Journal of Environmental Management 327 (2023) 116820

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Is the technical efficiency green? The environmental efficiency of agricultural production in the MENA region

Wei Huang [a,*], Qian Liu [b], Assem Abu Hatab [a,c,d,**]

[a] Department of Economics, Swedish University of Agricultural Sciences, Box 7013, Uppsala 75007, Sweden
[b] Department of Food and Resource Economics, University of Copenhagen, Rolighedsvej 23, 1958 Frb. C., Copenhagen, Denmark
[c] The Nordic Africa Institute, Box 1703, Uppsala 75147, Sweden
[d] Department of Economics and Rural Development, Arish University, Arish, Egypt

ARTICLE INFO

Subject classification codes:
O13
Q52
Q56
R24

Keywords:
Directional distance function
Technical efficiency
Shadow price
Elasticity

ABSTRACT

There is widespread recognition of the global environmental impact of agricultural production on greenhouse gas emissions, but evidence is sparse regarding the impact in the Middle East and North Africa (MENA) region. In this study, we treat agricultural emissions as an undesirable output from agricultural production and apply the directional distance function to measure environmentally-adjusted technical efficiency, defined as environmental efficiency in agricultural production, in six countries in the MENA region (Algeria, Egypt, Israel, Jordan, Morocco, Tunisia) during the period 1980–2016. The results show that all six countries have clear scope to improve their environmental efficiency. Agricultural production is greener in Jordan and Israel, while environmental efficiency is currently lowest in Egypt and Morocco. Estimated relative shadow price of agricultural emissions is −1.002, implying that the 'cost' of removing agricultural emissions is almost equal to the value of producing one unit of good output. These findings suggest there is a trade-off between agriculture emissions and production, which should be considered in efforts to enhance the sustainability of agricultural production in the MENA region.

1. Introduction

The Middle East and North Africa (MENA) region is a hotspot and fragile world area in terms of achieving the United Nations Sustainable Development Goals (SDGs) and mitigating negative environmental impacts. The MENA countries are extremely vulnerable to food insecurity and climate change effects, with critical water scarcity hampering expansion of agriculture and large numbers of undernourished people needing food. Apart from supplying food in challenging climate conditions, agriculture also provides employment for many people in the MENA region. To promote agricultural production and boost food supply, MENA countries have begun to adopt improved crop genotypes and have increased their use of fertilisers, pesticides and other agricultural chemicals (Albanito et al., 2017). However, these interventions have been coupled with marked increases in greenhouse gas (GHG) emissions, particularly of nitrous oxide (N_2O) and methane (CH_4). The dominant sources of N_2O emissions are fertiliser application, irrigation, soil tillage and other farming activities and management practices, while the main sources of CH_4 emissions are enteric fermentation, livestock manure and irrigated rice cultivation. For instance, between 1980 and 2016, combined agricultural emissions (mainly N_2O and CH_4) in Algeria, Egypt, Israel, Jordan, Morocco, and Tunisia grew by 56%, 146%, 94%, 207%, 20% and 94%, respectively.[1] It is projected that GHG emissions per capita in the MENA region will continue to increase (Pörtner et al., 2022). These human-induced climate change drivers will intensify water scarcity, reduce agricultural productivity and exacerbate food insecurity in the MENA region, making the current situation much worse. Therefore, it is important that researchers and policymakers examine the environmental outcomes of agricultural production and farming activities in this densely populated region, in order to achieve food security goals while adapting to climate change and minimising the contribution of the agricultural sector to GHG emissions.

Analyses of agricultural production performance and associated GHG emissions in countries in the MENA region have received limited

* Corresponding author.
** Corresponding author. The Nordic Africa Institute, Box 1703, Uppsala 75147, Sweden.
E-mail addresses: wei.huang@slu.se (W. Huang), assem.abu-hatab@nai.uu.se (A. Abu Hatab).

[1] According to authors' calculation based on data from World Development Indicators (WDI) database of the World Bank.

https://doi.org/10.1016/j.jenvman.2022.116820
Received 9 May 2022; Received in revised form 2 November 2022; Accepted 15 November 2022
Available online 29 November 2022

research attention to date. In recent decades an emerging strand of research has applied country-cross analyses to evaluate environmental outcomes of agricultural activities by modelling 'undesirable' outputs (referred to as "bad outputs" or "bads" in some studies) from agricultural production (*e.g.* GHG emissions). For example, Vlontzos et al. (2014) and Expósito and Velasco (2020) examined the environmental efficiency (EE) of the European agriculture sector and found large variation in EE scores, leading to the conclusion that there is significant scope for EU countries to improve their EE. Agostino (2016) investigated the agricultural and environmental performance of OECD member countries and found that the rank index of these countries and their environmental performance index were quite insensitive to weighting for GHG emissions. Tang et al. (2016) estimated the marginal abatement costs of on-farm GHG emissions for a broadacre farming system in the Great Southern Region of Western Australia. However, there is a dearth of studies on EE in developing countries, although the relationship between agricultural production and environmental impacts may be much more intense in this context due to low agricultural input efficiency (Clark and Tilman, 2017; Yang et al., 2017; Expósito and Velasco, 2020; Tang and Ma, 2022). Even fewer studies have explicitly assessed the EE of agricultural production in MENA countries. Lin et al. (2016) evaluated the potential impact of agricultural emissions on production in five African countries (South Africa, Egypt, Nigeria, Kenya, DR Congo) between 1980 and 2012, and identified a need for context-specific interventions to minimise emissions from agriculture and maintain sustainable development. Only two studies have examined this topic in MENA countries. Zamanian et al. (2013) investigated agricultural production efficiency in 21 MENA countries in the period 2007–2008, but did not consider 'bad outputs', *i.e.* agricultural emissions. Mazrou (2021) estimated EE for 10 Arab countries in the period 2007–2017 and compared the cross-country differences in EE. They found that all sampled Arab countries had potential for a significant increase in production and EE.

In this paper, we examine the EE of agricultural production in MENA countries, taking into account GHG emissions from agricultural production (N_2O and CH_4 emissions) in the period 1980–2016. We define environmentally adjusted technical efficiency using production function as EE, which is in line with previous studies of EE (Reinhard et al., 2000; Huang and Bruemmer, 2017). Based on data availability, our empirical analysis focuses on six of the 19 countries[2] in the MENA region: Algeria, Egypt, Israel, Jordan, Morocco and Tunisia. Specifically, we develop a directional distance function with agricultural emissions as an undesirable output in agricultural production and then calculate EE.

The rest of the paper is structured as follows: Section 2 presents the theoretical foundation, method and empirical model specification. Section 3 describes the data. Section 4 reports the results of the empirical analysis, and finally Section 5 summarises the study and outlines policy implications.

