climate change with other agricultural factors in several countries (Ghana (Asumadu-Sarkodie & Owusu 2016), Pakistan (Arshed & Abduqayumov 2016), and Europe (Acaravci & Ozturk 2010)) because of its difference in the ability to identify long-/short-run relationships among variables compared to the previous approach. The ARDL is applied respectively to find the integrations of variables, which is also a good fit for small sample data. Therefore, this study was organized to find the short- and long-run impact of climatic factors, technical factors, and agricultural policy (1990) on rice production of Korea by using the ARDL model. Based on the results, the study will also provide some possible suggestions.

DATA COLLECTION AND METHODOLOGY

Data collection

The study uses important factors that are responsible for affecting rice production in South Korea (Republic of Korea). Previous studies of Yang (2007), Zhou (2012), and Guo (2015) stated that natural factors and agricultural technology significantly affect agricultural production. Hence, the study jointly uses agricultural technology (e.g., area and fertilizer) and natural factors (e.g., carbon dioxide (CO_2) emission, mean temperature, and rainfall) along with an additional variable of agricultural policy as an explanatory variable and rice production is used as an explained variable. The annual data covering the period from 1973 to 2018 for rice production, CO_2, mean temperature, rainfall, area under rice, and fertilizers were gathered from the Korean Statistical Information System (KOSIS 2019), as shown in Table 1. The study highlights the 1990 agricultural policy of Korea in the model which hugely affects domestic

Table 1 | Variable description and data source

Variables	Descriptions	Measurement Units	Source
Rpro	Rice production in South Korea	Thousands of tons	KOSIS
CO_2	Carbon dioxide emission	Thousands of kilotons	KOSIS
MT	Mean temperature	Degree Celsius	KOSIS
MRF	Mean rainfall	Millimeters	KOSIS
Area	Area under rice	Thousands of hectares	KOSIS
Fert	Fertilizer used	Thousands of tons	KOSIS
D	Dummy for agricultural policy (1990)	D = 1 after 1990, otherwise 0	

rice production. The data are converted into log form before applying the ARDL bound test.

Methodology

The study applied a well-known approach by Pesaran *et al.* (2001) called the autoregressive distributed lag (ARDL) approach. The ARDL model is considered as the best econometric method compared to others in a case when the variables are stationary at I(0) or integrated of order I(1). Based on the study objectives, it is a better model than others to catch the short-run and long-run impact of independent variables on rice production.

The ARDL approach is appropriate for generating short-run and long-run elasticities for a small sample size at the same time and follow the ordinary least square (OLS) approach for cointegration between variables (Duasa 2007). ARDL affords flexibility about the order of integration of the variables. ARDL is suitable for the independent variable in the model which is I(0), I(1), or mutually cointegrated (Frimpong & Oteng 2006), but it fails in the presence I(2) in any variables. To find the relation between dependent and independent, the following model was constructed as:

$$RPro_t = \alpha_0 + \alpha_1 CO_2 + \alpha_2 MT + \alpha_3 MRF + \alpha_4 Area + \alpha_5 Fert + \alpha_6 D + \in_t \quad (1)$$

By converting all variables of Equation (1) into the natural log, the model is designed below:

$$\ln RPro_t = \alpha_0 + \alpha_1 \ln CO_2 + \alpha_2 \ln MT + \alpha_3 \ln MRF + \alpha_4 \ln Area + \alpha_5 \ln Fert + \alpha_6 D + \in_t \quad (2)$$

where *RPro* represents rice production, while *t* represents the time period from 1973 to 2018. α_0 represents the constant while α_1 to α_6 are the coefficients of variables and CO_2, *MT*, *MRF*, *Area*, *Fert* and *D* are the CO_2 emission, mean temperature, mean rainfall, area under rice, fertilizer use, and the dummy (dummy = 0 before 1990, above 1990 = 1) used for agricultural policy, while $\in_t$ represents the error term. Equation (2) can be written in ARDL form as follows:

$$\begin{aligned}\Delta \ln RPro_t = {} & \alpha_0 + \sum_{k=1}^{n} \alpha_1 \Delta \ln RPro_{t-k} + \sum_{k=1}^{n} \alpha_2 \Delta \ln CO_{2_{t-k}} \\ & + \sum_{k=1}^{n} \alpha_3 \Delta \ln MT_{t-k} + \sum_{k=1}^{n} \alpha_4 \Delta \ln MRF_{t-k} \\ & + \sum_{k=1}^{n} \alpha_5 \Delta \ln Area_{t-k} + \sum_{k=1}^{n} \alpha_5 \Delta \ln Fert_{t-k} \\ & + \sum_{k=1}^{n} \alpha_6 \Delta D_{t-k} + \lambda_1 \ln RPro_{t-1} + \lambda_2 \ln CO_{2_{t-1}} \\ & + \lambda_3 \ln MT_{t-1} + \lambda_4 \ln MRF_{t-1} \\ & + \lambda_5 \ln PArea_{t-1} + \lambda_6 \ln Fert_{t-1} + \lambda_7 D_{t-1} + \epsilon_t \quad (3)\end{aligned}$$

where α_0 represents drift component while Δ shows the first difference, ϵ_t shows the white noise. The study uses the Akaike information criterion (AIC) for choosing the lag length. After finding the long-run association existing between variables, the study uses the error correction model (ECM) to find the short-run dynamics. The ECM general form of Equation (3) is formulated below in Equation (4):

$$\begin{aligned}\Delta \ln RPro_t = {} & \alpha_0 + \sum_{k=1}^{n} \alpha_1 \Delta \ln RPro_{t-k} + \sum_{k=1}^{n} \alpha_2 \Delta \ln CO_{2_{t-k}} \\ & + \sum_{k=1}^{n} \alpha_3 \Delta \ln MT_{t-k} + \sum_{k=1}^{n} \alpha_4 \Delta \ln MRF_{t-k} \\ & + \sum_{k=1}^{n} \alpha_5 \Delta \ln Area_{t-k} + \sum_{k=1}^{n} \alpha_5 \Delta \ln Fert_{t-k} \\ & + \sum_{k=1}^{n} \alpha_6 \Delta D_{t-1} + \varnothing ECM_{t-1} + \epsilon_t \quad (4)\end{aligned}$$

where Δ represents the first difference while $\varnothing$ is the coefficients of *ECM* for short-run dynamics. *ECM* shows the speed of adjustment in long-run equilibrium after a shock in the short run.

Estimation procedure

After analyzing data through Equation (2), the long-run association among all variables is verified by using the Wald test. The null hypothesis of the Wald test suggests the existence of no cointegration, while the alternative hypothesis shows the existence of cointegration. The calculated F-statistics are compared to lower and upper bound values (Pesaran & Shin 1999). If the estimated F-statistic value is larger than the lower and upper bound then there will be cointegration.

CUSUM and CUSUMSQ test

By confirming that the long-run associations exist between variables, the study applies the cumulative sum (CUSUM) and cumulative sum of square (CUSUMSQ) tests (Brown et al. 1975). Previous studies (Pesaran & Shin 1999; Pesaran et al. 2001) suggested these tests portray the good fitness of the ARDL model. These tests are used to plot the residual of ECM. If the statistics in the plot fall in critical bounds at a 5% significant value, the results suggest that the coefficients of the ARDL model are stable.

