




# Agricultural technologies and carbon emissions: evidence from Jordanian economy

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Received: 16 May 2017 / Accepted: 17 January 2018 / Published online: 3 February 2018  
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## Abstract

Theoretically, agriculture can be the victim and the cause of climate change. Using annual data for the period of 1970–2014, this study examines the interaction between agriculture technology factors and the environment in terms of carbon emissions in Jordan. The results provide evidence for unidirectional causality running from machinery, subsidies, and other transfers, rural access to an improved water source and fertilizers to carbon emissions. The results also reveal the existence of bidirectional causality between the real income and carbon emissions. The variance error decompositions highlight the importance of subsidies and machinery in explaining carbon emissions. They also show that fertilizers, the crop and livestock production, the land under cereal production, the water access, the agricultural value added, and the real income have an increasing effect on carbon emissions over the forecast period. These results are important so that policy-makers can build up strategies and take in considerations the indicators in order to reduce carbon emissions in Jordan.

**Keywords** CO<sub>2</sub> emissions · Agricultural technologies · Improved water source · Jordan

**JEL classification** C10 · C51 · Q16 · Q54

## Introduction

In the recent decades, significant attention has been placed on developing actions and regulations aimed to protect the environment and allow for sustainable development. In order to meet the challenges facing development and environmental issues, financial resources are needed to increase the capacity of implementing institutions as well as the need for greater cooperation among and between countries so as to accelerate and achieve a sustainable development process.

Global warming and climate change are key sustainable development issues (Dolsak 2009). Policy-makers around the world must understand the risks involved beyond the emissions of greenhouse gas (carbon dioxide, methane, and

nitrous oxide). As greenhouse gas emissions increase, environmental sustainability is under threat. Therefore, many governments are taking steps toward reducing the emissions of greenhouse gases by introducing carbon and energy taxes and regulations on energy efficiency and emissions (Kroll and Shogren 2008).

It is now evident that agriculture and the environment are firmly related. Carbon dioxide can be emitted from agricultural activity especially “factory farming” methods of production (NRDC 2006). In the agricultural production process, the existence of irrational utilization of land and water, the overuse of chemical fertilizers and energy utilization enhances the effect of agriculture production on environment quality through high emissions of greenhouse gas. However, the application of appropriate technology and environment friendly innovations could allow agriculture to produce less greenhouse gases, for example, by applying low-energy expenditure methods (Popp et al. 2009).

In 2014, the agricultural sector contributed to about 3.8% of the GDP in Jordan and employed 2% of the total labor force. The sector was developing and growing during the last decades. In fact, the value added by the sector to the GDP increased from JD31.9 million in 1964 to about JD

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Responsible editor: Philippe Garrigues

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134.7 million in 2002 and then to about JD 845.7 million in 2014. During this development and growth, the use of agricultural inputs has increased dramatically, which might cause an increase in carbon (CO<sub>2</sub>) emission. Specifically, the number of agricultural tractors and machines had increased from 2507 in 1968 to 5077 in 2014. Farmers' expenditures on fertilizers had increased from USD 2.1 million in 1968 to USD 27.5 million in 2014. Moreover, water scarcity is an even greater problem for agriculture sector because Jordan has one of the lowest levels of water resources availability, per capita, in the world (UNFCCC 2014). Thus, the impact of water access and subsidies on water may be important since the non-renewable water comes from non-renewable and fossil groundwater extraction and the reuse of reclaimed water (UNFCCC 2014). According to the World Resources Institute Climate Analysis Indicators Tool (WRI CAIT 2016), Jordan emitted 27 million metric tons of carbon dioxide equivalent (MtCO<sub>2</sub>e) in 2011 compared to 16.8 MtCO<sub>2</sub>e in 1990. However, the agriculture sector was responsible for 4% of emissions (around 1.1 MtCO<sub>2</sub>e) in 2011 compared to 2.62% (around 0.44 MtCO<sub>2</sub>e) in 1990. In sum, total greenhouse gas (GHG) emissions grew 10.2 MtCO<sub>2</sub>e from 1990 to 2011, averaging 2.3% annually, while GHG emissions from agriculture sector grew by 152.02%, averaging 4.5% annually. The Higher Council for Science and Technology has set research priorities in different fields in Jordan for the period of 2011–2020. Among these priorities is the focus on the size of CO<sub>2</sub> emission from agriculture.

In order to understand the principal causes of agricultural CO<sub>2</sub> emissions and to achieve a sustainable agricultural green economy, we consider the relationship between agriculture sector and the environment. In particular, we focus on the impact of agricultural technologies on carbon emissions in Jordan using annual data from 1970 to 2014. Our contribution to the existing literature is threefold: first, until now, no one has emphasized the importance of this subject for Jordan. Second, the analysis of the relationship between agricultural technologies and CO<sub>2</sub> emissions will be undertaken by taking into account the role of subsidies and the rural access to an improved water source as potential determinants of environmental pollution. Finally, Toda-Yamamoto version of Granger non-causality tests and generalized error variance decomposition analysis will be used in order to establish the direction of causations and impact of various shocks in the system. Hence, the objective of the paper is more specifically to investigate the nature of the long-run equilibrium and the causal relationship between carbon emissions and agricultural technologies. Up to our knowledge, there is no research that has been done in Jordan covering the linkage between agricultural technologies and CO<sub>2</sub> emissions. This study attempts to fill this gap. In this respect, we argue that this research is essential for

policy-makers and decision-makers to understand the main determinant of carbon emissions in order to develop an efficient policy to limit the pollution arising from agriculture production.