2. Theoretical background, methodology and empirical model specification

A multi-input, multi-output directional distance function incorporating agricultural emissions as the undesirable output to measure environmentally adjusted technical efficiency (EE in this paper) is presented, where a higher EE value implies greener technical efficiency of agricultural production in a country. The directional distance function allows for a directional efficiency measurement, *i.e.* non-simultaneous proportional reductions in inputs or expansion of outputs. Directional distance analysis is commonly used for modelling technologies that produce pollution as a by-product, such as air pollution for electric utilities from producing electricity, dairy farms producing polluted runoff (Njuki and Bravo-Ureta, 2015; Sauer and Latacz-Lohmann, 2015) or grazing pressure in the agricultural sector (Huang and Bruemmer, 2017). The directional distance function including a hyperbolic distance function has become a popular method for dealing with undesirable outputs in recent years (Huang and Bruemmer, 2017; Serra et al., 2011). In modelling technology producing undesirable outputs or by-products, two axioms are required for defining output, namely null-jointness and weak disposability (Färe et al., 2005). Null-jointness implies that a good output can only be produced if some undesirable output is produced. This can be also interpreted as no undesirable output produced means no good output produced. Empirically, this is the case for agricultural emissions, which are released when agricultural outputs are produced. Weak disposability requires simultaneous reduction of good output and undesirable output to be feasible, *i.e.* there is an abatement cost in decreasing the undesirable output. Theoretically, the role that agricultural emissions play in agricultural production meets the regularity conditions of undesirable output. Therefore, it makes sense both theoretically and empirically to incorporate agricultural emissions as an undesirable by-product of agricultural production.

The output-oriented directional distance function has the advantage of expanding the desirable output and contracting the undesirable output, while leaving inputs unchanged (Chambers, 2002; Färe et al., 1993, 2005). Assuming the decision-making unit (DMU) improves production along the directional vector $g = (g_y, -g_b)$, *i.e.* adding ϑg_y to desirable output y while subtracting ϑg_b from undesirable output b, then:

$$\overrightarrow{D_o}\left(x, y, b; g_y, -g_b\right) = sup\left\{\vartheta : \left(y + \vartheta g_y, b - \vartheta g_b\right) \in P\right\} \tag{1}$$

While satisfying the translation property, equation (1) can be written as:

$$\overrightarrow{D_o}\left(x, y + \vartheta g_y, b - \vartheta g_b; g_y, -g_b\right) = \overrightarrow{D_o}\left(x, y, b; g_y, -g_b\right) - \vartheta \tag{2}$$

We parametrically estimate the directional distance using stochastic estimation methods following Kumbhakar and Lovell (2000), where the empirical stochastic specification form is written as:

$$-\vartheta_i = \overrightarrow{D_o}\left(x, y + \vartheta g_y, b - \vartheta g_b; g_y, -g_b\right) + v_i - u_i \tag{3}$$

In the present case, we impose these restrictions by choosing $\vartheta = b_i$ and assume $g = (g_y, -g_b) = (1, -1)$. The quadratic form of the empirical specification for agricultural production is then:

$$\begin{aligned} -b_i = \overrightarrow{D_o}(x, y + b, 0) + v_i - u_i = \sum_{k=1}^{4} \alpha_k x_k + \beta_1 y^* + \frac{1}{2}\sum_{k=1}^{4} \alpha_{kk}(x_k)^2 \\ + \frac{1}{2}\beta_{11}(y^*)^2 + \sum_{k=1}^{4}\sum_{l=1,k\neq l}^{4} \alpha_{kl} x_k x_l + \sum_{k=1}^{4} \gamma_{k1} x_k y^* + v_i - u_i \end{aligned} \tag{4}$$

where $y^* = y + b$, y describes the desirable output of agricultural production, denoted by the agricultural value added each year; b denotes the undesirable output, agricultural emissions; X is the vector of inputs where x_1 is agricultural land, x_2 is agricultural labour , x_3 is agricultural machinery and x_4 denotes fertiliser; v_i is a random error term, intended to capture events beyond the control of the government; and u_i is a non-negative random error term, intended to capture technical inefficiency in agricultural production.

The EE is defined as ratio of observed environmentally adjusted outputs to the corresponding potential outputs given the production function, specified as:

$$EE_i = e^{-u_i} \tag{5}$$

The environmentally adjusted technical inefficiency model is written as:

$$u_i = \tau_0 + \sum_{c=1}^{8} \tau_c * Z_{ci} \tag{6}$$

[2] Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar Saudi Arabia, Syria, Tunisia, United Arab Emirates and Yemen.

where Z is a vector of explanatory variables determining inefficiency effects, including foreign direct investment (z_1), gross fixed capital formation (z_2), female labour force (z_3), rural population (z_4) and employment to population ratio (z_5).

As agricultural emissions not directly tradable on the market, we follow Färe and Primont (1996) and Shepherd (2016) and derive shadow prices of agricultural emissions in terms of agricultural value added, to further investigate their relationships. Based on duality between the output-oriented distance function and revenue function, we derive shadow prices for non-market goods. These shadow prices reflect the trade-off between desirable (agricultural value added) and undesirable (agricultural emissions) outputs, and can be interpreted as the cost of abating GHG emissions (in our case) and other environmental externalities (*e.g.* soil pollution, environmental pressure or ecological diversity loss) from human economic activity. The relative shadow price, R_{yb}, can be calculated as:

$$R_{yb} = \frac{r_y^*}{r_b^*} = \frac{\partial \overrightarrow{D_o}(x, y, b; 1, -1) \Big/ \partial y}{\partial \overrightarrow{D_o}(x, y, b; 1, -1) \Big/ \partial b} \tag{7}$$

where r_y^* and r_b^* are the shadow price of output y and b, respectively. The ratio R_{yb} is the relative shadow price of desirable output y with respect to undesirable output b (Rahman et al., 2010).

3. Data description and study region

The MENA region consists of 19 core countries, but a further 16 countries (including Mauritania, Sudan and Turkey) are sometimes included in other regional groupings by international organisations, depending on context. Our empirical analysis focuses on Algeria, Egypt, Israel, Jordan, Morocco and Tunisia. Other MENA countries are excluded from the empirical analysis due to data unavailability and inconsistency, particularly lack of information regarding N_2O and CH_4 emissions from their agricultural sector during the study period. Like other countries in MENA region, the six selected countries are facing critical natural resources constriction, but strong demand for food. Algeria, Egypt, Jordan and Tunisia have a large agriculture sector but a limited natural resource base, while Israel and Morocco have no immediate water or agricultural land constraints (Mubarak, 1998). Due to lack of comparable annual time-series data on N_2O and CH_4 emissions from the selected countries, our dataset is restricted to a 37-year period (1980–2016). Data on all variables included in the empirical analysis are extracted from the World Development Indicators (WDI) database of the World Bank. For the sub-period 1980–1990, the WDI database has several missing values, particularly on the input variable 'fertiliser input' and the output variables 'N_2O emissions' and 'CH_4 emissions'. Missing data on these variables are compiled from the statistical reports of the United States Environmental Protection Agency (US-EPA) and statistical reports and yearbooks of the national statistics agencies of the selected countries (the Central Agency for Public Mobilization and Statistics in Egypt, the National Institute of Statistics in Tunisia, the National Office of Statistics in Algeria, the National Statistical Office at the High Commission for Planning in Morocco, the Jordanian Department of Statistics in Jordan, the Central Bureau of Statistics in Israel) and statistical bulletins from the Arab Organization for Agricultural Development. Detailed descriptions are given below of inputs and outputs in the production function, and variables of inefficiency determinants in the inefficiency model.

