https://doi.org/10.17221/58/2022-AGRICECON

Present and future: Does agriculture affect economic growth and the environment in the Kingdom of Saudi Arabia?

Abda Emam[1,2]*

[1]*Department of Agribusiness and Consumer Sciences, College of Agricultural Sciences and Food, King Faisal University, Al-Ahsa, Kingdom of Saudi Arabia*
[2]*Department of Agricultural Economics, Faculty of Agricultural Studies, Sudan University of Science and Technology, Khartoum, Sudan*

**Corresponding author: aaeali@kfu.edu.sa, abdaemam@hotmail.com*

Citation: Emam A. (2022): Present and future: Does agriculture affect economic growth and the environment in the Kingdom of Saudi Arabia? Agric. Econ. – Czech, 68: 380–392.

Abstract: Global climate change is a crucial environmental issue. Worldwide warming is primarily caused by carbon dioxide (CO_2) emission levels. Agricultural production is among many economic activities driving CO_2 creation and environmental degradation. In this study, we aim to disclose the effect of agricultural production (date production) on the agricultural gross domestic product (AGDP) and the environment (CO_2 emissions). We collected data on date production, AGDP and CO_2 emissions from different resources covering the period from 1990 to 2019. To analyse the data, we used the Engle-Granger two-step procedure, autoregressive distributed lag (ARDL) bounds methods of analysis, regression analysis and forecasting tests. Results from fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) analyses helped confirm the results of the ARDL model. The results revealed that there are long-run relationships between AGDP and date production and between CO_2 emissions and date production. The first result is consequent with theory and leads to economic growth, whereas the second result indicates a negative effect on the environment. To ascertain which production factors were responsible for this negative result, we ran a regression analysis, and the results indicated that the coefficient of electricity consumption (independent variable) was positive and highly significant in explaining the variability of CO_2 emissions. The results of the regression analysis also showed that agriculture affected the environment negatively through increasing CO_2 emissions during the study period. Forecasting analysis results showed a decrease in CO_2 emissions for the period from 2020 to 2026. The study results lead us to recommend that, to increase economic growth, date production should be increased along with the synchronised use of renewable sources of electricity. The governmental effort to sustain the environment also should be increased and continued through increasing the share of renewable electricity in total electricity consumption.

Keywords: CO_2 emission; date production; econometric analysis; electricity consumption; forecasting analysis; impulse test

Climate change is an important environmental issue worldwide (Tiba and Anis 2017). International warming mainly comes from carbon dioxide (CO_2) emission levels (Talbi 2017). Many economic activities have driven CO_2 creation. Agricultural production is one of the activities which leads to environmental degradation (Ahmad and

Supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia (Grant No. 1482).

https://doi.org/10.17221/58/2022-AGRICECON

Shoukat 2020). Biomass fuel burning, deforestation and brush burning are considered unmaintainable agricultural activities which can result in environmental degradation (Matysek et al. 2019). Biomass fuel burning comes from irrigation directly or indirectly from water desalination and treated wastewater. However, agriculture can play a vital role in reducing CO_2 emissions through the use of improved agricultural activities, such as using organic fertiliser (Poeplau and Axel 2015). Worldwide and in the Kingdom of Saudi Arabia (KSA), the release of CO_2 emissions equals 492 145.2 tons and 11 293.6 tons, respectively, coming from on-farm energy use (FAO 2019b).

Date production in the KSA. A key driver of crop production in the KSA is the date palm (*Phoenix dactylifera*) (Aleid et al. 2015). It is cultivated on 1 396.727 ha, with a universal yearly production of 9 248.033 tonnes (Mohammed et al. 2021a). In the KSA, it is grown on 136 992 ha with a yearly production of 1 539.756 tonnes (FAO 2022). In addition, in the KSA, the percentage of the harvested area of date palm (ha) and quantities produced of dates (tonnes) constitute 33.2% and 27.4% of total crop production (primary), respectively (FAO 2022). Date palms also account for 75% of fruit production in the country (Elfeky and Elfaki 2019).

Cultivation of date palms in the KSA involves many steps, including fertilisation, irrigation, and pest control (Aleid et al. 2015). The amount of irrigation water required for 100 date palms per ha ranges from 7 299 m^3/ha to 9 495 m^3/ha (Mohammed et al. 2021b). The sources of water for agriculture are desalinated water, surface water, advanced treated water, and groundwater (Napoli and García-Téllez 2016). Because of the scarcity of good quality water, saline water is used in date palm irrigation because of the general idea that the date palm is a salt-tolerant tree (Elfeky and Elfaki 2019). Generally in irrigation, energy plays a vital role in the extraction, treatment and transportation of water (Napoli and García-Téllez 2016). Approximately 80% of the energy consumed is created by the burning of fossil fuels, which increases pollution (Tlili 2015). The KSA depends on fossil fuels to produce electricity and fresh water through desalination (Chandrasekharam et al. 2015). The desalination process results in substantial emissions of CO_2 (Ghaffour et al. 2014); therefore, CO_2 emissions are closely connected to the electricity produced from the fossil fuels used for desalination (Chandrasekharam et al. 2015). Hence, biomass fuel burning derives from irrigation directly or indirectly from water desalination and the treatment of wastewater. Biomass fuel burning can also cause environmental degradation. In the KSA, the interval for applying fertiliser varies considerably among farmers and ranges from one to three years. Generally, manure fertiliser is used in date production, with limited quantities of inorganic fertiliser, which is applied in some areas such as Al Madinah and Al-Hasa (Abdul-Baki et al. 2002). Al-Wijam disease and the red palm weevil [*Rhynchophorus ferrugineus* (Olivier)] are the major disease and pest, respectively, affecting date palms in the KSA (Alhudaib et al. 2007). Controlling the red palm weevil by using insecticides harms the environment and human health, so biological control is considered through using natural enemies (Alanazi 2019).