The remainder of the paper is organized as follows: the following section provides a brief review of the literature, the “Methodology and data” section outlines the specifications of the methodology and data, the “Empirical results” section presents the obtained results, and the “Conclusion and policy implications” section gives the concluding remarks and policy implications.

## Brief literature review

The effect of agricultural technologies on environmental pollution and climate change has received growing attention in the literature. Indeed, efforts to reduce emissions are of relevance to the agriculture sector because the natural processes associated with food production result in emissions of some greenhouse gases, particularly methane and nitrous oxide. In addition, agriculture will also be impacted by climate change because increasing global temperatures, changes in rainfall patterns, extreme events like floods, droughts, and heat waves will put pressure on the worldwide capacity to produce food.

Kennedy (2000) argues that not only machines can influence the environment but also fertilizers. The impact of agricultural machines and the use of fertilizers, the fore can be studied and included in the model. Further, Acemoglu et al. (2012) consider a model with direct technical changes to study the different effects of several technological innovations on environment. Their results reveal that government intervention in the form of subsidies and taxes is required only momentarily, although delaying the intervention is costly.

Based on panel data, Valin et al. (2013) focus on the effects of crop yields on GHG emissions from agriculture and land use in developing countries using different technological paths. It is shown that yield increase could mitigate some agriculture-related emission growth in the long run. In particular, sustainable land intensification would decrease GHG emissions by one third comparing to fertilizer intensive path. Moreover, Seebauer (2014) evaluates existing GHG quantification tools to quantify GHG emissions and removals in smallholder conditions by conducting cluster analysis to identify different farm typology GHG quantification using sustainable land management practices (SALMs) and verified carbon standard (VCS). The results show that the adoption of SALMs has a significant impact on emission reduction. In particular, the mitigation benefits range between 4 and 6.5 tCO<sub>2</sub>/ha/year depending on crop typologies (maize, beans, sweet potatoes, and cowpeas) and their agricultural practices such

as general farm structure, cropping system, crop yields, and current and future management practices.

While different kinds of crops have different experiences in carbon emissions, Arapatsakos and Gemtos (2008) investigate the contribution of the tractors in the environmental pollution by focusing on grain and maize tillage. They found that CO<sub>2</sub> contribution to the environment during tillage is the greatest compared to other gases, which means that tractors are considered as main pollutant. Using official statistical data and market surveys for the year 2010, Zou et al. (2015) estimate GHG emissions from agricultural irrigation in China aiming to reduce environmental pollution through water irrigation mechanism. The results indicate that the total CO<sub>2</sub> emissions from agricultural irrigations are from 36.72 to 54.16 Mt. In addition, emissions from energy activities in irrigation (including water pumping) account around 60% of total emissions from energy activities in the agriculture sector.

Using energy input-output analysis, Soni et al. (2013) study energy consumption in agricultural production systems associated with their corresponding GHG in Thailand. It is shown that transplanted rice provides the highest CO<sub>2</sub> emission among crops. At the same time, the reduction of mineral fertilizers and the reduction of exploitation of fossil energy consumption of agricultural equipment lead to decline the emissions of GHG in France (Pellerin et al. 2013; Directorate-General for Internal Policies 2014).

Based on tillage technologies in maize cultivation, Šarauskis et al. (2014) assess the energy efficiency of maize cultivation technologies in different systems of reduced tillage in Lithuania. The study considers five different tillage systems: deep plowing, shallow plowing, deep cultivation, shallow cultivation, and no tillage. It is shown that the greatest amount of fuel was used in the traditional deep plowing. The reduced tillage systems required 12–58% less fuel, and the lowest energy input was associated with no tillage technology. Lower fuel consumption reduces the technology costs and thus the emissions of CO<sub>2</sub>. Buragiene et al. (2011) focus on the impact of previously mentioned tillage machines on the emission of CO<sub>2</sub> from soil. The results expose that the highest CO<sub>2</sub> gas emissions were found in the case of intensive plowing, and the lowest emissions were observed from no tillage soil. Similarly, Silva-Olaya et al. (2013) use different tillage methods in Brazilian sugarcane fields to study their effects on CO<sub>2</sub> emissions. They find that conventional tillage method produces CO<sub>2</sub> emissions more than both reduced and minimum methods. In particular, 350.09 g/m<sup>2</sup> of CO<sub>2</sub> is generated in conventional method, while 51.7 and 5.5 g/m<sup>2</sup> are produced by using the reduced and minimum methods, respectively. Likewise, Rádics et al. (2014) show that conservation tillage methods generate less pollution.