EMPIRICAL RESULTS AND DISCUSSION

Descriptive statistics

The empirical study uses the time series data to find the effects of climate variation, technology variation, and agricultural policy on rice production in South Korea. The descriptive statistics of the important variables stated in Table 2 specified that the Jarque–Bera test for entire variables used in the study is insignificant, which implies that all the selected variables are normally distributed. The trend in rice production shows that the rice production was high in 1988 but after 1990 it shows a continuous reduction untill 2018, as shown in Figure 1. The descriptives statistics show that the CO_2 emission during the time period was 345.243 thousand kilotons with the lowest emission of 73.09 kilotons in 1973, while the highest emission was noted as 592.50 kilotons in 2018, as shown in Table 2. The trend line in Figure 2 shows that the CO_2 emission continuously increases at a rate of 0.05% each year. Similarly, the mean temperature observed during the study period

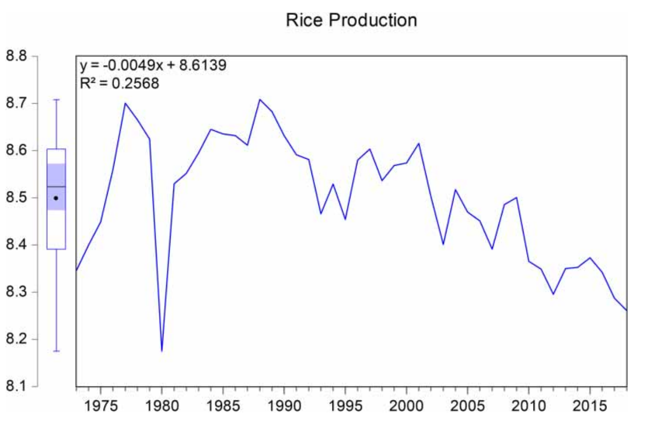


Figure 1 | The trend in rice production of South Korea (1973–2018).

Table 2 | Descriptive statistics of the variable used

Variables	RPro	CO_2	MT	MRF	Area	Fert	D
Median	5,029.956	369.802	17.763	1,161.150	1,062.565	821.500	1.000
Mean	4,947.337	345.243	17.669	1,142.507	1,062.460	766.500	0.609
Std. Dev	626.493	180.803	0.586	229.723	159.855	206.856	0.493
Maximum	6,053.482	592.499	18.925	1,697.400	1,262.324	1,104.000	1.000
Minimum	3,550.257	73.094	16.350	729.800	737.673	423.000	0.000
Skewness	−0.207	−0.062	−0.326	0.217	−0.416	−0.451	−0.445
Kurtosis	2.114	1.533	2.840	2.605	2.078	1.870	1.198
Jarque–Bera	1.833	4.156	0.866	0.662	2.957	4.010	7.742
Prob.	0.400	0.125	0.648	0.718	0.228	0.135	0.021
Observations	46	46	46	46	46	46	46

Note: The results are taken before using Logarithm. *RPro, CO_2, MT, MRF, Area, Fert, D* represent rice production, CO_2 emission, mean temperature, mean rainfall, area under rice, fertilizer used for rice, and agricultural policy in 1990.

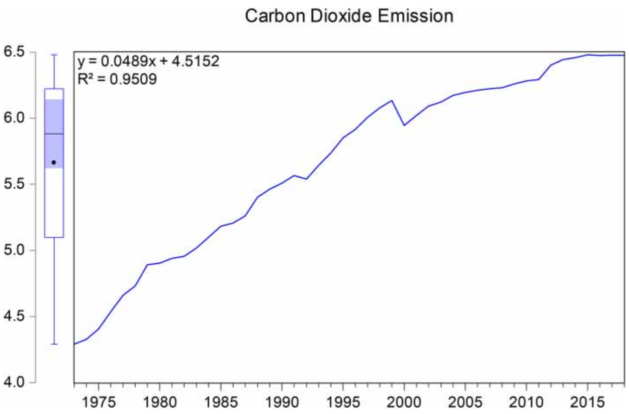


Figure 2 | The trend in carbon dioxide emission of South Korea (1973–2018).

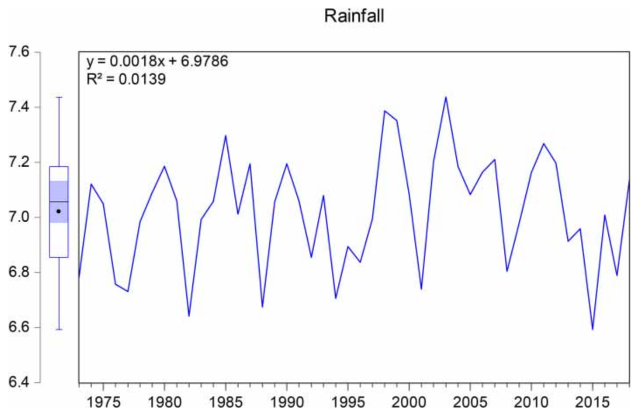


Figure 4 | The trend in rainfall of South Korea (1973–2018).

was 17.67 °C ranging from 16.35 °C (in 1980) to 18.93 °C (in 2015). The observed trend line in Figure 3 shows a continuous variation in mean temperature going upward with a speed of 0.002% each year. The mean rainfall during the study area was observed as 1,142.51 millimeters, ranging from 729.8 to 1,697.4 millimeters. The trend line in rainfall shows high volatility during the time period with an upward movement of 0.002% each year, as shown in Figure 4. The estimated trend in rainfall is similar to the previous study of Alahmadi & Rahman (2019), which stated that climate change causes extreme rainfall. The mean area under rice and fertilizer used for rice is 1,062.46 thousand hectares and 766.5 thousand tons. The trend lines of area and fertilizer are observed going downward, as shown in Figures 5 and 6.

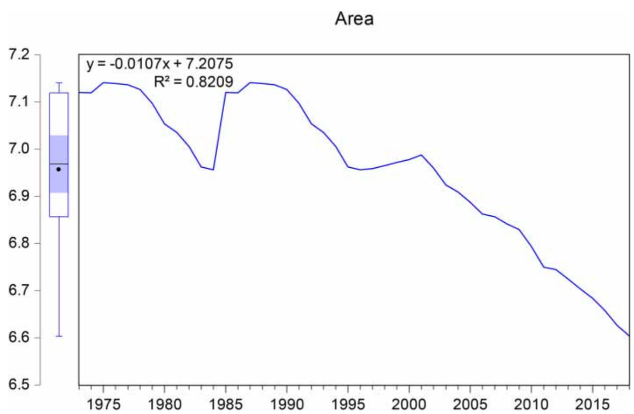


Figure 5 | The trend in area under rice of South Korea (1973–2018).

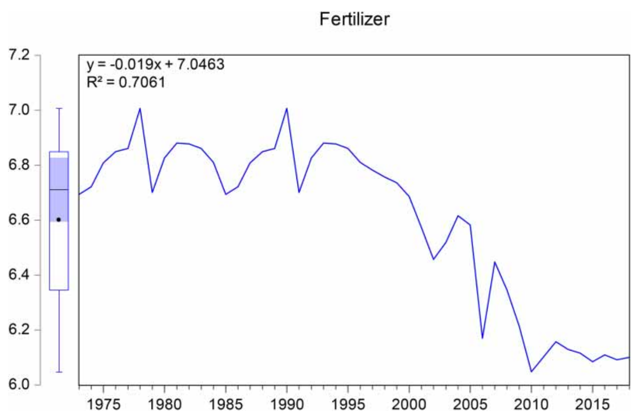


Figure 6 | The trend in fertilizer used for rice of South Korea (1973–2018).