Output variables. We have one desirable output and one undesirable output. *Agricultural value added* represents the "good" output from agricultural production. This variable (measured in billions of US dollars in 2010 values) is defined as the net output of the agricultural sector in a given country, after adding up all the outputs and subtracting intermediate inputs. Here, the agricultural sector is a broader sector composed of agriculture, forestry, animal husbandry and fishery. The undesirable output is GHG emissions, obtained by adding the quantity of 'agricultural N_2O emissions' and the quantity of 'agricultural CH_4 emissions', both measured in millions metric tonnes of CO_2-equivalents (MMTCDE).

Input variables. Four input variables are used in the empirical estimations: i) *agricultural land* (measured in thousands of square kilometres), which represents the area of arable land in each country under permanent crops or permanent pasture; ii) *agricultural machinery* (measured in thousands of tractors), which 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; iii) *agricultural labour* (measured in millions of people), which is defined as people of working age engaged in agricultural activities that produce goods or provide services for pay or profit; and iv) *fertiliser* (measured in millions of kilograms), which refers to the quantity of fertilisers used for agricultural production, including nitrogenous, potash and phosphate fertilisers.

Determinants of inefficiency. Five variables are introduced to capture the effects of key factors that may influence the inefficiency of agricultural production in the selected countries: i) *foreign direct investment* (FDI), which refers to direct investment equity flows in the reporting country, calculated as the sum of equity capital, reinvestment of earnings and other capital, measured in billions of US dollars (2010 values). FDI is an important proxy to indicate trade openness with suggested potential to improve agricultural efficiency through innovation in EU countries (Hart et al., 2015), but it has not been determined whether it improves agricultural performance in MENA countries; ii) *gross fixed capital formation* (billions of US dollars), which refers to outlay on additions to fixed assets (*e.g.* construction of roads, railways, and commercial and industrial buildings) in the economy and net changes in the level of inventories. Physical investment in agriculture in a country often brings sustained improvement in agricultural performance (Le et al., 2019); iii) *female labour force* (%), which is the proportion of female labour in each country's total labour force. Gender inequality in the agricultural sector in developing countries has been raised recently (Teklewold et al., 2019) and thus we look to obtain empirical evidence on the role of female labour in influencing EE in the MENA region; iv) *rural population ratio* (%), which refers to the percentage of people living in rural areas as defined by the national statistics offices of the countries studied; and v) *employment to population ratio*, which represents the civilian labour force currently employed relative to the total working-age population of the country, calculated by dividing the number of people employed by the total number of people of working age. Descriptive statistics for all variables included in the econometric estimations are given in Table 1. Fig. 1 shows trends in agricultural N_2O and CH_4 emissions from the six countries studied in relation to agricultural value added during the period 1980–2016. Together, the results in Table 1 and Fig. 1 indicate that agricultural value added in the six countries during the period went hand in hand with total emissions from their agricultural sector during the study period.

4. Results and discussion

4.1. Parametric estimation of directional distance function and elasticities

Table 2 presents the estimation results of the one-step approach for both the directional distance function of environmental efficiency and the inefficiency model using maximum likelihood. In order to avoid magnitude bias and measurement unit differences, all input and output variables are normalised by dividing by their sample mean. Most coefficients are statistically significant, in particular those related to the good output y. According to the restrictions implied by the translation property, $\partial^2(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial b^2 = \partial^2(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial y \partial b = \beta_{11}$, β_{11} is estimated to be -0.001 (significant at the 1% level). We calculate the input elasticity and output elasticity to investigate the

Table 1
Summary statistics.

Variable	Symbol	Measurement unit	Algeria		Egypt		Morocco		Tunisia		Israel		Jordan		Overall	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Output variables																
Agricultural value added	y_1, good output	1 billion US$	8.67	4.85	21.00	6.99	8.10	3.19	2.63	0.87	2.73	0.72	0.67	0.28	7.30	7.75
Agricultural emissions	y_2, bad output	MMTCDE	6.82	9.36	24.73	6.77	9.62	1.17	3.40	0.60	1.81	0.39	0.74	0.22	7.85	8.62
Input variables																
Agricultural land	x_1	1000 km^2	401.50	12.16	31.62	4.81	301.76	5.79	94.06	5.06	5.49	0.25	10.65	0.53	140.85	15.50
Agricultural labour	x_2	1 million persons	155.00	0.30	689.00	93.90	220.00	213.00	66.10	5.17	6.02	0.90	5.13	1.84	190.00	255.00
Agricultural machinery	x_3	1000 tractors	143.16	227.10	80.07	24.09	40.75	6.07	33.05	6.50	26.25	1.41	5.78	0.74	54.840	102.83
Fertiliser	x_4	1 million kg	4.97	27.10	1160.00	457.00	512.00	196.00	89.10	29.70	82.40	8.69	335.00	245.00	363.00	455.00
Characteristic variables																
Foreign direct investment (FDI)	z_1	1 billion US$	0.01	0.01	0.06	0.05	0.01	0.01	0.01	0.01	0.11	0.23	0.01	0.01	0.03	0.10
Gross fixed capital formation	z_2	1 billion US$	1.37	1.41	1.14	1.31	0.21	0.06	0.09	0.02	13.70	48.40	0.07	0.03	2.76	20.20
Female labour force	z_3	%	13.95	2.73	23.50	1.78	26.30	0.92	24.00	2.47	42.24	4.48	13.70	3.09	23.95	9.95
Rural population ratio	z_4	%	41.85	8.42	56.79	0.43	48.08	5.62	38.92	5.25	9.10	0.95	22.83	8.32	36.26	16.93
Employment to population ratio	z_5	%	34.14	2.14	37.74	3.21	38.95	5.54	39.56	0.97	53.65	4.61	31.75	3.37	39.3	7.86
Number. Of observations			37		37		37		37		37		37		222	

Note: SD = standard deviation. MMTCDE is the abbreviation of 1 million metric tonnes of CO_2 equivalents. The variables FDI, agricultural value added and gross fixed capital formation are measured in US dollars. The reference base for CPI indexes is 2010 = 100.

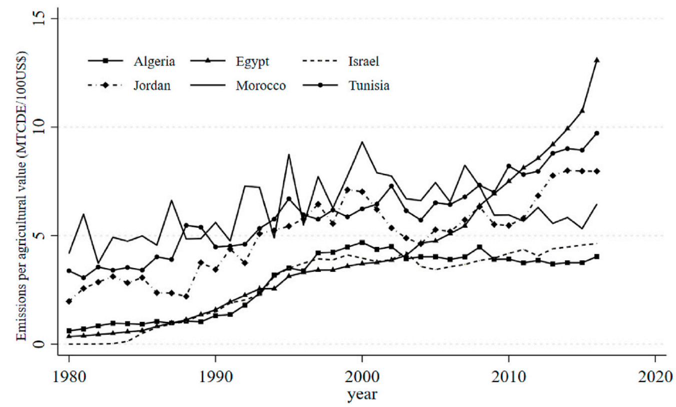

Fig. 1. Changes in agricultural emissions per unit agricultural value added, by country (1980–2016). Notes: The unit of agricultural emissions per agricultural value is metric tonnes of CO2-equivalents (MTCDE)/100 US$.

complementary/substitutionary relationships within inputs and outputs, respectively, for the six MENA countries. Elasticities of the sample mean are presented in Table 3.