## Methodology and data

To investigate the impact of agricultural technology factors on carbon emissions, we consider the following multivariate model:

$$CO_{2t} = \alpha + \beta_1 Machinery_t + \beta_2 Fertilizers_t + \beta_3 Land_t + \beta_4 AVA_t + \beta_5 GDP_t + \beta_6 Crop + \beta_7 Livestock + \varepsilon_t \quad (1)$$

where  $t$  and  $\varepsilon$  denote the time and the error term. CO<sub>2</sub> is carbon emissions (estimated in kilo ton per capita), GDP is the per capita real gross domestic products (measured in LCU), Machinery refers to the number of wheel and crawler tractors in use in agriculture at the end of the calendar year specified or during the first quarter of the following year, Fertilizers refer to the amount of fertilizers used in agricultural production (measured in kilograms per hectare of arable land), land indicates the land area under cereal production (measured in hectares), AVA stands for the agriculture value added (measured in percent of GDP), and Crop and livestock are the crop production index and livestock production index, respectively. They show agricultural production for each year relative to the base period 2004–2006.

While the parameters  $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6,$  and  $\beta_7$  measure the long-run elasticity of CO<sub>2</sub> emissions with respect to the number of machines, the amount of fertilizers, the cereal land, the agriculture value added, the real GDP, the crop production, and the livestock production, respectively. The annual data is obtained from World Development Indicators published by the World Bank (2015) and covers the period from 1970 to 2014. The temporal dimension was restricted due to data availability. The per capita real GDP is obtained from the Jordan Department statistics for the period of 1970–1974, and fertilizer consumption is extracted from the Jordanian ministry of the agriculture.

## Unit root tests

A necessary condition for cointegration between  $N$  variables is that these variables are I(1), i.e., stationary in first differences. To test for stationarity, we first perform the conventional DF-GLS test of Elliott et al. (1996), which applies the well-known ADF test after a GLS correction to demean and the conventional Kwiatkowski et al. (1992) or (KPSS) unit root technique for each variable. The first and the second techniques test the null hypothesis of a unit root against the alternative of stationarity. The KPSS method tests the hypothesis that the series is stationary against the alternative of non-stationarity.

Perron (1989) states that conventional unit root tests are subject to misspecification bias and size distortion when the series involved undergo structural breaks, which leads to a

spurious acceptance of the unit root hypothesis. To capture a possible structural break during the sample periods, we also apply the Zivot and Andrews (1992) sequential test procedure for unit roots in which the breakpoint is estimated endogenously. Zivot and Andrews (1992) consider three alternative models. Model A allows for a one-time shift in the intercept, model B allows for a break in the slope of the trend function, and model C includes the hybrid of the two.

a. Cointegration test

Practically, researchers usually use Johansen (1988, 1991) test to test the cointegration since it can check the existence of more than one long-run relationship if data contains more than two series.

Let  $M$  be a  $P \times 1$  vector that contains

$$M_t = (CO_2, Machinery, Fertilizers, Land, AVA, GDP, Crop, Livestock) \tag{2}$$

where all variables in this vector are in the first-differenced stationary I(1). Once first-order stationary variables exist, then according to Johansen (1991),  $M_t$  has a vector autoregressive (VAR) representation taking the following form:

$$M_t = \alpha + \pi_1 M_{t-1} + \pi_2 M_{t-2} + \dots + \pi_k M_{t-k} + \nu_t \tag{3}$$

where  $\alpha$  is the intercept and  $\nu_t$  is a vector of white noise processes together with zero mean. All information regarding the long-term relationship between variables exists in  $\Pi$  matrix. This VAR equation can be written as

$$\Delta M_t = \alpha + \psi_1 \Delta M_{t-1} + \psi_2 \Delta M_{t-2} + \dots + \psi_k \Delta M_{t-k} + \nu_t \tag{4}$$

where the rank of the parameter  $\Psi_k$  represents the number of cointegrating vectors.

Furthermore, Johansen (1988) proposes different approaches to study the long-run relationship between variables, the trace test ( $\lambda_{trace}$ ) and the maximum eigenvalue test ( $\lambda_{max}$ ). If the above two tests provide different results regarding the number of cointegrated equations, then the researcher must consider the  $\lambda_{max}$  since it is more reliable in a small size data.

b. Granger causality tests

In order to assess the long-run relationship between the series, we follow the Toda-Yamamoto (TY hereafter) procedure (Toda and Yamamoto 1995). This procedure has been found to be superior to ordinary Granger causality tests, since it ignores any possible non-stationarity or cointegration between the series between the series when testing for causality. TY procedure employs a modified Wald (MWALD) test for restriction on the parameters of the vector autoregression

(VAR) ( $k$ ) ( $k$  is the lag length). The correct order of the system ( $k$ ) is augmented by the maximal order of integration ( $d_{max}$ ). VAR ( $k + d_{max}$ ) is estimated with the coefficients of the last lagged  $d_{max}$  vector being ignored. The Wald statistics follows chi-squared distribution asymptotically with degrees of freedom equal to the number of the excluded lagged variables.