The KSA's efforts to sustain the environment. The KSA is conducting various efforts to sustain the environment, such as introducing renewable energy and the Circular Carbon Economy National Program. Figure 1 shows that there is an increase in the share of 1 000 renewable energy sources to total energy consumption, from 0.001% in 2011 to 0.087% in 2019 (Ritchie et al. 2020). The KSA launched the Circular Carbon Economy concept during a G20 meeting, and

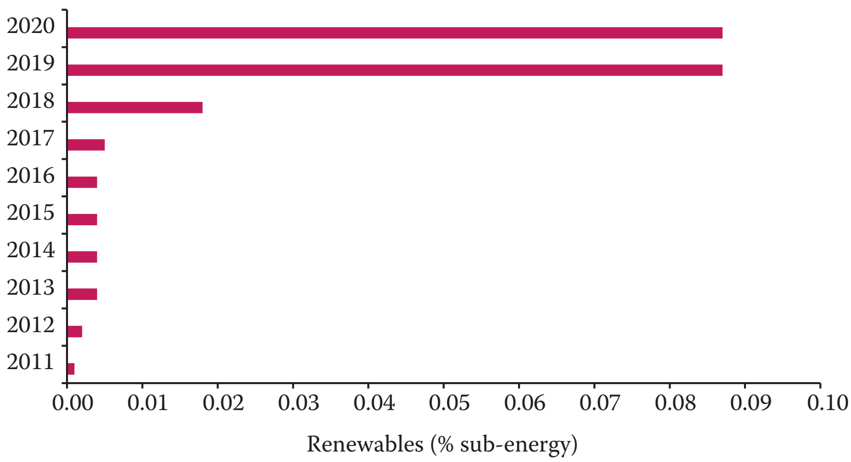

Figure 1. Percentage of renewable electricity to total electricity consumption

Source: Author calculations based on Ritchie et al. (2020)

https://doi.org/10.17221/58/2022-AGRICECON

the G20 countries approved it as a combined, complete framework for reducing greenhouse gas emissions through four main strategies: reduce, reuse, recycle and remove. These four strategies are in line with Saudi Vision 2030's ambitious programs, which aim at achieving social transformation. Implementation of the KSA Circular Carbon Economy National Program includes technological localisation and advancement. This program aims to attain sustainable social and economic growth, promote integrated climate change solutions and ensure global leadership in the field of the circular carbon economy.

To protect the environment, the KSA instituted a sustainable development program to decrease irrigation losses of water, nurture water efficiency and use agronomic tools (Zaharani et al. 2011). The KSA is characterised by very little rainfall, and only 2% of the country's total area is arable land for the production of dates and fruits. The KSA has more than 400 date palm varieties that occupy approximately 12% of the total area cultivated (FAO 2019a). The cultivation of date palms and their growth and fruiting regimens are adaptable to the local climates of seven provinces (Rahman et al. 2014). In 2019, the cultivated area and total production quantities of dates equalled 117 881 ha and 1 539.756 tonnes, respectively, in the KSA (FAO 2019a).

Emam et al. (2021) aimed to measure the effect of some economic variables on the agricultural gross domestic product (AGDP). They conducted their study in the KSA and designed it to assess the relationships among selected agricultural products (dates, honey, fish, chicken, and cattle) and AGDP. The data covered the period from 1985 to 2017 and were analysed using the Johansen cointegration test and vector error correction, and multiple regression models. The results revealed long-run cointegration between selected variables and short-run causality between a few variables and the presence of positive and significant association among the AGDP (dependent) and the independent variables, except fish and dates.

Ahmed and Walid (2018) tested the relationship between the agricultural share of gross domestic product (GDP) and agricultural exports. They analysed the data by using the Johansen method and error correction model (ECM)-generalised autoregressive conditional heteroscedasticity. They discovered long-run and short-run relationships between the variables under study. The study results also revealed that agricultural exports positively influenced the agricultural share of the GDP.

Muhammed and Alhiyali (2018) designed a study of stimulating growth in the Iraqi agricultural sector. The research was based on quantitative multivariate cointegration using the autoregressive distributed lag (ARDL) model and the test of causality for determining the direction of the relationships between the economic variables. Their results showed the long-term effect between the agricultural GDP index and the other economic variables under study.

Investigators in various studies assessed the effect of agricultural activity on the environment in terms of CO_2 emissions. These studies' results are not in agreement; some indicated that there is a direct relationship between agricultural production and environmental pollution, thus strengthening the case for climate alteration (Ozkan and Omer 2012; Bakhtiari et al. 2015; Asumadu-Sarkodie and Owusu 2016), and others indicated an inverse relationship (Pant 2009; Edoja et al. 2016).

Khan et al. (2018) examined the associations among agricultural productivity, energy consumption, forest area, vegetable area, renewable energies, and CO_2 emissions during the period from 1981 to 2015. Their results showed causality between the variables and CO_2 emissions.

Asumadu-Sarkodie and Owusu (2017) tested the causality relationship between the agricultural ecosystem and CO_2 emissions during the period from 1961 to 2012. They noted bidirectional causality between study variables.

Ullah et al. (2018) examined the agricultural ecosystem and climate change in Pakistan. They used Johansen cointegration and autoregressive tests as methods of analysis. Their results indicated a long-run relationship between that agricultural system and CO_2 emissions. In addition, the results showed that energy consumption, use of fertilisers, agricultural production and agricultural machinery encouraged an increase in CO_2 emissions. They found bidirectional causality between CO_2 emissions and rice production.

Asumadu-Sarkodie and Owusu (2016) examined the relationships among CO_2 emissions (dependent variable) and the total production of roots and tubers, annual change of agricultural area, total livestock per change in area, total production of primary vegetables, total production of pulses, total production of coarse grain, cocoa bean production and total fruit production (independent variables). Regression analysis results showed that all variables, except vegetable production, affected CO_2 emissions.

Bakhtiari et al. (2015) used the Cobb-Douglas function to look at the associations among CO_2 emissions, saffron production, and energy. The results revealed that saffron production increased CO_2 emissions.

https://doi.org/10.17221/58/2022-AGRICECON

Waheed et al. (2018) examined the effects of agricultural production, forests, and renewable-energy consumption on CO_2 emissions in Pakistan. The data covered the period from 1990 to 2014 and were analysed with econometric analysis methods. The results indicated that agricultural production was the main cause of CO_2 emissions.

Asumadu-Sarkodie and Owusu (2017) tested the associations among livestock production index, crops, and CO_2 emissions. They used ARDLs and variance decomposition to analyse the data. The results revealed that the livestock production index and crop production had a positive and direct relationship with CO_2 emissions.

Doğan (2018) examined the long-run associations among real income, energy consumption and agricultural production under the hypothesis of the environmental Kuznets curve in China. The data covered the period from 1971 and 2010 and were analysed using the ARDL model. The results showed the presence of a long-run relationship between agricultural production and CO_2 emissions. These results were confirmed by using fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS) and canonical cointegrating regression. Hence, these results showed cointegration between series, indicating the existence of an inverse U-shaped agriculture-induced environmental Kuznets curve.

With reference to these previous studies, we found the importance of our study objectives. In this study, we aimed to test the effects of agricultural production on economic growth and the environment (CO_2 emissions). In other words, we aimed to examine the effect of agricultural production on economic growth and, at the same time, test the effect of agricultural production on the environment.