With the exception of input x_4 (fertiliser), the elasticity of distance with regard to other inputs, namely x_1 (agricultural land), x_2 (agricultural machinery) and x_3 (agricultural labour), has the expected positive sign,[3] implying that increasing any of these three inputs would increase production potential substantially. A closer look at the estimated elasticities of outputs in relation to those of inputs shows that 'agricultural land' contributes most to agricultural production in the countries studied. Specifically, the elasticity of the directional distance with respect to the 'agricultural land' input suggests that a 1% increase in land under agricultural production in the MENA countries would boost agricultural production potential by 1.904%. This is in line with previous findings that agricultural production in MENA countries responds significantly to changes in agricultural land (Soliman, 2015). In this regard, Tanyer-i-Abur (2015) showed that agricultural land resources in MENA countries have been steadily degrading and decreasing, due to population growth and urban sprawl, desertification, erosion, soil salinisation and other environmental changes. This combination of demographic and environmental pressures together with unsustainable agricultural land use practices presents profound challenges for the productive capacity of agricultural production systems in the MENA region, underscoring the fundamental effect that agricultural land has in determining agricultural output and productivity.

At country level, the results reveal that the largest elasticities with regard to 'agricultural land' are in Israel (3.508), followed by Jordan (2.697). These large elasticities are expected, because Israel and Jordan are both countries that have traditionally faced severe land resource scarcity. With regard to Israel, Hadas and Gal (2014) showed that the productive capacity of Israeli agriculture faces increasing pressures from shortages of land resources and their continuous degradation due to environmental sociodemographic stressors. Similarly, Figueroa et al. (2018) concluded that the major challenge to agricultural production in Jordan is limited land (and water) resources, since of the country's total land area (89.3 thousand km^2), only 10% is arable. Moreover, Al-Bakri et al. (2013) showed that Jordanian agricultural land is at increasing risk of degradation due to inappropriate farming practices, overgrazing and uncontrolled expansion of urban and rural settlements.

The smallest elasticities of directional distance with regard to 'agricultural land' are in Morocco (0.657) and Algeria (0.768). These two countries have abundant arable land resources, averaging 301.8 and

[3] The monotonicity conditions require the first order derivative of the directional distance function $\partial(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial x \geq 0$.

Table 2
Parametric estimation of directional distance function.

Variables	Coef.	SD	Variables	Coef.	SD
Directional frontier Directional vector g = (1,-1) Technical inefficiency model dep. Var.: v					
x_1	−2.852***	0.421	Usigma		
x_2	−0.087	0.096	Constant	−23.105***	1.876
x_3	−0.939**	0.456	z_1	−0.180	0.127
x_4	0.041***	0.012	z_2	0.025	0.065
$0.5\bullet(x_1)^2$	0.837***	0.131	z_3	−0.249	0.925
$0.5\bullet(x_2)^2$	0.053***	0.005	z_4	6.198***	0.524
$0.5\bullet(x_3)^2$	0.072	0.128	z_5	12.333***	2.174
$0.5\bullet(x_4)^2$	−0.002	0.009	Vsigma		
$x_1\bullet x_2$	−0.204***	0.046	Constant	−9.542***	0.557
$x_1\bullet x_3$	0.367**	0.157			
$x_1\bullet x_4$	0.116***	0.018	E (σ_u)	0.132	
$x_2\bullet x_3$	−0.211***	0.082	σ_v	0.008***	0.002
$x_2\bullet x_4$	−0.044***	0.012			
$x_3\bullet x_4$	0.060***	0.019			
y^*	−0.052	0.036			
$0.5\ y^{*2}$	−0.000***	0.000			
$x_1\bullet y$	−0.168***	0.044	Statistics		
$x_2\bullet y$	0.175**	0.077	Prob > chi^2 = 0.0000		
$x_3\bullet y$	0.067***	0.011	Log likelihood = 377.977		
$x_4\bullet y$	−0.129***	0.013	Wald chi^2 (14) = 10,698.27		

Notes: *significant at P < 0.10, **significant at P < 0.05, ***significant at P < 0.01.

Table 3
Elasticity of distance with respect to inputs and outputs.

Elasticity	Algeria		Egypt		Morocco		Tunisia		Israel		Jordan		Overall	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Inputs elasticity ε_{x1}	0.768***	0.843	1.521***	0.408	0.657***	0.428	2.273***	0.016	3.508***	2.321	2.697***	0.078	1.904***	1.453
ε_{x2}	0.631***	0.228	0.693***	0.323	0.756***	0.242	0.263***	0.006	−0.567	2.415	0.14***	0.028	0.319***	1.093
ε_{x3}	0.355*	0.872	0.612***	0.111	0.128	0.084	0.776***	0.013	0.761***	0.920	0.875***	0.042	0.585***	0.578
ε_{x4}	−0.25***	0.180	−0.016	0.176	−0.296***	0.064	−0.102***	0.002	0.458	1.786	−0.042***	0.002	−0.041	0.769
Outputs elasticity ε_y	−0.021	0.709	−0.004	0.081	−0.387***	0.091	−0.067***	0.011	−0.002	0.006	−0.163***	0.089	−0.107***	0.323
ε_b	0.979***	0.709	0.996***	0.081	0.613***	0.091	0.933***	0.011	0.998***	0.006	0.837***	0.089	0.893***	0.323

Notes: T-test for elasticity different from 0, *significant at 5% level (P < 0.1), **significant at 1% level (P < 0.05), ***significant at 0.1% level (P < 0.01).

401.5 thousand km^2 respectively, during the study period, compared with on average between 5.5 and 94.1 thousand km^2 in the other four MENA countries studied.

The elasticity of 'agricultural labour' has significant estimates with positive sign for all MENA countries studies except Israel. Overall, a 1% increase in agricultural labour in the region would increase agricultural production potential by 0.32%. At country level, the highest elasticity estimates are for Morocco (0.756) and Egypt (0.693). The significant effect of 'agricultural labour' on agricultural production in the MENA region can be attributed to the prevalence of household labour (family farming) in agricultural production in the MENA countries, representing around 85% and 80.2% of total agricultural labour in Tunisia and Morocco, respectively (Santos and Ceccacci, 2015). Labour, as a household's greatest resource, is often allocated to a mixture of on-farm and off-farm activities, despite the importance of labour to farm output and agricultural production. For example, the agricultural labour market in Egypt is now at its lowest level of supply because labourers are migrating to more competitive and remunerative sectors, such as industry and services (Hopkins and Nicholas, 2019). As the agricultural labour supply in MENA countries continues to decline due to labour moving out of the sector, labour productivity becomes increasingly important.

The estimated elasticities for 'agricultural machinery' show that it has a significant and positive effect on agricultural production potential in all six countries studied. At country level, Jordan (0.875) has the highest elasticity estimates for agricultural machinery. Soliman and Mashhour (2012) observed that machinery is intensively used in Jordanian agriculture due to the scarcity of agricultural labour, which makes increasing agricultural wages a necessity in order to attract labourers, who tend to prefer urban jobs to farming.