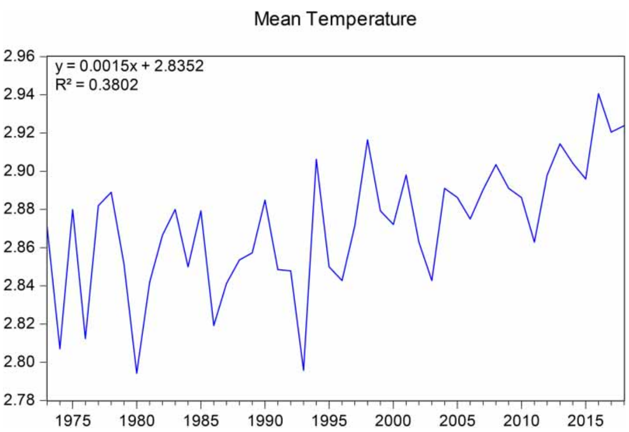


Figure 3 | The trend in mean temperature of South Korea (1973–2018).

Unit root test

It is important to check the unit root of each variable before applying the ARDL bound test. For finding the bound

F-statistic test, all the variables must be stationary at I(0), I(1), or both. To check the integration order of each variable, the study incorporates the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root test as used by the previous study of Rizwanullah *et al.* (2020). The result of ADF and PP reflects that there is no unit root in the series. Table 3 shows that rice production, CO_2 emission, mean temperature, and mean rainfall is stationary at order I(0), while the area under rice, fertilizer used, and agricultural policy is stationary at order I(1).

Structural break unit root test

Due to numerous policy and macroeconomic shifts, earlier unit root tests did not reflect a break in a series thus leading to biases in regression results. Therefore, Narayan & Popp (2010) proposed a structural break unit root test with two breaks in the level and slope with the supposition of unknown timing. Employing Narayan & Popp's (2010) structural break method demonstrates stable power, correct size, and identifies structure break more clearly than the previous study of Zivot & Andrews (1992). The estimated results of the structural break unit root test are reported in Table 4.

Lag selection criteria

Before applying the ARDL bound test for checking cointegration exists or not among rice production, carbon dioxide emission, mean temperature, rainfall, area under rice, fertilizer used, and agricultural policy, it is important to select an appropriate lag order of the variable. The study employed the optimal lag order of the vector autoregression (VAR) model for the selection of appropriate lag order. The observed results in Table 5 show the entire lag selection criteria for employing the ARDL bound test which implies that the model gives better results at lag 1 as compared to lag 2 and 3.

Additionally, the polynomial graph is also used for the confirmation of appropriate lag length under the VAR method, as shown in Figure 7. The graph shows that the dots inside the circle confirm the validation of good results at lag 1.

Table 4 | Unit root test with two structural breaks (Narayan & Popp 2010)

	Break in intercept (M1)			Break in intercept and trend (M2)		
Variables	t-statistics	TB1	TB2	t-statistics	TB1	TB2
LnRPro	−4.583	1987	2009	−4.719	1987	2009
LnCO$_2$	−0.831	1987	1997	−0.742	1987	1997
LnMT	−5.290	1987	1997	−7.485	1987	2012
LnMRF	−5.745	1997	2012	−6.122	1997	2014
LnArea	−1.092	1996	2002	−1.958	1996	2009
LnFert	−4.308	2005	2012	−5.287	1987	2005
D	−6.178	1989	1990	−5.604	1989	1990

Note: Critical values for both Model M1 (−4.735, −4.194, −3.863) and Model M2 (−5.151, −4.644, −4.376) are at 1, 5, and 10%, respectively. M1 and M2 are the first and second model while TB1 and TB2 are the first time and second time break. *RPro, CO_2, MT, MRF, Area, Fert, D* represent rice production, CO_2 emission, mean temperature, mean rainfall, area under rice, fertilizer used for rice, and agricultural policy in 1990.

Table 3 | Unit root test

	ADF		PP		
Variable	Levels	1st differences	Levels	1st differences	Order of integration
LnRPro	−2.861[c]	−8.658[a]	−2.765[c]	−10.808[a]	I (0)
LnCO$_2$	−3.505[b]	−5.427[a]	−4.003[a]	−5.476[a]	I (0)
LnMT	−4.548[a]	−7.660[a]	−4.564[a]	−34.036[a]	I (0)
LnMRF	−5.501[a]	−18.209[a]	−5.501[a]	−18.209[a]	I (0)
LnArea	0.869	−5.169[a]	0.676	−5.161[a]	I (1)
LnFert	−0.848	−9.278[a]	−0.402	−9.989[a]	I (1)
D	−1.232	−6.633[a]	−1.232	−6.633[a]	I (1)

Note: Critical values at level are −3.585, 2.928, and 2.602 at 1, 5, and 10% level, while at first difference the critical values are −3.589, −2.930, and −2.603 at 1, 5, and 10% level. [a], [b], and [c] represent the 1, 5, and 10% significance level. *RPro, CO_2, MT, MRF, Area, Fert, D* represent rice production, CO_2 emission, mean temperature, mean rainfall, area under rice, fertilizer used for rice, and agricultural policy in 1990.

Table 5 | Lag order criteria by using VAR (vector autoregression)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	203.2938	NA	2.56×10^{-13}	−9.129945	−8.843238	−9.024216
1	412.4829	340.5403*	1.53×10^{-16}*	−16.67829*	−14.28694*	−15.73477*
2	457.7475	58.94933	2.19×10^{-16}	−16.58060	−12.10626	−14.82093
3	512.5832	53.56040	2.84×10^{-16}	−16.40686	−10.37073	−13.35226

*Represents the criterion selecting the lag order. LR, FPE, AIC, SC, and HQ represent the sequential modified LR test statistic, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan–Quinan information criterion, respectively.

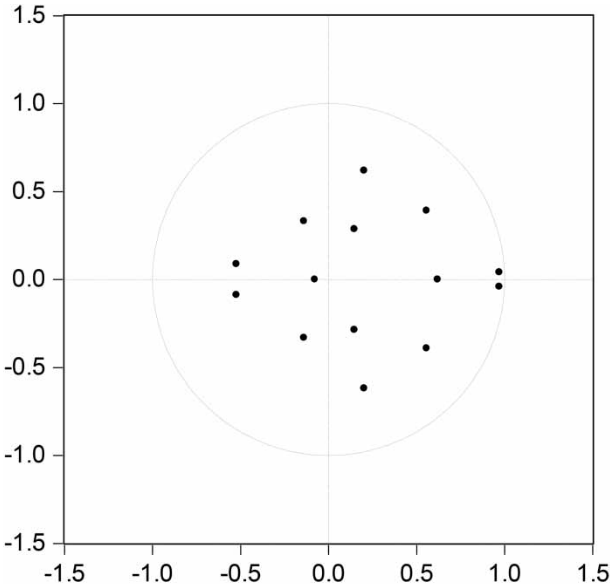


Figure 7 | Inverse roots of AR characteristic polynomial.

ARDL bound test for cointegration

Before finding the long- and short-run relations that exist between variables, it is important to use the ARDL bound test (Pesaran *et al.* 2001) for the confirmation of cointegration. The estimated results shown in Table 6 portray that the value of F-statistics is larger than lower and upper bound at 1% significance level when rice production, mean temperature, rainfall, area, fertilizer, and agricultural policy are the dependent variables. Hence, the alternative hypothesis of cointegration is accepted and the ARDL bound test approves the existence of long-run association among rice production, CO_2, mean temperature, mean rainfall, the area, fertilizer used for rice, and agricultural policy. Furthermore, the study also applies the cointegration approach of Johansen & Juselius (1990) to check the robustness of existing long-run association among variables. The empirical results of Johansen's cointegration, shown in Table 7, provide the evidence of robustness and effective long-run association among the variables.