A VAR of order  $p$  can be represented by

$$y_t = a_0 + a_1 t + \sum_{i=1}^p \phi_i y_{t-i} + \gamma w_t + u_t$$

where  $y_t$  is a  $(n \times 1)$  vector of endogenous variables,  $t$  is the linear time trend,  $a_0$  and  $a_1$  are  $(n \times 1)$  the vectors,  $w_t$  is a  $(g \times 1)$  vector of exogenous variables, and  $u_t$  is a  $(n \times 1)$  vector of unobserved disturbances where  $u_t \sim N(0, \Omega)$ ,  $t = 1, 2, \dots, T$ .

In our case, TY version of VAR ( $k + d_{max}$ ) can be written as

$$\begin{bmatrix} CO_{2t} \\ Machinery_t \\ Fertilizers_t \\ Land_t \\ AVA_t \\ GDP_t \\ Crop_t \\ Livestock_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \end{bmatrix} + \begin{bmatrix} A_{11,1} & \dots & A_{18,1} \\ \vdots & \ddots & \vdots \\ A_{81,1} & \dots & A_{88,1} \end{bmatrix} \begin{bmatrix} CO_{2t-1} \\ Machinery_{t-1} \\ Fertilizers_{t-1} \\ Land_{t-1} \\ AVA_{t-1} \\ GDP_{t-1} \\ Crop_{t-1} \\ Livestock_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} A_{11,k} & \dots & A_{18,k} \\ \vdots & \ddots & \vdots \\ A_{81,k} & \dots & A_{88,k} \end{bmatrix} \begin{bmatrix} CO_{2t-k} \\ Machinery_{t-k} \\ Fertilizers_{t-k} \\ Land_{t-k} \\ AVA_{t-k} \\ GDP_{t-k} \\ Crop_{t-k} \\ Livestock_{t-k} \end{bmatrix} + \begin{bmatrix} A_{11,p} & \dots & A_{18,p} \\ \vdots & \ddots & \vdots \\ A_{81,p} & \dots & A_{88,p} \end{bmatrix} \begin{bmatrix} CO_{2t-p} \\ Machinery_{t-p} \\ Fertilizers_{t-p} \\ Land_{t-p} \\ AVA_{t-p} \\ GDP_{t-p} \\ Crop_{t-p} \\ Livestock_{t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \\ \epsilon_{5t} \\ \epsilon_{6t} \\ \epsilon_{7t} \\ \epsilon_{8t} \end{bmatrix}$$

**Table 1** Conventional unit root test

Variable	ADF-GLS		KPSS	
	Level Test statistic	First difference Test statistic	Level Test statistic	First difference Test statistic
CO <sub>2</sub>	-0.25	-3.19***	0.68**	0.43
Land	-1.45	-10.24***	0.74**	0.5
AVA	-1.05	-3.92***	0.73**	0.13
GDP	-0.28	-1.16***	0.58**	0.35
Crop	-2.16	-14.83***	0.84**	0.36
Livestock	-1.68	-5.12***	0.83**	0.23

Note: ADF-GLS; Elliot-Rothenberg-Stock Dickey-Fuller GLS detrended. KPSS; Kwiatkowski-Phillips-Schmidt-Shin. ADF-GLS critical values are taken from MacKinnon (1991); KPSS critical values are sourced from Kwiatkowski et al. (1992). \*\*\* Rejection of the null hypothesis at the 1% significance level. \*\* Rejection of the null hypothesis at the 5% significance level

where  $d$  is the first-difference operator and the order of  $p$  represents  $(k + d_{max})$ . Directions of Granger causality can be detected by applying standard Wald tests to the first “ $k$ ” VAR coefficient matrix. For example,

**H<sub>01</sub>:**  $A_{12,1} = A_{12,2} = \dots = A_{12,k} = 0$ , implies that Machinery does not Granger cause CO<sub>2</sub>.

**H<sub>02</sub>:**  $A_{21,1} = A_{21,2} = \dots = A_{21,k} = 0$ , implies that CO<sub>2</sub> does not Granger cause Machinery and so on for the other pairs.

c. Generalized forecast variance decomposition analysis

The decomposition of variance measures the percentage of a variable’s forecast error variance that occurs as the result of a shock from a variable in the system. Therefore, by employing this technique, one can find the relative importance of a set of variables that affect a variance of another variable.

Generalized forecast variance decomposition can be defined as

$$\frac{\sigma_{ij}^{-1} \left( \sum_{l=0}^n (e' G_l \sum e_j)^2 \right)}{\sum_{l=0}^n (e' G_l \sum G_l^i \sum e_j)^2}$$

where  $G_n = \Phi_1 G_{n-1} + \Phi_2 G_{n-2} + \dots + \Phi_p G_{n-p}$ ;  $n = 1, 2, 3, \dots$ .  $G_0 = I$ ,  $G_n = 0$  for  $n < 0$ ; and  $e_j$  is a  $(8 \times 1)$  selection vector with unity as its  $j$ th element and zero elsewhere and covariance  $\Sigma = \sigma_{ij}$ .

d. The role of water access and subsidies

Jordan is considered as one of the driest countries in the region and has the lowest levels of water supply resources. The world water poverty line is around 500 m<sup>3</sup> per person, while the annual water consumption in Jordan is around 147 m<sup>3</sup> (UNFCCC 2014). Every year, the renewable water

resources consist of 130 m<sup>3</sup> per person, while actual total uses of water are much more than the renewable supply. To afford the difference, government use non-renewable and fossil groundwater extraction (UNFCCC 2014).