In the KSA, the date palm occupies approximately 12% of the total area cultivated, and date production quantities accounted for approximately 27% of total agricultural production, indicating that date production constitutes more than one-fourth of total agricultural production (FAO 2019a). Because of the scarcity of water in the KSA, date palm irrigation depends mainly on underground water, desalinated water, and treated water (Elfeky and Elfaki 2019). Generally, the date palm tree produces approximately 40 kg of burnable waste, including dried leaves, spathes, sheaths, and petioles annually (Mallaki and Rouhollah 2014), which is why we selected date production as a variable in this study.

MATERIAL AND METHODS

Data description

Date production (tonnes), AGDP (1 000 riyals = = USD 266.06), CO_2 emissions (kilotonnnes) and electricity consumption (*EL*) (GWh) are the study variables. We collected the data for this study for the period from 1990 to 2019 from different sources. We analysed the data by using the EViews 9 program. Table 1 summarises information about the series.

Analysis methods

Cointegration tests. Choosing appropriate methods for testing a long-run relationship requires specifying the order of integration, as clarified later. The order of integration was specified by using a unit root test (Emam 2020).

Unit root test. According to the following equations, we used an augmented Dickey-Fuller (ADF) test for the order of integration of the series (Dickey and Wayne 1979):

$$\Delta X_t = C_{t1} + b_1 X_{t-1} + E_{t1} \tag{1}$$

$$\Delta X_t = C_{t2} + \beta_t + b_2 X_{t-1} + E_{t2} \tag{2}$$

where: b_1, b_2 – ADF coefficients to be valued; β – trend; C – constant; t – time selected; E_t – error term.

In testing null hypothesis, X has a unit root against alternative hypothesis, and X has a stationary. If the t-statistic of the ADF coefficient is larger than t critical values, the series are stationary.

ARDL model bounds test. We used the ARDL model test to assess long-run relationships between the series

Table 1. Variables description

Variable description	Variable	Unit	Sources
Agricultural gross domestic product	*AGDP*	1 000 riyals = USD 266.06	World Bank (2022a)
CO_2 emission	CO_2	kilotonnne	FAO (2019b)
Dates production	*dates*	tonne	FAO (2019a)
Electricity consumption in commercial sector	*EL*	GWh	World Bank (2022b)

https://doi.org/10.17221/58/2022-AGRICECON

under study. Moreover, this test is regarded as superior to other related tests; it is efficient for small samples using ordinary least squares, regardless of the series order 1(0) and 1(1) but not 1(2). The method uses the following equations (Pesaran et al. 2001):

$$\Delta X_t = C_1 + \sum_{t-1}^{p} a_1 \Delta Y_{t-1} + b_3 X_{t-1} + b_4 Y_{t-1} + e_1 \quad (3)$$

$$\Delta Y_t = C_2 + \sum_{t-1}^{p} a_2 \Delta X_{t-1} + b_5 Y_{t-1} + b_6 X_{t-1} + e_2 \quad (4)$$

where: a_1, a_2 – coefficients of the difference of lag independent variable in Equations (3, 4), respectively; b_3, b_5 – coefficients of lag dependent variable in Equations (3, 4), respectively; b_4, b_6 – coefficients of independent variable in Equations (3, 4), respectively; e_1, e_2 – error terms in Equations (3, 4), respectively.

ARDL tests the presence of long-run connections between the series wherever there is acceptance of the null hypothesis, which indicates that there is no long-run relationship: For null hypothesis, $b_1 = b_2 = 0$ [Equation (3)] against the alternative hypothesis $b_1 \neq b_2 \neq 0$. We also ran the same test for Y as an independent variable with the null hypothesis $b_3 = b_4 = 0$ [Equation (4)] against the alternative hypothesis $b_3 \neq b_4 \neq 0$.

To examine the stability of the ARDL model estimates, we used the cumulative sum (CUSUM) method (Pesaran and Pesaran 1997). A residual within the 5% critical boundaries indicates that, at the 5% level of significance, the estimated coefficients are stable. Equations (3, 4) have lower and upper bounds (two critical F-values) conforming the integrated order 1(0) and 1(1) of the variables, respectively (Pesaran et al. 2001).

To confirm the results of ARDL statistics, we used FMOLS and DOLS models (Ahmad et al. 2017). The FMOLS and DOLS model results provide fair valuations of long-run associations among the variables under study. Also, the methods are considered to correct serial correlation problem when occurred between a variable with its lag.

Engle-Granger test. Running the Engle-Granger test requires performing the first unit root test to specify the series order of integration [same order of integration 1(1)]. Examining whether the two series are cointegrated with each other requires performing the Engle-Granger two-step procedure on the two series jointly. The procedure involves the followings steps:

i) The first regression equation is as follows:

$$X_t = a_1 + b_7 Y_t + z_t \quad (5)$$

where: z_t – error term; b_7 – slope coefficient estimate.

$$Y_t = a_2 + b_8 X_t + i_t \quad (6)$$

where: i_t – error term; b_8 – slope coefficient.

ii) An ADF test is run on the residuals (z_t and i_t) to investigate whether the series are integrated. If the ADF statistics resulting from the Equations (5, 6) are larger and more negative than the critical t-value (of order 1), then coefficients b_1 and b_2 are expected to be statistically significant and the series are cointegrated. If the results of the ADF and Engle-Granger two-step procedure tests prove that each series is 1(1) and that the linear combination of them is 1(1), then the two series taken together are said to be cointegrated of order 1(1).

ECM test. If the cointegration test shows long-run associations among the series, the ECM test can be used to assess the speed parameter of the short-run association between the two series (Venujayakanth et al. 2017). The following are the ECM equations:

$$\begin{aligned}\Delta(\log CO_2) = \Delta b_9(\log CO_2)_{t-1} + \\ + \Delta b_{10}(\log dates)_{t-1} + b_{11} U_1 + V_1\end{aligned} \quad (7)$$

$$\begin{aligned}\Delta(\log dates) = \Delta b_{12}(\log dates)_{t-1} + \\ + \Delta b_{13}(\log CO_2)_{t-1} + b_{14} U_2 + V_2\end{aligned} \quad (8)$$

where: b_9, b_{12} – coefficients of difference of lag dependent variable; b_{10}, b_{13} – coefficients of difference of lag independent variable; b_{11}, b_{14} – speed of adjustment (must be significant and negative to correct model disequilibrium); *dates* – date production quantities; CO_2 – CO_2 emission; U_1, U_2 – error correction terms; V_1, V_2 – error terms.