Table 6 | ARDL bound test for cointegration

Equation	Lag	F-statistics	*P*-value
$RPro = f(CO_2, MT, MRF, Area, Fert, D)$	(1, 0, 0, 0, 0, 1, 0)	5.048[a]	0.000
Critical value	10%	5%	1%
Lower bound I(0)	2.12	2.45	3.15
Upper bound I(1)	3.23	3.61	4.43

[a]Represents the 1% significance level.

Short- and long-run estimation of parameters

After verifying the existence of a long- and short-run association between variables from the ARDL bound test, the study finds the short- and long-run parameters of the variables. Rice is a major staple food crop in South Korea which is highly affected by the various factors of climate change. The empirical results of climatic factors are shown in Table 8 for a long-run association which implies that an increase in carbon dioxide emission in South Korea can significantly increase rice production. The estimated outcomes imply that a rise of 1% in CO_2 emission can increase rice production up to 0.15%. Chunhua *et al.* (2020) stated that elevated atmospheric CO_2 can increase rice production in the future because elevated CO_2 improves the photosynthesis process in rice. Wang *et al.* (2015) also stated that elevated CO_2 increases rice yield by 20%. Similarly, the mean temperature in South Korea has a significant positive long-run association with rice production at a 1% level while

Table 7 | Johansen cointegration estimation

Hypothesis	Test statistics	5% critical value	*P*-value
Trace statistics			
$r \leq 0$	163.9797[a]	125.6154	0.0000
$r \leq 1$	111.9238[a]	95.75366	0.0024
$r \leq 2$	68.55279	69.81889	0.0628
$r \leq 3$	41.18989	47.85613	0.1827
$r \leq 4$	24.36719	29.79707	0.1854
$r \leq 5$	11.80508	15.49471	0.1665
$r \leq 6$	1.568229	3.841466	0.2105
Maximum eigenvalue			
$r \leq 0$	52.05589[a]	46.23142	0.0107
$r \leq 1$	43.37100[b]	40.07757	0.0206
$r \leq 2$	27.36290	33.87687	0.2444
$r \leq 3$	16.82270	27.58434	0.5952
$r \leq 4$	12.56211	21.13162	0.4933
$r \leq 5$	10.23685	14.26460	0.1968
$r \leq 6$	1.568229	3.841466	0.2105

[a] and [b] represent the 1 and 5% significance level.

Table 8 | Long-run estimation of parameters from ARDL models (34 observations from 1973 to 2018).

Variables	Coefficient	Std. error	t-statistics	Prob.
$LnCO_2$	0.152[a]	0.048	3.144	0.003
LnMT	1.162[a]	0.452	2.569	0.014
LnMRF	−0.129[b]	0.060	−2.141	0.039
LnArea	0.728[a]	0.196	3.379	0.000
LnFert	0.189[b]	0.086	2.186	0.035
D	−0.110[b]	0.0489	−2.261	0.029
C	−1.037	1.852	−0.559	0.579

[a] and [b] represent 1, 5, and 10% significance levels. Dependent variable is rice production. ARDL (1, 0, 0, 0, 0, 1) based Akaike information criteria.

the mean rainfall has a substantial negative long-run association with rice at a 5% significant level. This outcome implies that a rise of 1% in mean temperature can increase rice production by 1.16% while an increase in 1% of rainfall can decrease rice production by 0.13%. Minasny *et al.* (2012), Shakoor *et al.* (2015) stated that due to severe cold weather in Korea, rice production decreases. It is also reported from the results that the mean temperature (17.67 °C) of Korea during rice growth is less than the previous study of Kashyap & Agarwal (2020) and Chandio *et al.* (2018), which is 23.46 °C and 20.27 °C. Therefore, an increase in mean temperature can increase rice production. Korres *et al.* (2017) stated that increase in temperatures from 25 to 35 °C can reduce the growth as well as rice yield. Chandio *et al.* (2020) and Mahmood *et al.* (2012) specified that in the long run, increase in rainfall can decrease rice production. Rotich & Mulungu (2017) reported that due to climate change the rain pattern was not stable, which is a serious threat for agricultural production and food security. Similarly, Mosammam *et al.* (2016) stated that a change in the frequency of rainfall can decrease agricultural production. The trend line of rainfall also shows a continuous variation due to which rice production decreases in Korea. Kakumanu *et al.* (2019) stated that heavy rainfall is the major constraint for rice productivity. The study also observed a significant impact of the area under rice on the production of rice at a 1% level in the long run. Rice production increases 0.73% with the increase of 1% cultivated area under rice in the long run, which is similar to the previous study of Hussain (2012). Similarly, fertilizer also plays an important role in soil fertility and crop nutrients. Any adverse shock in fertilizer consumption can decrease rice production. The study shows that in the long run, 1% increase in fertilizers can significantly increase rice production by 0.19%. The estimated findings of the study coincide with a previous study of Rehman *et al.* (2017). Agricultural policy plays a significant role in the development of agricultural and rural communities. The Korean government has implemented a policy to withdraw agricultural subsidies for the up-gradation of the environment. The current study implies that in the long run, the agricultural policy in 1990 significantly decreases rice production by 0.11%. The estimated results are similar to the previous study of Bala *et al.* (2014), which stated that removing agricultural subsidies not only discourages the farming community but also increases the prices of agricultural commodities.

In the short run, the coefficient of climatic factors such as CO_2, mean temperature, and rainfall significantly influence rice productivity. The results shown in Table 9 indicate that in the short run an increase of 1% carbon dioxide emission and mean temperature in the Republic of Korea can increase rice production by 0.15% and 1.11%. The study also finds that a 0.12% reduction in rice production occurs due to an increase of 1% in rainfall in the

Table 9 | Short-run estimation of parameters from ARDL models (34 observation from 1973 to 2018)

Variables	Coefficient	Std. error	t-statistics	Prob.
$DLnCO_2$	0.145[a]	0.052	2.781	0.009
DLnMT	1.105[a]	0.406	2.721	0.010
DLnMRF	−0.122[b]	0.053	−2.313	0.026
DLnArea	0.693[a]	0.207	3.341	0.002
DLnFert	−0.079	0.094	−0.844	0.404
D	−0.105[b]	0.049	−2.149	0.036
ECM(-1)	−0.951	0.129	−7.375	0.000

[a] and [b] represent 1, 5, and 10% significance level. Dependent variable is rice production. ARDL (1, 0, 0, 0, 0, 1) based Akaike information criteria.

short run. In technical factors, rice cultivated area is significant at a 1% level which shows that in the short run the rice productivity increases by 0.69% with a 1% increase in a cultivated area. The study also finds that fertilizer used in the short run has no impact on rice production. This result is opposite to a previous study by Saddozai *et al.* (2015), which implies that inappropriate use of fertilizer can decrease the production level, while Nasrullah *et al.* (2019) stated that fertilizer used has an insignificant effect on rice production, and Zulfiqar *et al.* (2020) found a significant positive impact of fertilizer on production. Similarly, Minasny *et al.* (2012) stated that the Korean government removed the subsidy on fertilizer during 1990 because of the continuous increase in soil organic component (SOC). Therefore, due to removing the subsidy the fertilizer use in Korea decreased showing no impact on rice production. Likewise, Nasrullah *et al.* (2020) stated that various trade barriers and distances significantly decrease the flow of trade due to which the use of chemical fertilizer in Korea is inappropriate for rice. The dummy variable used for agricultural policy significantly reduces agriculture production by 0.11%. The results are similar to existing studies of Chandio *et al.* (2018, 2020); Korres *et al.* (2017), Janjua *et al.* (2014), Mahmood *et al.* (2012), and Hussain (2012).