All estimated output elasticities are in line with expectations and comply with economic theory.[4] Overall, elasticity of desirable outputs (ε_y) is −0.107 and that of the undesirable output agricultural emissions (ε_b) is 0.893 (both significant at 1% level). A 1% increase in agricultural production would reduce the distance by 10.7%, while a 1% increase in agricultural emissions would increase the distance by 89.3%, meaning that producers can achieve higher agricultural production output with lower agricultural emissions. This exciting finding is estimated to be significant for Jordan, Tunisia and Morocco. The largest directional distance elasticity of good output is seen for Morocco ($\varepsilon_y = -0.387$). Compared with other countries in the Southern and Eastern Mediterranean region, Santos and Ceccacci (2015) showed that Morocco has substantially reduced the proportion of agricultural GHG emissions within its total emissions, from 30% in 1990 to around 15% in recent years, which is mainly attributable to a decreasing trend in the value added generated by agriculture in terms of total GDP. The largest

[4] The monotonicity conditions of the directional distance function for outputs require $\partial(\overrightarrow{D_o}(x,y,b;1,-1))/\partial y \le 0$ and $\partial(\overrightarrow{D_o}(x,y,b;1,\ -1))/\partial b \ge 0$.

elasticity of agricultural emissions is shown for Israel (0.998), perhaps because Israeli efforts to reduce agricultural GHG emissions are offset by increases in its livestock production. It might also be partly attributable to the fact that Israel does not have sector-specific policy measures for GHG mitigation in the agricultural sector, because of the limited share of agriculture in total GHG emissions (less than 3%) in Israel (OECD, 2022).

Across the six MENA countries studied, elasticity of agricultural emission is significantly positive, which implies that agricultural pollution is increasingly becoming an environmental threat to the region. The overarching goal of government policies in the MENA region is currently to push farmers to maximise, rather than optimise, input use and production, without proper consideration of environmental aspects. Current use of chemical pesticides, herbicides and fertilisers is not environmentally friendly and is resulting in contamination of water, atmospheric pollution and release of harmful residues into soils. For example, there are negative externalities of degradation in chemical and physical characteristics of soil in Egypt, due to excessive use of chemical fertilisers, especially nitrogen, irrational use of pesticides and release of sewage and industrial waste into water canals and farm ditches (Al Said, 2011). In Tunisia, Thabet et al. (2015) pointed out that the implementation of successive agricultural policies has involved intensification of agricultural activities, primarily through irrigation and increased use of industrial inputs, such as fertilisers, which are supplied to farmers at below cost price. In Algeria, the country with the largest elasticity of agricultural emissions, the government has made considerable investments in agricultural development in order to modernise the sector. According to Kachi et al. (2016), these investments have been accompanied by intensive use of nitrogen fertilisers and inappropriate farming techniques and crop types, which has made a significant contribution to nitrate pollution and soil salinisation in agriculture.

4.2. Environmental efficiency scores and determinants of inefficiencies

Calculated EE after estimation of the directional distance function is on average 0.913 across the six MENA countries, indicating that, on average, the environmental efficiency in these countries can be improved by 8.7% without increasing inputs under current conditions. This is consistent with the finding by Mazrou (2021) that there is clear scope for MENA countries to improve agricultural performance while mitigating ecologically damaging effects. Based on the kernel and normal distributions of EE scores (Fig. 2), there are relatively large differences in mean environmental performance and distribution in the agricultural sector among the studied countries. Jordan, Tunisia, Algeria and Israel show more efficient environmental performance, while Morocco and Egypt have lower EE. This implies that environmentally adjusted technical efficiencies of agricultural production are greener in Jordan and Israel than in Egypt and Morocco. The distribution also shows that EE in Egypt is diversified, while that in Jordan is more homogenous. Future studies should seek to formulate context-specific policy interventions for each country.

To further explore the relationship between agricultural emissions and environmental efficiency, we calculate agricultural emissions per unit environmental efficiency by dividing the ratio of EE by agricultural emissions (Fig. 3). Through this calculation, we reveal the amount of agricultural emissions generated by one unit of EE, which can be taken as the environmental cost of one unit of environmental performance. The results clearly indicate an increase in emissions per unit efficiency in all six countries between 1980 and 2016, supporting claims that there is a trade-off between intensification of agricultural production and increasing use of fertilisers, pesticides and other agricultural chemicals (Albanito et al., 2017). We show that Jordan and Israel have comparatively lower agricultural emissions to gain one unit of EE, while Egypt has the highest emissions.

Estimates of the environmental inefficiency model are given in the

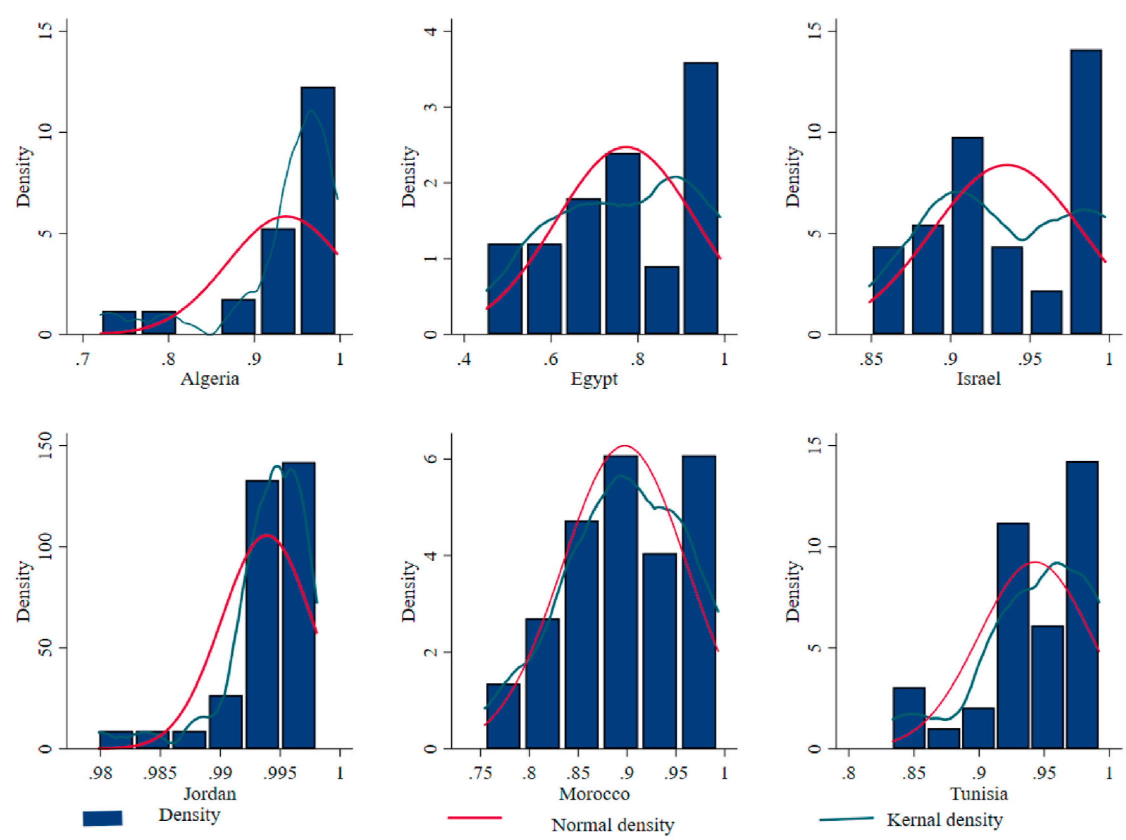

Fig. 2. Kernel distributions of environmental efficiency scores by country.