We checked ECM feasibility by testing residual diagnostic tests. We performed the tests as described next.

Heteroscedasticity test. In the Breusch-Pagan-Godfrey test, the null hypothesis is homoscedasticity, and the alternative hypothesis is heteroscedasticity. Acceptance of the null hypothesis when the P-value is more than 0.05 means that the residual is homoscedastic.

Residual normality test. When the probability of the Jarque-Bera statistic is more than 0.05, then the residual is normally distributed. The results of ECM feasibility are then acceptable for conducting the forecasting analysis.

https://doi.org/10.17221/58/2022-AGRICECON

We also used the impulse response test to ascertain the dynamic behaviour of vector autoregression models and to define the model response to a shock in one or more variables (Lütkepohl 2010).

Regression analysis method. We used regression analysis to evaluate the effect of KSA *EL*, insecticide and fertiliser (as nutrients) on KSA CO_2 emissions, but the regression model and coefficients of insecticide and fertiliser appeared unstable and nonsignificant, respectively. Accordingly, we used *EL* as the variable as follows:

$$\ln CO_2 = c + \beta_1 \ln EL \tag{9}$$

where: β – coefficient to be estimated; *c* – constant; *EL* – electricity consumption.

We conducted a CUSUM test to detect the stability of the CUSUM of the recursive residuals. The test is used to indicate parameter stability if the CUSUM found is inside the area between the two critical lines, indicating the stability of the model. Given these results, we used a linear regression model. The results suggested that the estimated model was significant, and we used them to estimate the contributions of the independent variable (*EL*) on CO_2 emissions.

Forecasting analysis

We used the ECM for forecasting analysis with CO_2 emissions as the dependent variable. We assessed the viability of the forecasting result with the root mean square error. A smaller root mean square error means a better forecasting result.

We also calculated the growth rate of CO_2 emissions for the period from 1990 to 2019 and for the forecasting period from 2020 to 2030. We used the following equation to calculate the growth rate of CO_2 emissions:

$$G_t = \frac{Y_{year} - Y_{year-1}}{Y_{year-1}} \tag{10}$$

where: G_t – growth rate between two successive years; Y – CO_2 emissions.

We calculated the growth rate of CO_2 emissions for the period from 1990 to 2019 and for the period from 2020 to 2030 as follows:

$$G_{t,\ldots,n} = \frac{\left(G_t + G_{t+1} + \ldots + G_n\right)}{N} \tag{11}$$

where: N – number of years; $G_{t,\ldots,n}$ – growth rate for a specific period.

RESULTS AND DISCUSSION

The study was designed to assess the effect of date production on economic growth and the environment. Consequently, it consists of two parts – one concerning the effect of date production on economic growth (AGDP) and the other concerning the effect of date production on the environment (CO_2 emissions).

Part one: Cointegration test analysis results (AGDP and date production)

Results of the unit root tests. We used a root test to analyse the stationary order of series of AGDP and date production. The ADF statistics were significant at the 1% level and first difference for date production and AGDP variables, respectively (Table 2). These results indicate that the two series are stationary at 1(0) and 1(1), respectively. Consequently, the two series did not have the same stationary order [1(0) and 1(1)]. Accordingly, we used the ARDL bounds test to evaluate the relationship between the two series.

Results of the ARDL tests. Table 3 presents the results of the ARDL tests. We used the Jarque-Bera test, Breusch-Pagan-Godfrey heteroscedasticity test and Breusch-Godfrey serial correlation Lagrange multiplier (LM) test to produce the ARDL model adequacy residual diagnostics. The results did not show heteroscedasticity and serial correlation. We also ran a CUSUM test for stability diagnosis (Zhai et al. 2013). The test results showed the stability of the CUSUM of the recursive residuals, indicating the strength of the model (Figures 2, 3).

Table 4 shows the bound test results for the two ARDL models. For model 1, the bound examined the *F*-test for the coefficients of AGDP (one lag period) and

Table 2. Results of unit root test

Time series	Intercept	Intercept and trend	Stationarity
At level			
$\ln AGDP$	–1.52	–4.09**	non stationary
$\ln CO_2$	–2.15	–2.14	non stationary
$\ln dates$	–0.87	–3.19	non stationary
At first difference			
$\ln AGDP$	–3.49**	–3.52***	stationary
$\ln CO_2$	–4.50*	–4.46*	stationary
$\ln dates$	–7.77*	–7.66*	stationary

*, **, ***Significance level at 1, 5, and 10%, respectively; *AGDP* – agricultural gross domestic product
Source: Author calculations based on collected data

https://doi.org/10.17221/58/2022-AGRICECON

Table 3. Results of autoregressive distributed lag (ARDL) tests

Model	Independent variable	Coefficient	Probability
Model 1 ln*AGDP* (dependent variable) Selected ARDL model (1, 4)	ln*AGDP* (–1)	0.880	0.000
	ln*dates*	–0.070	0.078
	ln*dates* (–1)	–0.010	0.803
	ln*dates* (–2)	0.002	0.957
	ln*dates* (–3)	0.030	0.484
	ln*dates* (–4)	0.170	0.000
	C	–0.460	0.114
	R^2	0.990	–
	Adjusted R^2	0.993	–
	F-statistics	588.660	0.000
	Serial correlation LM test: Breusch-Godfrey	0.890	0.360
	Breusch-Pagan-Godfrey heteroskedasticity test	0.540	0.770
Model 2 ln*dates* (dependent variable) Selected ARDL model (1, 0)	ln*dates* (–1)	0.400	0.056
	ln*dates* (–2)	0.360	0.088
	ln*AGDP*	–0.840	0.319
	ln*AGDP* (–1)	–0.140	0.917
	ln*AGDP* (–2)	1.160	0.174
	C	1.490	0.265
	R^2	0.850	–
	Adjusted R^2	0.810	–
	F-statistics	24.320	0.000
	Serial correlation LM test: Breusch-Godfrey	1.750	0.200
	Breusch-Pagan-Godfrey heteroskedasticity test	0.740	0.600

AGDP – agricultural gross domestic product; LM – Lagrange multiplier; *C* – constant
Source: Author calculations based on collected data

date production (independent variable). In model 2, the bound examined the *F*-test for the coefficients of date production (one lag period) and AGDP (independent