The estimated coefficient of ECM is negative and significantly verifies the existence of cointegration among variables. ECM shows the speed of adjustment in long-run equilibrium after short-run shocks. The ECM coefficient of rice production for South Korea is −0.95 and significant at a 1% level, showing that any deviation from the short-run equilibrium between variables and rice production can be adjusted and recovered each year at 0.95% in the long run, as shown in Table 9.

Diagnostic tests

Numerous diagnostic tests are used to find the errors in the model and are shown in Table 10. The estimated value of R-square and adjusted R-square is greater than 76 showing the model is a good fit. The projected Ramsey reset test (χ^2 Ramsey reset) illustrates that the functional form of the estimated model is correct. Similarly, the expected result of χ^2 Arch and χ^2 B-G shows that there is no heteroscedasticity problem in the model. The estimated scores of the Jarque–Bera test (χ^2 normality) and serial correlation (χ^2SC) imply that the existing model is normal and finds no serial correlation.

Stability check

Due to the presence of structural changes in all variables because of single or multiple structure breaks, the study using cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests for checking stability in the short-run and long-run coefficients proposed by Brown *et al.* (1975). The CUSUM and CUSUMSQ lines of rice production are at the 5% significance level over time, confirming the stability and good fitness of the ARDL model. The results of CUSUM and CUSUMSQ are shown in Figures 8 and 9. The results of the ARDL model are based on AIC. Figures 10 and 11 show 20 computed ARDL models based on AIC and SC.

Table 10 | Diagnostic tests

R-square	0.783
Adjusted R-square	0.734
Durbin–Watson statistics	1.975
χ^2 Ramsey reset	0.298 (0.767)
χ^2 ARCH	0.229 (0.635)
χ^2 B-G	0.441 (0.647)
χ^2 Normality	2.217 (0.330)
χ^2SC	0.441 (0.647)

Note: For Ramsey reset, the null is the correct functional form. For the Arch test, the null is no heteroscedasticity. For the Breusch-Pagan-Godfrey (B-G) test, the null is no serial correlation. For the J-B test, the null is normality. SC stands for no serial correlation. *P*-values are presented in parentheses.

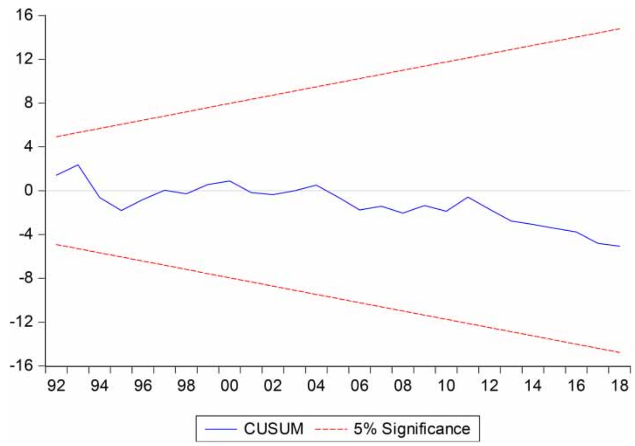


Figure 8 | Plot of CUSUM for coefficients' stability of ARDL model. Source: authors' estimates from data 1973–2018.

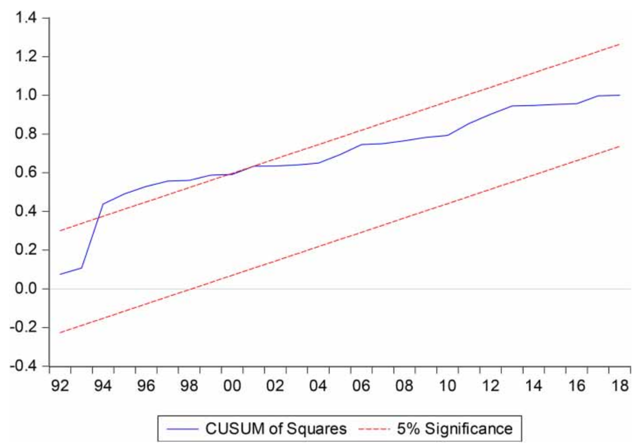


Figure 9 | Plot of CUSUMSQ for coefficients' stability of ARDL model. Source: authors' estimates from data 1973–2018.

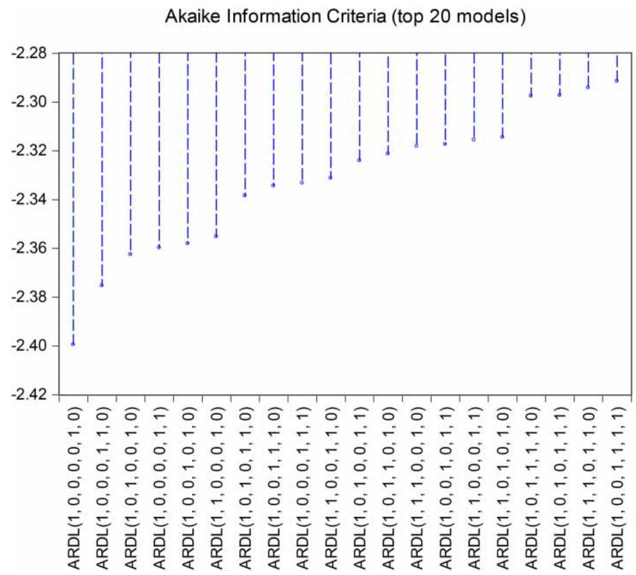


Figure 10 | Akaike information criteria graph. Source: authors' estimates from data 1973–2018.

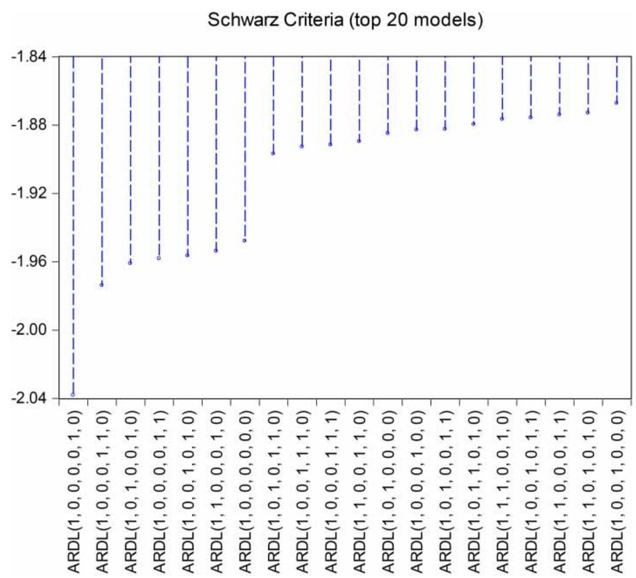


Figure 11 | Schwarz criteria graph. Source: authors' estimates from data 1973–2018.