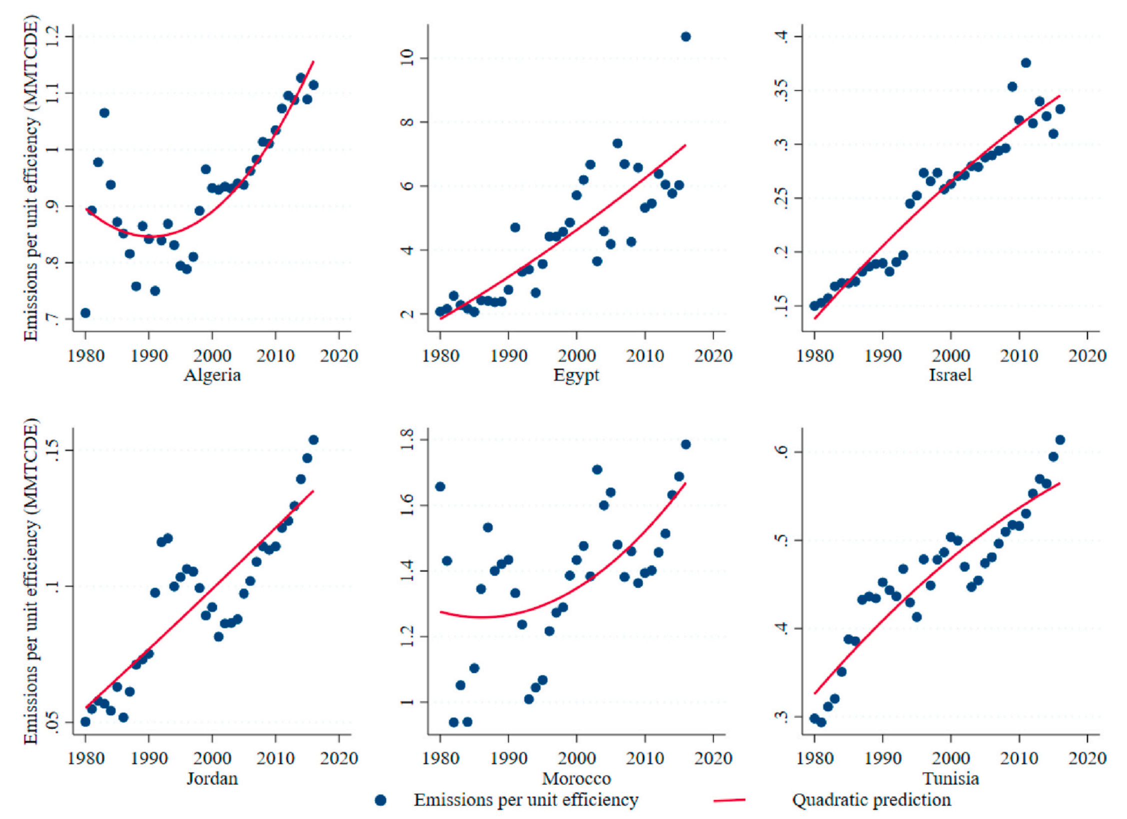

Fig. 3. Agricultural emissions per unit environmental efficiency by country. Notes: MMTCDE = million metric tonnes of CO_2 equivalents.

far-right column of Table 2. By applying inefficiency model along with directional distance function, we can explore social-economic factors that account for the EE gap among the different MENA countries studied. The dependent variable in the inefficiency model is inefficiency, so a negative parameter coefficient for the variables indicates a negative effect on environmental inefficiency and, conversely, a positive effect on EE. The results show that foreign direct investment *(z_1)*, gross fixed capital information *(z_2)* and female labour force *(z_3)* have insignificant effects on EE in the countries studied. In contrast, the estimates for rural population *(z_4)* and employment to population ratio *(z_5)* are significantly positive in the inefficiency model. This indicates that *i*) the greater the rural population, the lower the EE, and *ii*) the higher the employment ratio, the greater the inefficiency. These findings complement those presented in section 4.1 of this paper regarding the crucial role of labour in agricultural value added in MENA countries.

4.3. Shadow price of agricultural emissions

Table 4 summarises the relative shadow prices of agricultural emissions against agricultural value added. The shadow prices of agricultural emissions can be treated as the opportunity cost/marginal abatement cost of reducing an additional unit of agricultural emissions with respect to agricultural production. The overall relative shadow price is estimated to be −1.002 at the sample mean, *i.e.* the 'price' of agricultural emissions exceeds the 'price' of one unit of agricultural production. This may imply that there is great abatement scope for the countries studied to increase agricultural production without increasing agricultural emissions. Comparing the shadow prices across the six MENA countries, Algeria has the largest absolute values, followed by Egypt. In previous EE analyses, most shadow prices of environmental outputs have been assumed to be negative (Färe et al., 1993), meaning that these environmental outputs are 'undesirable' outputs. With an estimated M_{by} value of −0.022 for all samples, our results confirm that these environmental outcomes are undesirable outputs. More negative M_{by} values indicate greater change in the relative shadow price of agricultural emissions for the desirable output of agricultural value added, and thus a greater cost to remove the undesirable agricultural emissions. Israel has the largest absolute value of shadow price, implying that the abatement cost for decreasing a unit of agricultural emissions in Israel is considerably greater than in the other MENA countries studied. One possible explanation for this is that Israeli agriculture faces severe water scarcity challenges. This increases energy use for desalination of seawater and pumping groundwater for food production, which increases agricultural GHG emissions and makes the task of reducing such emissions financially costly (Borgomeo et al., 2018). In contrast, our results reveal that reducing one unit of agricultural emissions would cost less in Jordan compared with the other countries investigated. The fact that Jordan has significantly lower abatement cost for decreasing agricultural emissions,

Table 4
Relative shadow price of agricultural emissions.

Variable	Algeria	Egypt	Morocco	Tunisia	Israel	Jordan	Overall
Relative shadow price: $\frac{\partial \vec{D}(x,y,b)/\partial y}{\partial \vec{D}(x,y,b)/\partial b}$	−1.05614***	−1.03122***	−0.99406***	−0.93287***	−0.99813***	−1.00191***	−1.002388***
M_{by}: Morishima elasticity substitution of b to y	−0.0002***	0.00182	−0.00009***	−0.00014***	−0.13254	−0.00002***	−0.02186

Notes: T-test for elasticity different from 0, **significant at P < 0.10, **significant at P < 0.05, ***significant at P < 0.01.

despite being comparable with Israel in terms of water and land resource scarcity, could be due to its heavy reliance (more than 90% of total food) on the international market rather than domestic production to meet the food demands of its population (Khraishy, 2015).