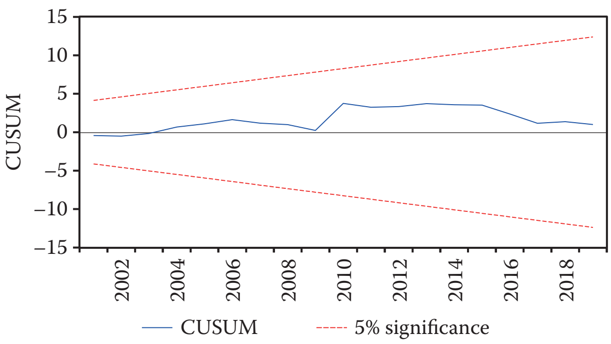

Figure 2. Stability diagnostic (ln*AGDP* as dependent variable)

AGDP – agricultural gross domestic product; CUSUM – cumulative sum
Source: Author calculations based on collected data

variable). The *F*-statistics are 23.39 and 3.77 for models 1 and 2, respectively, which are higher than the upper bound of the bounded critical *F*-statistics at 1% and 10%, respectively, indicating that there was a long-run relationship between AGDP and date production during the study period. This result coincided with those of a previous study (Emam et al. 2021) which also indicated that there is a long-run relationship between AGDP and date production.

To confirm the strength of the ARDL estimations, we used FMOLS and DOLS models. Table 5 shows that the FMOLS and DOLS results are parallel to the ARDL estimation. Date production has a positive coefficient and is highly significant at the 1% level, indicating the positive effect of date production on AGDP. This confirmatory result coincides with those of a study by Doğan (2018), who found a long-run relationship between agriculture and CO_2 emissions by using ARDL and confirmed those results with FMOLS and DOLS models.

https://doi.org/10.17221/58/2022-AGRICECON

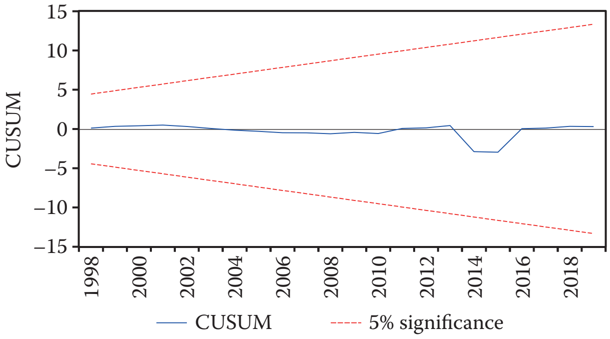

Figure 3. Stability diagnostic (ln*dates* as dependent variable)

CUSUM – cumulative sum
Source: Author calculations based on collected data

Part two: Cointegration test analysis results (CO_2 emissions and date production)

Results of the Engle-Granger test. The ADF statistics were significant at the 1% level for date production and CO_2 emissions. As the two series had the same stationary order 1(1), we used the Engle-Granger test to evaluate the relationship between the series.

We conducted the ADF tests on the residuals (i_t) and (z_t) in Equations (3, 4), respectively (Table 6). Table 6 shows that the ADF statistics are negative (–5.046 and –5.047) and statistically significant at the 1% level. These results led to an acceptance of the alternative hypothesis of integration, indicating that CO_2 emissions and date production have a long-run relationship, which is compatible with results from previous studies indicating that there is a long-run relationship between agricultural production and CO_2 emissions (Asumadu-Sarkodie and Owusu 2017; Waheed et al. 2018).

Table 4. Results of bounds test: Autoregressive distributed lag (ARDL)

Dependent–independent	*F*-statistic of bound test		
ln*AGDP*–ln*dates*		23.39	
ln*dates*–ln*AGDP*		3.77	
Significance	1%	5%	10%
Lower bound	4.94	3.62	3.02
Upper bound	5.58	4.16	3.51

AGDP – agricultural gross domestic product
Source: Author calculations based on collected data

Table 5. Long-run evidence

AGDP (dependent variable)	*ARDL*	*FMOLS*	*DOLS*
ln*dates*	0.174*	0.170*	0.174*

*Significance level at 1%; *AGDP* – agricultural gross domestic product; *ARDL* – autoregressive distributed lag; *FMOLS* – fully modified ordinary least squares; *DOLS* – dynamic ordinary least squares
Source: Author calculations based on collected data

Results of the ECM. We performed ECM to strengthen the result of the long-run relationship and to assess short-run associations among variables. Conducting ECM requires that the lag must be identified (Table 7). From Table 7, lag 2 was specified. To strengthen the result of a long-run relationship between CO_2 emissions and date production, which we obtained from the Engle-Granger test, we ran ECM (Table 8). The coefficient of adjustment for CO_2 emissions (as a dependent variable) was negative (–0.490) and significant (critical *t*-value, –2.66), meaning that the model was able to correct its past time disequilibrium. Also, the results suggest that the coefficients of adjustment for date production (as a dependent variable) were not statistically significant, indicating that the model may need more than one year to produce its preceding time imbalance accurately. To verify vector ECM adequacy, we used serial correlation of residual LM and residual heteroscedasticity tests. LM statistics for lag 1 and lag 2 were 1.21 with a probability of 0.88 and 5.10 with a probability of 0.28, respectively, indicating no serial correlation. A χ^2 of 59.49 with a probability of 0.49 does not indicate heteroscedasticity. These results of model adequacy led to the acceptance of the null hypothesis, no serial correlation of residuals and no heteroscedasticity.

In addition, we ran an impulse test to ascertain the leading series that considerably affects the other long-run series (Figure 4). The responses of CO_2 emissions and date production to the Cholesky one standard deviation (SD) innovation are presented in the Figure 4 (impulse response). The Figure 4 shows that date production had a positive response in the long-run to CO_2 emissions, indicating that date production can be considered the leading variable. This result coincides with those of prior studies (Holly 2015; Asumadu-Sarkodie and Owusu 2017; Waheed et al. 2018). The study results indicated that agricultural practices positively affected CO_2 emissions.