CONCLUSION AND POLICY IMPLICATIONS

Rice is the main staple food in South Korea but its production decreases gradually each year and is not sufficient to fulfill the domestic demand. This decline in rice production not only pressurizes the local farmers but also attracts the attention of policymakers. Therefore, the study's main aim is to scrutinize the short- and long-run relationship among rice production, technical factors, climatic factors, and agricultural policy of South Korea using annual data from 1973 to 2018. The ADF and PP are applied to check the stationarity before using the ARDL model which can mislead the desired results. The estimated results of ADF and PP proved that all the variables are stationary at I(0) and I(1). The result of the ARDL bound test verified the presence of long- and short-run relationships among variables. The estimated short- and long-run elasticity of the ARDL model discovers a significant direct impact of CO_2 and mean temperature. It is concluded that elevated atmospheric CO_2 in the respondent area during the study period increases rice production. The increase in CO_2 emission in Korea increases the photosynthesis process, which is highly valuable for the production of rice. Likewise, the climatic factor, mean temperature also increases rice production. It is concluded that the mean temperature has a valuable effect on the vegetation and production process. On the other hand, the climatic factor rainfall is not stable during the study period, and has an adverse shock on the production. The technical factors (area under rice and fertilizer) have a direct positive effect on rice production, which implies that an increase in area and fertilizer can boost rice production. The agricultural policy against subsidies on agricultural inputs is also responsible for the reduction in rice production. Similarly, the various stability and diagnostic tests verify that the model is a good fit, functional form is correct, the model is normal, and there are no problems of heteroscedasticity and serial correlation in the model.

The trend line in Figure 1 shows a significant decline in rice production after the withdrawal of agricultural subsidies. Similarly, the trend line of fertilizer used also shows a continuous decline. Therefore, to avoid food shortage in the near future the government needs to avoid this kind of policy which discourages the farmers. The estimated elasticity of rainfall significantly decreases rice production; therefore, it is suggested that the Korean government needs to implement new policies and acquire advanced technology for weather forecasting. The government also needs to reinforce and develop a better irrigation system. The concerned authority needs to inform rice growers about future weather and climate changes. The study also specifies that the area under rice has a significant effect on rice production, but the trend line shows that the agricultural area continuously decreases. Therefore, it is recommended that the Korean government needs to provide virgin arable undivided land to deserving rice growers based on ownership/lease for future food security. In short, the study specifies that the concerned authorities and policy-makers should spot the aggressive effect of climate change on the main food crops. Therefore, the legislators should recommend some strong policies regarding sustainable food security by introducing new agricultural technologies, subsidies on agricultural inputs, and a new variety of seeds that absorb the adverse shock of climate and ensure a suitable amount of food for the massive population of Korea. The study also suggests that further research is needed to discover the impact of climate change and other factors that are responsible for the decrease in agricultural production in Korea and worldwide.

Scope and limitation of the study

The study provides evidence to the research community of how much climate change and other factors are responsible for the decrease in rice production in South Korea. This study provides a significant pathway to understanding the climatic changes and their various impacts on rice production. This study begins and helps to develop a strong understanding of current and potential impacts that will affect the agriculture of today and in coming decades worldwide. This understanding is crucial because it allows decision-makers to place climate change in the context of other large challenges facing the nation and the world.

The study is limited to finding out the impact climatic factors (CO_2, mean temperature, and rainfall), technical factors (area under rice and fertilizer used for rice), and agricultural policy (anti-subsidy policy for agricultural inputs in 1990) have on rice production from 1973 to 2018 in South Korea.

ACKNOWLEDGEMENTS

The authors extend heartfelt thanks to the editorial board and the anonymous reviewers for their valuable suggestions. This research was sponsored by the Innovation Platform Open Fund Project of Hunan Education Department, China (19K087).

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories (http://kosis.kr.eng/).

REFERENCES

Acaravci, A. & Ozturk, I. 2010 On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. *Energy* **35** (12), 5412–5420. https://doi.org/10.1016/j.energy.2010.07.009.

Alahmadi, F. S. & Rahman, N. A. 2019 Climate change impacts on extreme rainfall frequency prediction. *Journal of Water and Climate Change* **11** (1). https://doi:10.2166/wcc.2019.138

Arshed, N. & Abduqayumov, S. 2016 Economic impact of climate change on wheat and cotton in major districts of Punjab. *International Journal of Economics and Financial Research* **2** (10), 183–191.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Kumar, S. N., Nendel, C., O'Leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J. W. & Williams, J. R. 2013 Uncertainty in simulating wheat yields under climate change. *Nature Climate Change* **3**, 827–832. https://doi.org/10.1038/nclimate1916.

Asumadu-Sarkodie, S. & Owusu, P. A. 2016 The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. *Environmental Science and Pollution Research* **23** (11), 10968–10982. https://doi:10.1007/s11356-016-6252-x.

Bala, B. K., Alias, E. F., Arshad, F. M., Noh, K. M. & Hadi, A. H. A. 2014 Modelling of food security in Malaysia. *Simulation Modelling Practice and Theory* **47**, 152–164. https://doi:10.1016/j.simpat.2014.06.001.

Ben-Ari, T., Adrian, J., Klein, T., Calanca, P., Van der Velde, M. & Makowski, D. 2016 Identifying indicators for extreme wheat and maize yield losses. *Agricultural and Forest Meteorology* **220**, 130–140. https://doi:10.1016/j.agrformet.2016.01.009.

Brown, R. L., Durbin, J. & Evans, J. M. 1975 Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society. Series B (Methodological)* **37** (2), 149–192.

Butler, E. E. & Huybers, P. 2012 Adaptation of US maize to temperature variations. *Nature Climate Change* **3** (1), 68–72. https://doi:10.1038/nclimate1585.

Chami, E. D. & Daccache, A. 2015 Assessing sustainability of winter wheat production under climate change scenarios in a humid climate – an integrated modelling framework. *Agricultural Systems* **140**, 19–25. https://doi:10.1016/j.agsy.2015.08.008.

Chandio, A. A., Jiang, Y. & Magsi, H. 2018 Climate change impact on rice production in Pakistan: an ARDL-bounds testing approach to cointegration. *Preprints*. https://doi:10.20944/preprints201812.0095.v1.

Chandio, A. A., Jiang, Y., Rehman, A. & Rauf, A. 2020 Short and long-run impacts of climate change on agriculture: an empirical evidence from China. *International Journal of Climate Change Strategies and Management* **12** (2), 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026.

Chen, C., Baethgen, W. E. & Robertson, A. 2013 Contributions of individual variation in temperature, solar radiation and precipitation to crop yield in the North China Plain, 1961–2003. *Climatic Change* **116**, 767–788. https://doi.org/10.1007/s10584-012-0509-2.

Chunhua, L., Huang, Y., Sun, W., Yu, L. & Zhu, L. 2020 Response of rice yield and yield components to elevated [CO_2]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy* **112**. https://doi.org/10.1016/j.eja.2019.125961.

CIA Factbook. 2007 *Central Intelligence Agency*.

Conradt, T., Gornott, C. & Wechsung, F. 2016 Extending and improving regionalized winter wheat and silage maize yield regression models for Germany: enhancing the predictive skill by panel definition through cluster analysis. *Agricultural and Forest Meteorology* **216**, 68–81. https://doi.org/10.1016/j.agrformet.2015.10.003.

Duasa, J. 2007 Determinants of Malaysian trade balance: an ARDL bound testing approach. *Global Economic Review* **36** (1), 89–102. https://doi:10.1080/12265080701217405.