In addition, Jordan is in front of an enormous defy regarding the massive refugees coming from disturbed neighboring countries (recently, 2 million of Syrian refugees), and this of course puts higher pressure on the limited natural resources. This rapid growth in the number of populations imposes a questionable point regarding the energy efficiency and pollution of water pumping, overpumping of aquifers, and distribution systems.

In Jordan, government subsidizes irrigation water seriously. The subsidy consists of very small tariffs for surface water deliveries to the Jordan Valley, in addition to extremely low tariffs with almost no restrictions on abstraction of groundwater in the high mountains. As a result, for any possible increase in the costs of water supply, the government would face a higher burden budget in terms of higher investment and more subsidies (UNFCCC 2014).

Hence, it would be informative to include the access to an improved water source (measured as a percent of rural population with access) and the public subsidies (measured in

**Table 2** Zivot-Andrews minimum statistics

Variable	Level		First difference	
	t-statistics	Periods	t-statistics	periods
Machinery	-3.74	1995	-5.26**	1995
Fertilizers	-4.52	1980	-5.6***	1985

Note: t-statistics are estimated from a break in intercept. Critical values are those reported in Zivot and Andrews (1992), \*\*\* Rejection of the null hypothesis at the 1% significance level. \*\* Rejection of the null hypothesis at the 5% significance level



**Table 3** Results of the Johansen cointegration analysis (1970–2014 sample period)

Rank <i>r</i>	Eigenvalue	Maximum eigenvalue statistics	Trace test statistic
0	0.95	130.2**	393.64**
≤ 1	0.84	75.76**	263.44**
≤ 2	0.76	60.58**	187.68**
≤ 3	0.64	43.91**	127.1**
≤ 4	0.51	30.16	83.18**
≤ 5	0.44	24.33	53.03**

Note: Rank *r* expresses the number of cointegrating equation according to each tested hypothesis. No restriction is imposed in the cointegration test. The lag length has been chosen based on minimum Akaike information criterion (1 lag interval in first differences for each series). Critical values were taken from McKinnon (1991) \*\* denotes significance at 5% level

current LCU) as main indicators relating to the amount of pollution in Jordan over the period. As these two variables are available only for the 1990–2014 period, a second model is estimated by augmenting Eq. (1) with subsidies and the rural access to an improved water source, and we employ the fully modified OLS estimation approach. This technique allows for the consistency of the long-run relation along with short-run adjustment; it arranges with the problem of endogeneity, and it takes into account the time series properties of the data. Dynamic causal links are investigated using an eight variable error correction model (ECM).

### Empirical results

Empirical results are presented from two models. The first set of results investigates the relationship between machinery, fertilizers, land area under cereal production, agricultural value added, real income, crop and livestock production, and carbon emissions for the full sample period of 1970–2014. The second set of results investigates the relationship between machinery, fertilizers, land area under cereal production,

agricultural value added, real income, crop and livestock production, subsidies, rural access to an improved water source, and carbon emissions for the subsample period of 1990–2014. For the subsample period, Eq. (1) is augmented to include subsidies and rural access to an improved water source.

### Empirical results for the full sample period

#### Unit root tests

The purpose of unit root test is to check the stationary properties of the variables, and this is necessary to conduct the cointegration test. Table 1 summarizes the outcomes of the conventional unit root tests.

Results indicate that the unit root hypothesis cannot be rejected when CO<sub>2</sub>, land, AVA, GDP, crop, and livestock are taken in levels. However, when the first differences are used, the hypothesis of unit root non-stationary is rejected at the 1% level of significance for ADF GLS test and at 5% level for the KPSS test.

Table 2 reports the minimum t-statistics from testing the stationarity assuming a shift in mean for the two variables.

**Table 4** Toda-Yamamoto causality test results (1970–2014 sample period)

Causal flow	MWALD statistics	Probability	Causal flow	MWALD statistics	Probability	Accepted causal flow
Machinery → CO <sub>2</sub>	3.34*	0.06	Machinery ← CO <sub>2</sub>	4.02	0.55	Machinery → CO <sub>2</sub>
Fertilizers → CO <sub>2</sub>	3.43*	0.06	Fertilizers ← CO <sub>2</sub>	0.54	0.46	Fertilizers → CO <sub>2</sub>
Land → CO <sub>2</sub>	0.19	0.66	Land ← CO <sub>2</sub>	1.23	0.27	
AVA → CO <sub>2</sub>	0.53	0.47	AVA ← CO <sub>2</sub>	0.03	0.85	
GDP → CO <sub>2</sub>	6.1**	0.01	GDP ← CO <sub>2</sub>	9.58***	0.00	GDP ↔ CO <sub>2</sub>
Crop → CO <sub>2</sub>	1.31	0.25	Crop ← CO <sub>2</sub>	0.52	0.47	
Livestock → CO <sub>2</sub>	0.54	0.46	Livestock ← CO <sub>2</sub>	0.97	0.32	