5. Policy implications and conclusion

To the best of our knowledge, no previous study has examined the environmental efficiency of agricultural production in the MENA region, despite the significant contribution of agriculture to overall GHG emissions in the region. To address this research gap, we applied the directional distance function to estimate the environmental efficiency of agricultural production in six MENA countries (Algeria, Egypt, Israel, Jordan, Morocco, Tunisia) during the period 1980–2016. Based on the empirical findings presented and discussed in the previous section, there are a number of implications for policy formulation to improve the efficiency of agricultural production and reduce the environmental footprint of MENA agriculture.

First, our estimated elasticities of production inputs suggest that agricultural land remains the single most important factor in increasing agricultural production in the region, which calls for more effective land-use policies and stricter government control over urban growth boundaries, through urban spatial planning (Badreldin et al., 2019). For protection of basic cropland, legislation is required to minimise loss of agricultural land and maintain food production for the rapidly growing population in the rapidly urbanising MENA region.

Second, we show that an increase in the availability of agricultural labour in the MENA countries studied is associated with a positive and statistically significant impact on agricultural production. This implies that attracting and training an agricultural workforce, an issue often neglected by policymakers, can be an effective way to overcome the many factors currently slowing growth in agricultural productivity in rural areas and help match the dynamics of emerging regional and global food value chains. In particular, upgrading human capital and reforming vocational and tertiary agricultural education and extension services in MENA countries can be a source of productivity gains by changing attitudes and values about agricultural production and resource use, and promoting sustainable farming practices. To accomplish this, government interventions should focus on generating better economic opportunities and improving livelihoods and incomes for farmers and rural communities, which would make agriculture a more attractive sector for the labour force and unlock its potential to alleviate rural poverty and enhance the resilience of MENA agriculture.

Third, the results show that agricultural machinery has a significant positive effect on agricultural production potential in the countries studied. Policies to accelerate the mechanisation of agriculture and increase adoption of precision agriculture are therefore clear routes to increase agricultural productivity and output in MENA countries. In particular, addressing factors constraining the ability of smallholder farmers, who make a fundamental contribution to agricultural production in the region, to use agricultural equipment and machinery and adopt technologies is crucial for maximising outputs and reducing costs, increasing agricultural productivity and enhancing the competitiveness of small-scale farming systems.

Fourth, the EE values indicate that the six MENA countries studied can improve the efficiency of their agricultural production on average by about 9% without increasing inputs under current conditions. In parallel, the estimated overall and relative shadow prices indicate that the countries can lower agricultural emissions while increasing agricultural production. Together, these findings suggest a need for integrated and systematic approaches to build more sustainable agricultural production systems in the MENA region, to enable food security and provide resilient livelihoods within the environmental boundaries of each country while protecting natural ecosystems. Our results also demonstrate that there are trade-offs between intensifying agricultural production and increasing use of fertilisers, pesticides and other agricultural chemicals. Linking agricultural policies to environmental strategies and ecosystem protection programmes is essential to resolve these trade-offs and ensure that food production goals are not achieved at the expense of ecosystems.

Fifth, our results reveal large heterogeneities across the six countries studied in relation to environmental performance and technical efficiencies of agricultural production. Policymakers in the countries should capitalise on these heterogeneities to develop cross-government approaches and create platforms for continued dialogue between countries and stakeholders that promote experience sharing regarding the scaling-up of sustainable technologies and practices that increase agricultural productivity and reduce the environmental footprint of agriculture. There are some limitations to this study. First, there is an assumption that the quality of inputs and outputs is homogenous in different countries. Second, with the long-term panel data used, we ignore possible market disorders or market shocks due to natural disasters or wars. Third, water is excluded from the model, although the water resource is the greatest constraint for agricultural production in the MENA region. The irrigation systems in the countries studied differ significantly in terms of layout, irrigation methods and techniques, characteristics of the irrigated crops and the level of water scarcity, possible rendering comparison of country-level estimates less meaningful. In future work, it would be interesting to assess how environmental efficiency differs at different agricultural development stages.

Credit author statement

The authors contributed to this manuscript as below. Authors: Wei Huang (WH), Qian Liu (QL), Assem Abu Hatab (AH), WH: idea & conceptualization, analysis, methodology, modelling and simulation, original draft preparation, revise & editing, QL: modelling and simulation, revise & editing, AH: idea & conceptualization, research & investigation, data curation, original draft preparation, revise & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgement

The authors were grateful for helpful comments received from 16th European Workshop on Efficiency and Productivity Analysis (EWEPA) Conference in London in June 2019. The authors highly appreciated the Swedish Foundation for International Cooperation in Research and Higher Education (STINT) for the funding support on Joint China-Sweden Mobility program (CH2017-7302). The last author (Assem Abu Hatab) thanks the Arab-German Young Academy of Sciences and Humanities (AGYA) for partially supporting this work through AGYA's Research Mobility Programme.

References

Agostino, M., 2016. Organic agriculture, greenhouse gas emissions and environmental efficiency: an empirical study on OECD countries. Int. J. Econ. Finance 8 (11), 78–95. https://doi.org/10.5539/ijef.v8n11p78.

Al Said, A., 2011. *The Impact of Agricultural Policies on the Efficient Use of Resources* [Ph.D. Thesis]. Department of Agricultural Economics, Faculty of Agriculture, Menia University.

Al-Bakri, J., Salahat, M., Suleiman, A., et al., 2013. Impact of climate and land use changes on water and food security in Jordan: implications for transcending "the tragedy of the commons". Sustainability 5 (2), 724–748. https://doi.org/10.3390/su5020724.

Albanito, F., Lebender, U., Cornulier, T., et al., 2017. Direct nitrous oxide emissions from tropical and sub-tropical agricultural systems - a review and modelling of emission factors. Sci. Rep. *7* (1), 1–12. https://doi.org/10.1038/srep44235.

Badreldin, N., Abu Hatab, A., Lagerkvist, C.J., 2019. Spatiotemporal dynamics of urbanization and cropland in the Nile Delta of Egypt using machine learning and satellite big data: implications for sustainable development. Environ. Monit. Assess. 191 (12), 1–23. https://doi.org/10.1007/s10661-019-7934-x.

Borgomeo, E., Jagerskog, A., Talbi, A., et al., 2018. The Water-Energy-Food Nexus in the Middle East and North Africa: Scenarios for a Sustainable Future. World Bank, Washington DC, USA. https://doi.org/10.1596/29957.

Chambers, R.G., 2002. Exact nonradial input, output, and productivity measurement. Econ. Theor. 20 (4), 751–765. https://doi.org/10.1007/s001990100231.

Clark, M., Tilman, D., 2017. Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. Environ. Res. Lett. 12 (6), 064016 https://doi.org/10.1088/1748-9326/aa6cd5.

Expósito, A., Velasco, F., 2020. Exploring environmental efficiency of the European agricultural sector in the use of mineral fertilizers. J. Clean. Prod. 253, 119971 https://doi.org/10.1016/j.jclepro.2020.119971.

Färe, R., Primont, D., 1996. The opportunity cost of duality. J. Prod. Anal. 7 (2), 213–224. https://doi.org/10.1007/BF00157042.

Färe, R., Grosskopf, S., Lovell, C.A.K., Yaisawarng, S., 1993. Derivation of shadow prices for undesirable outputs: a distance function approach. Rev. Econ. Stat. 75 (2), 374–380. https://doi.org/10.2307/2109448.