Table 6. Cointegration test – Engle-Granger test results

Dependent	ln*dates*	lnCO_2
lnCO_2	–5.046*	–
ln*dates*	–	–5.047*

*Significance level at 1%
Source: Author calculations based on collected data

https://doi.org/10.17221/58/2022-AGRICECON

Table 7. Lag selection

Lag	log*L*	*LR*	*FPE*	*AIC*	*SC*	*HQ*
0	24.48	NA	0.0007	–1.61	–1.51	–1.58
1	55.10	54.69	0.0001	–3.51	–3.22	–3.42
2	61.92	11.20[a]	8.47e–05[a]	–3.71[a]	–3.23[a]	–3.56[a]

[a]Lag order selected by the criterion; log*L* – log lag variable; *LR* – sequential modified likelihood ratio (LR) test statistic (each test at 5% level); *FPE* – final prediction error; *AIC* – Akaike information criterion; *SC* – Schwarz information criterion; *HQ* – Hannan-Quinn information criterion; NA – not available

Source: Author calculations based on collected data

Table 8. Results of ECM

Error correction	$\ln CO_2$	ln*dates*
*CointEq*1	–0.49 [–2.66]	0.10 [0.27]
$\ln CO_2$ (–1)	0.33 [1.65]	–0.57 [–1.43]
$\ln CO_2$ (–2)	0.17 [0.70]	0.36 [0.76]
ln*dates* (–1)	–0.04 [–0.35]	–0.35 [–1.55]
ln*dates* (–2)	–0.05 [–0.49]	–0.20 [–0.95]
C	0.001 [0.08]	0.056 [1.98]
ECM residual serial correlation LM tests		
lags	LM statistics	probability
1	1.21	0.88
2	5.09	0.28
VEC residual heteroskedasticity tests		
χ^2		probability
59.49		0.49

Numbers in square brackets represent critical *t*-values; LM – Lagrange multiplier; CO_2 – CO_2 emission; *dates* – date production; *C* – constant; ECM – error correction model; VEC – vector error correction; *CointEq*1 – error correction term – co-integrated Equation (1)

Source: Author calculations based on collected data

Part three: Regression analysis results (CO_2 emissions and *EL*)

We ran the regression analysis to shed light on the effectors of increasing CO_2 emissions. The analysis results are presented in Table 9. We used different scenarios to find a stable model. Table 9 showed no autocorrelation between successive values of the disturbance term, which has a constant variance (ho-

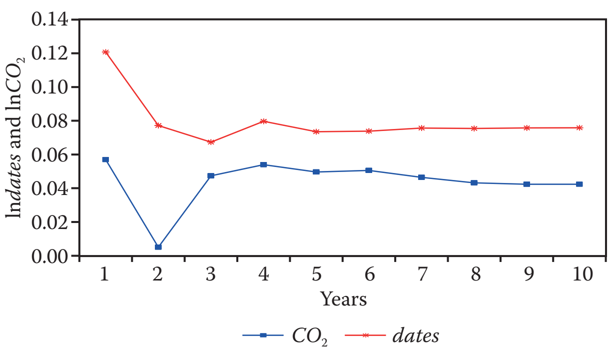

Figure 4. Response of dates to Cholesky one SD innovations

Source: Author calculations based on collected data

Table 9. Results of regression analysis ($\ln CO_2$ as dependent variable)

Variable	Coefficient	*t*-statistic	Probability
Ln*EL*	0.40	5.52	0.0006
C	3.93	5.14	0.0009
R^2	0.79		–
Adjusted R^2	0.77		–
F-statistic	30.47		0.0006
Durbin Watson (autocorrelation)	2.99		–
LM-statistics (Breusch-Godfrey serial correlation of residual)	1.17		0.3700

LM – Lagrange multiplier; *EL* – electricity consumption

Source: Author's calculations based on collected data

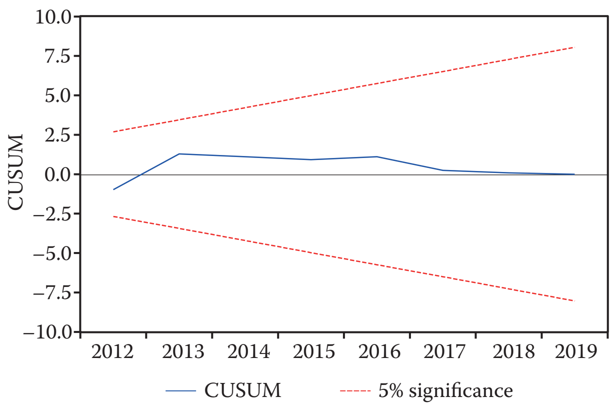

Figure 5. Stability diagnostic ($\ln CO_2$ as dependent variable)

CUSUM – cumulative sum

Source: Author calculations based on collected data

https://doi.org/10.17221/58/2022-AGRICECON

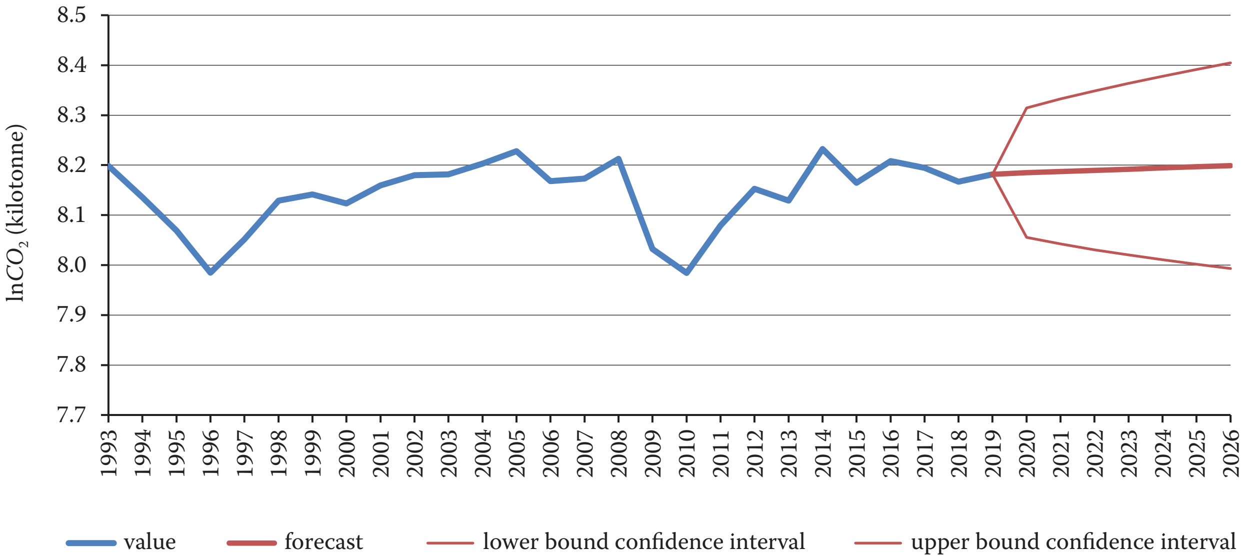

Figure 6. Forecasting graph

Source: Author calculations based on collected data

moscedastic). To test the model's stability, we conducted a CUSUM test to detect the stability of the CUSUM of the recursive residuals (Figure 5). Consequently, we used a regression model to estimate the influences of *EL* (independent variable) on CO_2 emissions. The R^2 value in the Table 9 indicates that 79% of the variations in CO_2 emissions are caused by *EL*. Also, the values of the *F*-statistics demonstrate a highly significant level for the model. The coefficients of *EL* (independent variable) are positive and highly significant in explaining the variability of CO_2 emissions, indicating that *EL* affects CO_2 emission accumulation. This result coincides with the theoretical notation. Based on Equation (11), a 1% increase in *EL* will increase CO_2 emissions by 0.40%. This result agrees with those of Raggad (2018), which showed that energy use has a positive effect on CO_2 emissions.