Note: → indicates the direction of causality

\*\*\*, \*\* and \* denote the significance at 1%, 5%, and 10%, respectively

**Table 5** Variance decomposition results for CO<sub>2</sub> (1970–2014 sample period)

Horizon	CO <sub>2</sub>	Machinery	Fertilizers	Land	AVA	GDP	Crop	Livestock
1	100	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	89.49	2.66	3.26	0.23	2.22	0.54	1.03	0.55
3	82.02	5.27	5.18	0.21	4.36	1.56	0.86	0.54
4	74.64	7.94	5.94	0.18	7.12	2.85	0.76	0.56
5	68.32	10.05	6.19	0.19	9.73	4.23	0.68	0.61
10	52.02	13.45	5.51	0.25	16.69	10.04	0.56	1.47

The results suggest that at 5% level of significance, none of the estimated variables are stationary around a shift in the mean. These results enable to test the cointegration among variables in I(1) level.

**Cointegration analysis**

In general, if two variables have long-run relationship, then these variables are cointegrated. If two variables are integrated of order one I(1), there could be a linear combination between them and integrated of order zero, I(0). Therefore, we have to check the possible cointegration relationship between CO<sub>2</sub>, AVA, machinery, GDP, fertilizers, land, crop, and livestock. In order to conduct cointegration test, we perform the Johansen cointegration test where the null hypothesis states that there is no cointegration. We use an intercept and but no trend. The optimum lag length for Johansen cointegration test is determined based on minimum Akaike information criterion (AIC) through unconstrained vector autoregression (VAR) estimation. The lag length is further validated by tests for normality and absence of serial correlation in the residuals in VAR to make sure that none of them violates the standard assumptions of the model.

Table 3 indicates that variables in the equation (CO<sub>2</sub>, machinery, fertilizers, land, AVA, GDP, crop, and livestock) for the 1970–2014 sample period have more than one cointegrating relationship ( $H_0: r = 0$  and  $r \leq 1$  is rejected at 5% level). The evidence of cointegration has two important consequences. It eliminates spurious correlations, and

suggests at least a unique channel for Granger causality test (either unidirectional or bidirectional).

**Granger causality results**

In order to select optimal lag length for the VAR expressed by Eq. (4), Lütkepohl’s (2005) procedure is employed by linking the lag length (mlag) and number of endogenous variables in the system (m) to the sample size (T) based on the formula,  $m \times mlag = T^{1/3}$ . On the basis of Schwarz Bayesian (SBC) and adjusted log-likelihood ratio (LR) test criteria, the optimal lag order of the VAR is chosen as 2. In the next stage, we augment the VAR by the maximum order of integration of the series ( $d_{max}$ ) and estimate VAR (8) model. The residual series passes the required diagnostic tests for serial correlation, heteroscedasticity, miss-specification of functional form, and normality. Table 4 presents the results of the TY version of the Granger causality tests. The significance of the  $p$  values of the MWALD statistic indicates that there is unidirectional causality running from machinery and fertilizers to CO<sub>2</sub>. Findings similar to this were found in the studies by Ben Jebli and Ben Yousef (2015), West and McBride (2005), Rádics et al. (2014), and Rajaniemi et al. (2011). These results indicate that agricultural technologies are closely related to carbon emissions. There is also bidirectional causality between GDP and CO<sub>2</sub> emissions. This bidirectional causality can be explained by the fact that an increase in CO<sub>2</sub> emissions is associated with higher consumption of fertilizers, machinery, oil, and other

**Table 6** Conventional unit root test

	ADF-GLS		KPSS	
	Level Test statistic	First difference Test statistic	Level Test statistic	First difference Test statistic
Subsidies	0.44	−4.44***	0.68**	0.17
Water	−0.42	−5.38***	0.73**	0.12

Note: ADF-GLS; Elliot-Rothenberg-Stock Dickey-Fuller GLS detrended. KPSS; Kwiatkowski-Phillips-Schmidt-Shin. ADF-GLS critical values are taken from MacKinnon (1991). KPSS critical values are sourced from Kwiatkowski et al. (1992). ADF-GLS null hypothesis is unit root; while, in KPSS, null is stationarity. \*\*\* Rejection of the null hypothesis at the 1% significance level. \*\* Rejection of the null hypothesis at the 5% significance level

energy intensive economic activities. These energy resources are primary inputs to agriculture and hence raise real income if their use increases and consequently enhance CO<sub>2</sub> emissions.