Färe, R., Grosskopf, S., Noh, D.-W., Weber, W., 2005. Characteristics of a polluting technology: theory and practice. J. Econom. 126 (2), 469–492. https://doi.org/10.1016/j.jeconom.2004.05.010.

Figueroa, J.L., Mahmoud, M., Breisinger, C., 2018. *The role of agriculture and agro-processing for development in Jordan* (MENA RP Working Paper No. 5). Intl Food Policy Res Inst. https://doi.org/10.2499/1024320700.

Hadas, E., Gal, Y., 2014. Barriers preventing food security in Israel, 2050. Manag. Global Transit. 12 (1), 3–22.

Hart, J., Miljkovic, D., Shaik, S., 2015. The impact of trade openness on technical efficiency in the agricultural sector of the European Union. Appl. Econ. 47 (12), 1230–1247. https://doi.org/10.1080/00036846.2014.993134.

Hopkins, Nicholas, S., 2019. Agrarian Transformation in Egypt. Routledge.

Huang, W., Bruemmer, B., 2017. Balancing economic revenue and grazing pressure of livestock grazing on the Qinghai-Tibetan-Plateau. Aust. J. Agric. Resour. Econ. 61 (4), 645–662. https://doi.org/10.1111/1467-8489.12225.

Kachi, N., Kachi, S., Bousnoubra, H., 2016. Effects of irrigated agriculture on water and soil quality (case perimeter Guelma, Algeria). Soil Water Res. 11 (2), 97–104. https://doi.org/10.17221/81/2015-SWR.

Khraishy, M., 2015. Market Overview and Guide to Jordanian Market Requirements. USDA Foreign Agricultural Service office at US Embassy, Amman, Jordan.

Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis. Cambridge University Press.

Le, T.L., Lee, P.P., Peng, K.C., Chung, R.H., 2019. Evaluation of total factor productivity and environmental efficiency of agriculture in nine East Asian countries. Agric. Econ. 65 (6), 249–258. https://doi.org/10.17221/50/2018-AGRICECON.

Lin, B., Omoju, O.E., Nwakeze, N.M., Okonkwo, J.U., Megbowon, E.T., 2016. Is the environmental Kuznets curve hypothesis a sound basis for environmental policy in Africa? J. Clean. Prod. 133, 712–724. https://doi.org/10.1016/j.jclepro.2016.05.173.

Mazrou, Y., 2021. Assessing agricultural malmquist total factor productivity and environmental efficiency for some Arab countries via data envelope analysis. Journal of Agricultural Economics and Social Sciences 12 (4), 311–324.

Mubarak, J.A., 1998. Middle East and North Africa: development policy in view of a narrow agricultural natural resource base. World Dev. 26 (5), 877–895. https://doi.org/10.21608/jaess.2021.169537.

Njuki, E., Bravo-Ureta, B.E., 2015. The Economic costs of environmental regulation in U. S. dairy farming: a directional distance function approach. Am. J. Agric. Econ. 97 (4), 1087–1106. https://doi.org/10.1093/ajae/aav007.

OECD, 2022. Climate change. In: Environment at a Glance Indicators. OECD Publishing, Paris. https://doi.org/10.1787/5584ad47-en.

Pörtner, Hans O., Roberts, Debra C., Adams, Helen, et al., 2022. Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. https://policycommons.net/artifacts/2679314/climate-change-2022/3702620/.

Rahman, S., 2010. Women's labour contribution to productivity and efficiency in agriculture: empirical evidence from Bangladesh. J. Agric. Econ. 61 (2), 318–342. https://doi.org/10.1111/j.1477-9552.2010.00243.x.

Reinhard, S., Lovell, C.A.K., Thijssen, G.J., 2000. Environmental efficiency with multiple en- vironmentally detrimental variables; estimated with SFA and DEA. Eur. J. Oper. Res. 121, 287–303.

Santos, Nuno, Ceccacci, Iride, 2015. Egypt, Jordan, Morocco and Tunisia: Key Trends in the Agrifood Sector. Investment Centre Division, FAO and EBRD.

Sauer, J., Latacz-Lohmann, U., 2015. Investment, technical change and efficiency: empirical evidence from German dairy production. J. Econom. 42 (1), 151–175. https://doi.org/10.1093/erae/jbu015.

Serra, T., Lansink, A.O., Stefanou, S.E., 2011. Measurement of dynamic efficiency: a directional distance function parametric approach. Am. J. Agric. Econ. 93 (3), 756–767. https://doi.org/10.1093/ajae/aaq175.

Shepherd, R.W., 2016. Theory of Cost and Production Functions. Princeton University Pres.

Soliman, I., 2015. Diagnosis and challenges of sustainable agricultural development in Egypt, 46. In: Petit, M., Montaigne, E., El Hadad-Gauthier, F., García Álvarez-Coque, J.M., Mattas, K., Mili, S. (Eds.), Cooperative Management. Sustainable Agricultural Development. Springer, pp. 19–64. https://doi.org/10.1007/978-3-319-17813-4_2.

Soliman, I., Mashhour, A., 2012. National agro-food policies in Jordan: national agro-food policies in Jordan. MPRA Archive. *Paper No. 66782*.

Tang, Kai, Ma, Chunbo, 2022. The Cost-Effectiveness of Agricultural Greenhouse Gas Reduction under Diverse Carbon Policies in China. China Agricultural Economic Review, 202102020926.

Tang, Kai, Hailu, Atakelty, Kragt, Marit E., Ma, Chunbo, 2016. Marginal abatement costs of greenhouse gas emissions: broadacre farming in the great Southern region of Western Australia. Aust. J. Agric. Resour. Econ. 60 (3), 459–475.

Tanyeri-Abur, A., 2015. Food security in the Southern Mediterranean/North Africa. In: Vastola, A. (Ed.), The Sustainability of Agro-Food and Natural Resource Systems in the Mediterranean Basin. Springer International Publishing, pp. 3–14.

Teklewold, H., Gebrehiwot, T., Bezabih, M., 2019. Climate smart agricultural practices and gender differentiated nutrition outcome: an empirical evidence from Ethiopia. World Dev. 122, 38–53. https://doi.org/10.1016/j.worlddev.2019.05.010.

Thabet, B., Laajimi, A., Thabet, C., et al., 2015. Agricultural and food policies in Tunisia: from a seemingly solid performance to unsustainable revealed achievements. In: Petit, M., et al. (Eds.), Cooperative Management. Sustainable Agricultural Development. Springer, pp. 83–101.

Vlontzos, G., Niavis, S., Manos, B., 2014. A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. Renew. Sustain. Energy Rev. 40, 91–96. https://doi.org/10.1016/j.rser.2014.07.153.

Yang, Lin, Tang, Kai, Wang, Zhaohua, An, Haizhong, Fang, Wei, 2017. Regional eco-efficiency and pollutants' marginal abatement costs in China: a parametric approach. J. Clean. Prod. 167, 619–629.

Zamanian, G.R., Shahabinejad, V., Yaghoubi, M., 2013. Application of DEA and SFA on the Measurement of Agricultural Technical Efficiency in MENA Countries.