The following is the estimated equation:

$$\ln CO_2 = 3.93 + 0.40 \ln EL \quad (12)$$

Part four: Forecasting analysis result

Figure 6 shows the forecasting graph; the blue and red parts reflect the actual CO_2 emissions for the period from 1990 to 2019 and the forecast period from 2020 to 2026, respectively. Also, the growth rates of CO_2 emissions were 0.000157 and –0.091 for the period from 1990 to 2019 and the forecast period from 2020 to 2030, respectively, indicating that CO_2 emissions decreased (–0.091) during the forecast period. This result may be due to governmental efforts to sustain the environment.

CONCLUSION

In this study, we aimed to assess the effect of agricultural production (date production) on economic growth (AGDP) and the environment (CO_2 emissions). We collected data on date production, AGDP and CO_2 emissions from different sources covering the period from 1990 to 2019. The ARDL bounds revealed that there are long-run relationships between AGDP and date production and that date production has a positive significant effect on AGDP, indicating that date production enhances economic growth. The Engle-Granger two-step procedure results showed the long-run relationship between date production and CO_2 emissions. ECM showed the model has the ability to restore its long-run equilibrium and short-run relationship, with CO_2 emissions as a dependent variable. The impulse test results showed that date production had a positive long-run relationship to CO_2 emissions, indicating that date production can be considered the leading variable. To strengthen the results of the relationship between AGDP and date production, we assessed the diagnosis stability of long-run and short-run relationships. The FMOLS and DOLS model results were also compatible with the results of the ARDL model. The results related to date production and AGDP validate the theory and lead to economic growth, whereas date

https://doi.org/10.17221/58/2022-AGRICECON

production appeared to influence CO_2 emissions positively, indicating that date production negatively affected the environment. In addition, the results of the regression analysis showed that the *EL* coefficient (independent variable) was positive and highly significant in explaining the variability of CO_2 emissions, indicating that *EL* has been a driving force in the production of CO_2 emissions. The results of the regression analysis indicated that agriculture affected the environment negatively through increasing CO_2 emissions during the study period. The growth rates of CO_2 emissions were 0.000157 and −0.091 for the period from 1990 to 2019 and the forecast period from 2020 to 2030, respectively, indicating that CO_2 emissions decreased (−0.091) during the forecast period. Given the study's results, we recommend that date production should be enriched to enhance economic growth at the same time as enhancing the use of renewable electricity. Also, the governmental effort to sustain the environment should be increased and continued through increasing the use of renewable energy.

REFERENCES

Abdul-Baki A., Aslan S., Linderman R., Cobb S., Davis A. (2002): Soil, Water, and Nutritional Management of Date Orchards in the Coachella Valley and Bard. Washington, D.C., USA, US Department of Agriculture (USDA). Available at https://www.ars.usda.gov/research/publications/publication/?seqNo115=98543 (accessed Jan 15, 2022).

Ahmad M., Shoukat K. (2020): Is aggregate domestic consumption spending (ADCS) per capita determining CO_2 emissions in South Africa? A new perspective. Environmental and Resource Economics, 75: 529–552.

Ahmad N., Liangsheng D., Jiye L., Jianlin W., Hong-Zhou L., Muhammad H. (2017): Modelling the CO_2 emissions and economic growth in Croatia: Is there any environmental Kuznets curve? Energy, 123: 164–172.

Ahmed O., Walid S. (2018): Studying the volatility effect of agricultural exports on agriculture share of GDP: The case of Egypt. African Journal of Agricultural Research, 13: 345–352.

Alanazi N.A. (2019): Isolation and identification of bacteria associated with red palm weevil, *Rhynchophorus ferrugineus* from Hail region, northern Saudi Arabia. Bioscience Biotechnology Research Communications, 12: 266–274.

Aleid S.M., Al-Khayri J.M., Al-Bahrany A.M. (2015): Date palm status and perspective in Saudi Arabia. In: Al-Khayri J.M., Jain S.M., Johnson D.V. (eds.): Date Palm Genetic Resources and Utilization. Dordrecht, the Netherlands, Springer: 49–95.

Alhudaib K., Arocha Y., Wilson M., Jones P. (2007): "Al-Wijam", a new phytoplasma disease of date palm in Saudi Arabia. Bulletin of Insectology, 60: 285.

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 Pollution Research International, 23: 10968–10982.

Asumadu-Sarkodie S., Owusu P.A. (2017): The causal nexus between carbon dioxide emissions and agricultural ecosystem – An econometric approach. Environmenatal Science and Pollution Research, 24: 1608–1618.

Asumadu-Sarkodie S., Owusu P.A. (2017): The relationship between carbon dioxide, crop and food production index in Ghana: By estimating the long-run elasticities and variance decomposition. Environmental Engineering Research, 22: 193–202.

Bakhtiari A., Amir H., Azin S. (2015): Energy analyses and greenhouse gas emissions assessment for saffron production cycle. Environmental Science and Pollution Research, 22: 16184–16201.

Chandrasekharam D., Lashin A., Al Arifi N., Al Bassam A., El Alfy M., Ranjith P.G., Varun C., Singh H.K. (2015): The potential of high heat generating granites as EGS source to generate power and reduce CO_2 emissions, western Arabian shield, Saudi Arabia. Journal of African Earth Sciences, 112: 213–233.

Dickey A., Wayne F. (1979): Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74: 427–431.

Doğan N. (2018): The impact of agriculture on CO_2 emissions in China. Panoeconomicus, 66: 257–271.

Edoja E., Goodness A., Orefi A. (2016): Dynamic relationship among CO_2 emission, agricultural productivity and food security in Nigeria. Cogent Economics & Finance, 4: 1–13.

Elfeky A., Elfaki J. (2019): A review: Date palm irrigation methods and water resources in the Kingdom of Saudi Arabia. Journal of Engineering Research and Reports, 9: 1–11.

Emam A. (2020): The impacts of COVID-19: An econometric analysis of crude oil prices and rice prices in the world. Journal of Agriculture Sciences, 35: 137–143.