Frimpong, M. J. & Oteng, E. F. 2006 *Bound Testing Approach: An Examination of Foreign Direct Investment, Trade and Growth Relationships*. MPRA Paper No. 352, pp. 1–19.

Gornott, C. & Wechsung, F. 2016 Statistical regression models for assessing climate impacts on crop yields: a validation study for winter wheat and silage maize in Germany. *Agricultural and Forest Meteorology* **217**, 89–100. https://doi.org/10.1016/j.agrformet.2015.10.005.

Guo, J. P. 2015 Advances in impacts of climate change on agricultural production in China. *Journal of Applied Meteorological Science* **1**, 1–11. https://www.fao.org/nr/water/aquastat/countries_regions/KOR/KOR-CP_eng.pdf.

Huang, W., Deng, X. Z., He, S. J. & Lin, Y. Z. 2010 An econometric analysis on the impacts of climatic change on grain production at counties of China. *Progress in Geography* **29**, 677–683. https://doi.org/10.11820/dlkxjz.2010.06.006.

Hussain, A. 2012 Impact of credit disbursement, area under cultivation, fertilizer consumption and water availability on rice production in Pakistan (1988–2010). *Sarhad Journal of Agriculture* **28** (1), 95–101.

Jalota, S. K., Vashisht, B. B., Harsimran, K., Samanpreet, K. & Prabhjyot, K. 2014 Location specific climate change scenario and its impact on rice and wheat in Central Indian Punjab. *Agricultural Systems* **131** (C), 77–86. https://doi.org/10.1016/j.agsy.2014.07.009.

Janjua, P. Z., Samad, G. & Khan, N. 2014 Climate change and wheat production in Pakistan: an autoregressive distributed lag approach. *NJAS-Wageningen Journal of Life Sciences* **68**, 13–19. https://doi.org/10.1016/j.njas.2013.11.002.

Johansen, S. & Juselius, K. 1990 Maximum likelihood estimation and inference on cointegration – with application to the demand for money. *Oxford Bulletin of Economics* **52**, 169–210.

Kakumanu, K. R., Kotapati, G. R., Nagothu, U. S., Kuppanan, P. & Kallam, S. R. 2019 Adaptation to climate change and variability: a case of direct seeded rice in Andhra Pradesh India. *Journal of Water and Climate Change* **10** (2), 419–430. https://doi:10.2166/wcc.2018.141.

Kashyap, D. & Agarwal, T. 2020 Temporal trends of climatic variables and water footprint of rice and wheat production in Punjab, India from 1986 to 2017. *Journal of Water and Climate Change*. https://doi:10.2166/wcc.2020.093

Korean Statistical Information System (KOSIS). 2017 Available from: http://kosis.kr.eng/

Korean Statistical Information System (KOSIS). 2019 Available from: http://kosis.kr.eng/

Korres, N. E., Norsworthy, J. K., Burgos, N. R. & Oosterhuis, D. M. 2017 Temperature and drought impacts on rice production: an agronomic perspective regarding short- and long-term adaptation measures. *Water Resources and Rural Development* **9**, 12–27. https://doi:10.1016/j.wrr.2016.10.001.

Leadley, P. W. & Drake, B. G. 1992 Open top chambers for exposing plant canopies to elevated CO_2 concentration and for measuring net gas exchange. *Plant Ecology* **104–105**, 3–15. https://doi.org/10.1007/BF00048141.

Li, T. X., Zhao, G. Q. & Li, Y. 2009 Climate change and its impacts on duration of winter wheat overwintering stage in Henan Province. *Chinese Journal of Agrometeorology* **30**, 143–146.

Li, Y., Conway, D., Wu, Y., Gao, Q., Rothausen, S., Xiong, W., Ju, H. & Lin, E. 2013 Rural livelihoods and climate variability in Ningxia, Northwest China. *Climatic Change* **119** (3–4), 891–904. https://doi:10.1007/s10584-013-0765-9.

Li, Z., Jin, X., Zhao, C., Wang, J., Xu, X., Yang, G., Lee, C. & Shen, J. 2015 Estimating wheat yield and quality by coupling the DSSAT-CERES model and proximal remote sensing. *European Journal of Agronomy* **71**, 53–62. https://doi.org/10.1016/j.eja.2015.08.006.

Licker, R., Kucharik, C. J., Doré, T., Lindeman, M. J. & Makowski, D. 2013 Climatic impacts on winter wheat yields in Picardy, France and Rostov, Russia: 1973–2010. *Agricultural and Forest Meteorology* **176**, 25–37. https://doi:10.1016/j.agrformet.2013.02.010.

Lobell, D. B. & Burke, M. B. 2010 On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology* **150** (11), 1443–1452. https://doi:10.1016/j.agrformet.2010.07.008.

Lobell, D. B., Schlenker, W. & Costa-Roberts, J. 2011 Climate trends and global crop production since 1980. *Science* **333** (6042), 616–620. https://doi:10.1126/science.1204531.

Mahmood, N., Ahmad, B., Hassan, S. & Bakhsh, K. 2012 Impact of temperature ADN precipitation on rice productivity in rice-wheat cropping system of Punjab province. *Journal of Animal and Plant Sciences* **22**, 993–997.

Meza, F. J. & Silva, D. 2009 Dynamic adaptation of maize and wheat production to climate change. *Climatic Change* **94** (1–2), 143–156. https://doi:10.1007/s10584-009-9544-z.

Minasny, B., McBratney, A. B., Hong, S. Y., Sulaeman, Y., Kim, M. S., Zhang, Y. S., Kim, Y. H. & Han, K. H. 2012 Continuous rice cropping has been sequestering carbon in soils in Java and South Korea for the past 30 years. *Global Biogeochemical. Cycles* **26**, GB3027. https://doi:10.1029/2012GB004406.

Mishra, A., Singh, R., Raghuwanshi, N. S., Chatterjee, C. & Froebrich, J. 2013 Spatial variability of climate change impacts on yield of rice and wheat in the Indian Ganga Basin. *Science of the Total Environment* **468–469**, S132–S138. https://doi:10.1016/j.scitotenv.2013.05.080.

Mosammam, H. M., Mosammam, A. M., Sarrafi, M., Nia, J. T. & Esmaeilzadeh, H. 2016 Analyzing the potential impacts of climate change on rainfed wheat production in Hamedan Province, Iran, via generalized additive models. *Journal of Water and Climate Change* **7** (1), 212–223. https://doi:10.2166/wcc.2015.153.

Mottaleb, K. A., Mohanty, S., Hoang, H. T. K. & Rejesus, R. M. 2013 The effects of natural disasters on farm household income and expenditures: a study on rice farmers in Bangladesh. *Agricultural Systems* **121**, 43–52.

Narayan, P. K. & Popp, S. 2010 A new unit root test with twostructural breaks in level and slope at unknown time. *Journal of Applied Statistics* **37** (9), 1425–1438. https://doi:10.1080/02664760903039883.

Nasrullah, M., Chang, L., Saddozai, K. N., Khalid, A. O., Bayisenge, R. & Hameed, G. 2019 Cost and net return of tobacco growers – a case study of district Mardan (KP-Pakistan). *Sarhad Journal of Agriculture* **35** (2), 565–571.

Nasrullah, M., Chang, L., Khan, K., Rizwanullah, M., Zulfiqar, F. & Ishfaq, M. 2020 Determinants of forest product group trade by gravity model approach: a case study of China. *Forest Policy and Economics* **113**, 102117. https://doi:10.1016/j.forpol.2020.102117.