### Variance decomposition results

The causality test presented above indicates only Granger causality within the sample period, and does not allow us to gauge the relative strength of the Granger causality among the series beyond the sample period. Thus, to complement the above, we decomposed the forecast error variance of CO<sub>2</sub> emissions into proportions attributed to shocks in all variables in the system including itself. By doing so, we can provide an indication of the Granger causality beyond the sample period. The variance decomposition results for CO<sub>2</sub> are presented in Table 5 over a horizon of 10 years. Results indicate that machinery will have an increasing effect on variability, explaining 10.05 and 13.45% at the end of 5 and 10 years, respectively. GDP, fertilizers, livestock, crop, and land have innovations in carbon emissions, accounting for 10.04, 5.51, 1.47, 0.56, and 0.25% of variation at the end of the forecast period, respectively. This seems to support the Granger causality results which found unidirectional causality running from machinery and fertilizers to CO<sub>2</sub> and bidirectional causality between GDP and CO<sub>2</sub>. Our results also imply that AVA is the most important component in explaining CO<sub>2</sub> variability accounting for 16.69% of variability in the long run.

### Empirical results for the subsample period

Subsidies and other transfers (current LCU) and rural improved water source (percent of rural population with access) are taken from World Development Indicators (2015). These two variables are not available for the full sample period 1970–2014, and thus, data availability necessitates that the original sample period be reduced to a subsample period of 1990–2014.

#### i. Unit root tests

Here, we perform the unit root test while including both subsidies and other transfers (subsidies) and rural improved water source (water). Table 6 summarizes the outcomes of stationarity test based on ADF-GLS and KPSS. Results show that the variables are non-stationary and integrated of order 1.

#### ii. Cointegration analysis

Table 7 reports the results of the fully modified OLS cointegration test for the relationship between machinery, fertilizers, land area under cereal production, agricultural value added, real income, subsidies, rural access to an improved water source, and carbon emissions.

**Table 7** FMOLS cointegration test result (1990–2014 subsample period)

	Test statistic	1% critical value
ADF	−6.41***	−2.67
PP	−6.54***	−2.67
KPSS	0.07***	0.74

Note: The adjusted *R*-squared of the FMOLS regression is 0.86. The 1% critical values are those for the null of a unit root in the residuals for the ADF and PP tests (Phillips and Ouliaris 1990) and no unit root in the residuals for the KPSS test. \*\*\* Rejection of null hypothesis of no cointegration at the 1% significance level

The ADF and the PP test reject the null of a unit root at 1% level in the residuals of this relationship. The KPSS test reinforces the results of ADF and PP tests and does not reject the contrary null of no unit root at 1% level. These tests show the presence of cointegrating relationship between the variables. In order to get the direction of these relationships, we consider the Granger causality test.

#### iii. Granger causality tests

Table 8 reports the results of the TY version of the Granger causality tests. The null hypothesis of non-causality from subsidies to CO<sub>2</sub> cannot be rejected at 5% level of significance. This result may be explained by the fact that Jordanian government, as previously mentioned, subsidizes heavily the irrigation water; as a result, farmers would utilize more water inputs in farming, which means more energy and more emissions (Karkacier et al. 2006; Turkekul and Unakitan 2011; Cleveland 1995). Further, if CO<sub>2</sub> emissions increase in the atmosphere, the government can motivate farmers and firms by increasing subsidies to green technologies and reduce subsidies to polluted technologies.

In addition, the existence of a unidirectional causality running from water to CO<sub>2</sub> is shown. This finding justifies the consideration of improved water source in our model. Indeed, Jordan is among the poorest countries in the world with regard to water availability. Around 92% of Jordanian regions receive less than 200 mm yearly of rainfall (Ministry of Water and Irrigation 2016a). The total amount of water utilization exceeds the renewable water supply; therefore, the use of non-renewable supply such as the groundwater extraction is necessary. According to data of the Ministry of Energy and Natural Resources, 17.6% of the GDP are spent on energy and water sectors (including pumping, piping, and equipment). Water sector consumes 14% of generated electricity<sup>1</sup> and half of consumption goes to water drinking pumping. The high cost of watering is because the water sector comprises an energy-

<sup>1</sup> Jordan is highly dependent on fossil fuel in producing electricity (Holtz and Fink, 2015).



**Table 8** Toda-Yamamoto causality test results (1990–2014 subsample period)

Causal flow	Wald statistic	Probability	Causal flow	Wald statistic	Probability	Accepted causal flow
Water → CO <sub>2</sub>	3.37*	0.06	Water ← CO <sub>2</sub>	0.78	0.38	Water → CO <sub>2</sub>
Subsidies → CO <sub>2</sub>	3.63**	0.05	Subsidies ← CO <sub>2</sub>	1.8	0.18	Subsidies → CO <sub>2</sub>

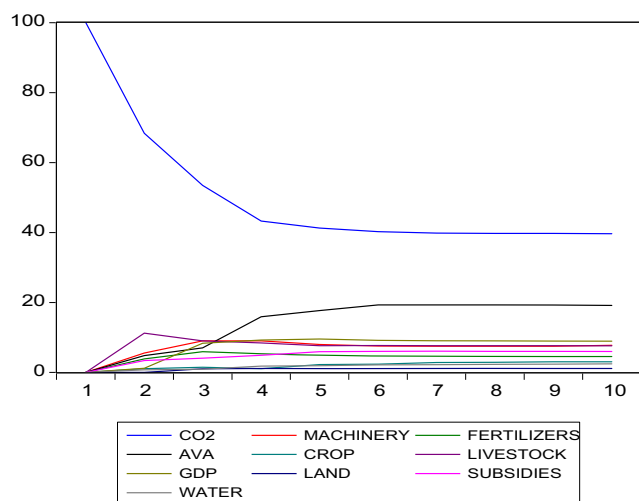
Note: → indicates the direction of causality. We only report results for water and subsidies to conserve place  
 \*\*\* and \*\*denote the significance at 1% and 5%, respectively

wide operation by installing big-size water pumping, improving and treatment, and distribution facilities (Busche and Hayek 2015).