Emam A., Abass A., Elmulthum N., Elresheed M. (2021): Status and prospects of agricultural growth domestic product in the Kingdom of Saudi Arabia. SAGE Open, 11: 1–10.

FAO (2019a): Crops and Livestock Products. [Dataset]. Food and Agriculture Organization of the United Nations (FAO). Available at https://www.fao.org/faostat/en/#data/QCL (accessed Oct 23, 2021).

FAO (2019b): Emissions Totals. [Dataset]. Food and Agriculture Organization of the United Nations (FAO). Available at https://www.fao.org/faostat/en/#data/GT (accessed Oct 23, 2021).

https://doi.org/10.17221/58/2022-AGRICECON

FAO (2022): Crops and Livestock Products. [Dataset]. Food and Agriculture Organization of the United Nations (FAO). Available at https://www.fao.org/faostat/en/#data/QCL (accessed Aug 11, 2022).

Ghaffour N., Lattemann S., Missimer T., Ng K.C., Sinha S., Amy G. (2014): Renewable energy-driven innovative energy-efficient desalination technologies. Applied Energy, 136: 1155–1165.

Holly R. (2015): The complicated relationship between agriculture and climate change. Investigate Midwest. Available at http://investigatemidwest.org/2015/07/09/the-complicated-relationship-between-agriculture-and-climate-change/ (accessed Jan 5, 2022).

Khan I., Qamar A., Muhammad A. (2018): The nexus between greenhouse gas emission, electricity production, renewable energy and agriculture in Pakistan. Renewable Energy, 118: 437–451.

Lütkepohl H. (2010): Impulse response function. In: Durlauf S.N., Blume L.E. (eds): Macroeconometrics and Time Series Analysis. London, United Kingdom, The New Palgrave Economics Collection, Palgrave Macmillan: 145–150.

Mallaki M., Rouhollah F. (2014): Design of a biomass power plant for burning date palm waste to cogenerate electricity and distilled water. Renewable Energy, 63: 286–291.

Matysek M., Jonathan L., Steven B., Irene J., Susan P., Jorg K., Alan S., Alexander C., Donatella Z. (2019): Impact of fertiliser, water table, and warming on celery yield and CO_2 and CH_4 emissions from fenland agricultural peat. Science of the Total Environment, 667: 179–190.

Mohammed M., Riad K., Alqahtani N. (2021b): Efficient iot-based control for a smart subsurface irrigation system to enhance irrigation management of date palm. Sensors, 21: 3942.

Mohammed M., Sallam A., Munir M., Ali-Dinar H. (2021a): Effects of deficit irrigation scheduling on water use, gas exchange, yield, and fruit quality of date palm. Agronomy, 11: 2256.

Muhammed F., Alhiyali A. (2018): Estimation of the impact of some variables of agricultural economic policy on the Iraqi domestic agricultural product for the period 1994–2015 using the method of conitegration and the ARDL model. The Iraqi Journal of Agricultural Science, 49: 1073.

Napoli C., García-Téllez B. (2016): Energy for Water in Agriculture: A Partial Factor Productivity Analysis. King Abdullah Petroleum Studies and Research Center (KAPSARC). Available at https://www.kapsarc.org/research/publications/energy-for-water-in-agriculture/ (accessed Apr 9, 2022).

Ozkan F., Omer O. (2012): An analysis of CO_2 emissions of Turkish industries and energy sector. Regional and Sectoral Economic Studies, 12: 65–85.

Pant P. (2009): Effect of agriculture on climate change: A cross country study of factors affecting carbon emissions. The Journal of Agriculture and Environment, 10: 72–88.

Pesaran H., Peseran B. (1997): Working with Microfit 4.0: Interactive Econometric Analysis. Oxford, United Kingdom, Oxford University Press: 505.

Pesaran H., Yongcheol S., Richard S. (2001): Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16: 289–326.

Poeplau C., Axel D. (2015): Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis. Agriculture, Ecosystems & Environment, 200: 33–41.

Raggad B. (2018): Carbon dioxide emissions, economic growth, energy use, and urbanization in Saudi Arabia: Evidence from the ARDL approach and impulse saturation break tests. Environmental Science and Pollution Research, 25: 14882–14898.

Rahman S., Ismat B., Mohammad A. (2014): Livestock in Bangladesh: Distribution, growth, performance and potential. Livestock Research for Rural Development, 26: 233–238.

Ritchie H., Roser M., Rosado P. (2020): Saudi Arabia: Energy Country Profile. OurWorldInData.org. Available at https://ourworldindata.org/energy/country/saudi-arabia#citation (accessed Mar 5, 2022).

Talbi B. (2017): CO_2 emissions reduction in road transport sector in Tunisia. Renewable and Sustainable Energy Reviews, 69: 232–238.

Tiba S., Anis O. (2017): Literature survey on the relationships between energy, environment and economic growth. Renewable and Sustainable Energy Reviews, 69: 1129–1146.

Tlili I. (2015): Renewable energy in Saudi Arabia: Current status and future potentials. Environment, Development and Sustainability, 17: 859–886.

Ullah A., Dilawar K., Imran K., Shaofeng Z. (2018): Does agricultural ecosystem cause environmental pollution in Pakistan? Promise and menace. Environmental Science and Pollution Research, 25: 13938–13955.

Venujayakanth B., Swaminathan A., Swaminathan B., Ardeshana N. (2017): Price integration analysis of major groundnut domestic markets in India. Economic Affairs, 62: 233–241.

Waheed R., Dongfeng C., Suleman S., Wei C. (2018): Forest, agriculture, renewable energy, and CO_2 emission. Journal of Cleaner Production, 172: 4231-4238.

World Bank (2022a): Commodity Markets. [Dataset]. World Bank. Available at https://www.worldbank.org/en/research/commodity-markets (accessed Feb 5, 2022).

World Bank (2022b): Sustainable Energy for All. [Dataset]. World Bank. Available at https://databank.worldbank.org/source/sustainable-energy-for-all# (accessed Feb 6, 2022).

https://doi.org/10.17221/58/2022-AGRICECON

Zaharani K.H., Al-Shaya M., Baig M.B. (2011): Water conservation in the Kingdom of Saudi Arabia for better environment: Implications for extension and education. Bulgarian Journal of Agricultural Science, 17: 389–395.

Zhai X., Zhongyuan G., Xue Z. (2013): Two-stage dynamic test of the determinants of the long-run decline of China's monetary velocity. Chinese Economy, 46: 23-40.

Received: March 6, 2022
Accepted: August 22, 2022
Published online: October 25, 2022