OECD 1999 *Review of Agricultural Policies in Korea*. https://www.oecd.org/korea/40417830.pdf.

Osborne, T. M. & Wheeler, T. R. 2013 Evidence for a climate signal in trends of global crop yield variability over the past 50 years. *Environmental Research Letters* **8** (2), 024001. https://doi:10.1088/1748-9326/8/2/024001.

Özdoğan, M. 2011 Modeling the impacts of climate change on wheat yields in Northwestern Turkey. *Agriculture, Ecosystems & Environment* **141** (1–2), 1–12. https://doi:10.1016/j.agee.2011.02.001.

Pesaran, M. & Shin, Y. 1999 *An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*. Chapter 11, Cambridge University Press, Cambridge. https://doi:10.12691/jfe-4-6-4

Pesaran, M. H., Shin, Y. & Smith, R. J. 2001 Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* **16** (3), 289–326. https://doi:10.1002/jae.616.

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C. & Foley, J. A. 2012 Recent patterns of crop yield growth and stagnation. *Nature Communications* **3** (1). https://doi:10.1038/ncomms2296

Ray, D. K., Mueller, N. D., West, P. C. & Foley, J. A. 2013 Yield trends are insufficient to double global crop production by

2050. *PLoS ONE* **8** (6), e66428. https://doi:10.1371/journal.pone.0066428.

Rehman, A., Chandio, A. A., Hussain, I. & Jingdong, L. 2017 Fertilizer consumption, water availability and credit distribution: major factors affecting agricultural productivity in Pakistan. *Journal of the Saudi Society of Agricultural Sciences*. https://doi:10.1016/j.jssas.2017.08.002

Reidsma, P., Ewert, F., Lansink, A. O. & Leemans, R. 2010 Adaptation to climate change and climate variability in European agriculture: the importance of farm level responses. *European Journal of Agronomy* **32**, 91–102.

Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, D., Fuglie, K., Hollinger, S., Izaurralde, C., Jagtap, S., Jones, J., Mearns, L., Ojima, D., Paul, E., Paustian, K., Riha, S., Rosenberg, N. & Rosenzweig, N. 2003 U.S. Agriculture and climate change: new results. *Climatic Change* **57**, 43–67. https://doi.org/10.1023/A:1022103315424.

Rizwanullah, M., Liang, L. Z., Yu, X. Y., Zhou, J. N., Nasrullah, M. & Ali, M. U. 2020 Exploring the cointegration relation among top eight Asian Stock Markets. *Open Journal of Business and Management* **8**, 1076–1088. https://doi.org/10.4236/ojbm.2020.83068.

Rotich, S. C. & Mulungu, D. M. M. 2017 Adaptation to climate change impacts on crop water requirements in Kikafu catchment Tanzania. *Journal of Water and Climate Change* **8** (2), 274–292. https://doi:10.2166/wcc.2017.058.

Saadi, S., Todorovic, M., Tanasijevic, L., Pereira, L. S., Pizzigalli, C. & Lionello, P. 2015 Climate change and Mediterranean agriculture: impacts on winter wheat and tomato crop evapotranspiration, irrigation requirements and yield. *Agricultural Water Management* **147**, 103–115. https://doi.org/10.1016/j.agwat.2014.05.008.

Saddozai, K. N., Nasrullah, M. & Khan, N. P. 2015 Stochastic frontier production analysis of tobacco growers in district Mardan, Pakistan. *Pakistan Journal of Agricultural Research* **28** (4), 346–353.

Shakoor, U., Saboor, A., Baig, I., Afzal, A. & Rahman, A. 2015 Climate variability impacts on rice crop production in Pakistan. *Pakistan Journal of Agricultural Research* **28** (1), 19–27.

Siddiqui, R., Samad, G., Nasir, M. & Jalil, H. H. 2012 The impact of climate change on major agricultural crops: evidence from Punjab, Pakistan. *The Pakistan Development Review* **4** (51), 261–274. http://www.jstor.org/stable/23734755

Slingo, J. M., Challinor, A. J., Hoskins, B. J. & Wheeler, T. R. 2005 Introduction: food crops in a changing climate. *Philosophical Transactions of the Royal Society B: Biological Sciences* **360** (1463), 1983–1989. https://doi:10.1098/rstb.2005.1755.

Tao, F. & Zhang, Z. 2013 Climate change, wheat productivity and water use in the North China Plain: a new super-ensemble-based probabilistic projection. *Agricultural and Forest Meteorology* **170**, 146–165. https://doi:10.1016/j.agrformet.2011.10.003.

Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y. & Zhang, Z. 2006 Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agricultural and Forest Meteorology* **138** (1–4), 82–92. https://doi:10.1016/j.agrformet.2006.03.014.

Tao, F. L., Yokozawa, M., Liu, J. Y. & Zhang, Z. 2008 Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends. *Climate Research* **38**, 83–94. https://doi.org/10.3354/cr00771.

Tao, F., Zhang, Z., Xiao, D., Zhang, S., Rötter, R. P., Shi, W., Liu, Y., Wang, M., Liu, F. & Zhang, H. 2014 Responses of wheat growth and yield to climate change in different climate zones of China, 1981–2009. *Agricultural and Forest Meteorology* **189–190**, 91–104. https://doi:10.1016/j.agrformet.2014.01.013.

Tian, W. & Wan, G. H. 2000 Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis* **13**, 159–174. https://doi.org/10.1023/A:1007805015716.

Urban, D., Roberts, M. J., Schlenker, W. & Lobell, D. B. 2012 Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields. *Climatic Change* **112** (2), 525–533. https://doi:10.1007/s10584-012-0428-2.

Wang, J., Wang, C., Chen, N., Xiong, Z., Wolfe, D. & Zou, J. 2015 Response of rice production to elevated [CO_2] and its interaction with rising temperature or nitrogen supply: a meta-analysis. *Climatic Change* **130** (4), 529–543. https://doi:10.1007/s10584-015-1374-6.

Wheeler, T. & von Braun, J. 2013 Climate change impacts on global food security. *Science* **341** (6145), 508–513. https://doi:10.1126/science.1239402.

Wilcox, J. & Makowski, D. 2014 A meta-analysis of the predicted effects of climate change on wheat yields using simulation studies. *Field Crops Research* **156**, 180–190. https://doi.org/10.1016/j.fcr.2013.11.008.

Yang, W. 2007 *A Study on Technological Change Pattern of Grain in China*. Doctoral thesis, Chinese Academy of Agricultural Sciences, Beijing, China.

Zhang, T. & Huang, Y. 2012 Estimating the impacts of warming trends on wheat and maize in China from 1980 to 2008 based on county level data. *International Journal of Climatology* **33** (3), 699–708. https://doi:10.1002/joc.3463.

Zhou, W. K. 2012 *Impact of Climate Change on Chinese Food Production and its Countermeasures*. Doctoral thesis, Nanjing Agricultural University, Nanjing, China.

Zivot, E. & Andrews, D. W. K. 1992 Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business Economic Statistics* **10** (3), 251–270. https://doi.org/10.1080.

Zulfiqar, F., Shang, J., Nasrullah, M. & Rizwanullah, M. 2020 Allocative efficiency analysis of wheat and cotton in district Khanewal, Punjab, Pakistan. *GeoJournal*. https://doi.org/10.1007/s10708-020-10228-x.

First received 28 January 2021; accepted in revised form 6 February 2021. Available online 22 March 2021