Moreover, according to Ministry of Water and Irrigation, the entire water supply in 2014 was 370 million cubic meter (MCM), with total electricity demand of 1592 GWh. The water demand is assumed to have an annual growth rate of 5%, which is equivalent to 521 MCM in 2021 and 633 MCM in 2025. Given the high attention of Jordanian government toward the clean energy, it is estimated that by 2025, Jordanian economy will save around 350 K tons/year of CO<sub>2</sub> emissions if government continues using both renewable energy and energy efficiency (Ministry of Water and Irrigation 2016b).

iv. Variance decomposition results

The results of the variance decomposition for CO<sub>2</sub> are reported in Fig. 1 over a horizon of 10 years. Compared to the results of the full period, the impact of AVA on CO<sub>2</sub> remains higher than any other variables in the system. Subsidies and water explain 5.96 and 2.41% of the forecast error variance of CO<sub>2</sub> at the end of horizon and confirming the Granger causality tests. Moreover, the variance of CO<sub>2</sub> is explained by GDP (8.92%), machinery (7.7%), livestock (7.57%), fertilizers (4.53%), crop (2.99%), and land (1.12%) by the 10th year. These results indicate that agricultural technologies are linked to carbon emissions in Jordan.



**Fig. 1** Variance decomposition of CO<sub>2</sub>

### Conclusion and policy implications

Jordan faces two main challenges, the scarcity of both water and fossil energy resources and the increase in demand for these goods in the recent time. The current policies regarding the management of water resources and the utilization of clean technologies will significantly affect the future environmental state. For policy implications, in order to perform the (2011–2020) target of CO<sub>2</sub> emissions in Jordan, policy-makers have to consider the amount of CO<sub>2</sub> emitted from agricultural technologies. Hence, the objective of this paper is to study the interrelationships between carbon emissions and agricultural technologies for Jordan. The cointegration approach and the Toda and Yamamoto (1995) Granger causality tests were employed before reporting the variance error decompositions.

Our results validated the presence of cointegration between carbon emissions, machinery, fertilizers, land area under cereal production (land), the agriculture value added (AVA), real income (GDP), crop and livestock production, water access, and subsidies. We find a unidirectional relationship running from machinery and fertilizers to carbon emissions. From a policy standpoint, policy-makers may be interested to develop and use advanced production methods and techniques with lower CO<sub>2</sub> emission in farm production processes. Our results also discover a unidirectional relationship running from subsidies to carbon emissions. The policy implication is that measures aimed at subsidies could ultimately affect carbon emissions. Therefore, Jordan can aim to mitigate adverse environmental effects from subsidies by implementing policies that alter carbon emissions. Moreover, the paper finds a unidirectional relationship running from access water to carbon emissions. This is important as water demand in Jordan continues to rise. From technical viewpoint, our result is comparable to Busche and Hayek (2015), where they show that the annual energy-saving potential from all the investigated pumps arrives to around 33%, equivalently to 3.3 million Euros. According to this study, if the authority raises the renewable energy resources in power consumption up to 10%, there will be a total saving of 0.31 kg of CO<sub>2</sub> emissions per each billed cubic meter of water (Ministry of Water and Irrigation 2016b). Hence, Jordanian authorities should design and adopt technologies that have a proven CO<sub>2</sub> reduction potential in the water extraction and delivery processes. The variance error decompositions highlight the importance of subsidies and water

access in explaining carbon emissions. They also show that AVA, GDP, machinery, fertilizers, livestock, crop, and land have an increasing effect on carbon emissions over the forecast period.

The above results provide an interesting view regarding the carbon emissions based on agriculture sector; however, one caveat of our analysis is that our results are drawn from a quantitative econometric analysis of the interaction effect between agricultural technologies and the emissions of CO<sub>2</sub>. Therefore, we are likely to ignore qualitative factors, such as the age of machinery and the type of livestock reared. Since data on qualitative factors are not available for our sample period, this topic will be left for future research.

**Acknowledgements** We would like to thank the editor and two anonymous referees whose helpful contributions have improved upon the quality of the paper. Thanks are also due to the participants of the Seconds Meetings on Economic and Quantitative Analysis: Sustainable Development Goals (Hammamet, 2016) for providing comments on earlier drafts of this article. The Financial support by the LABEX MME-DII is also gratefully acknowledged. Errors and omissions, if any, are our own.

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