Food security, climate change and environmental pollution in MENA region: evidence from second generation panel analysis

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Abstract

Food security is a critical issue in the Middle East and Northern Africa (MENA) region due to its population growth, as well as geographical and climatic conditions. From one point of view, most of the countries in the region benefit from an abundance of natural resources centered on fossil fuels. From another point of view, environmental issues, particularly emissions caused by production activities, and the pressures caused by climate variability, highlight the importance of food security. Hence, the effect of climate change, energy consumption, environmental pollution and other control variables on food security in the MENA region from 1990 to 2019 is explored. According to the cross-section dependency, the second-generation panel CS-ARDL estimator is employed. The empirical results indicated that energy consumption, crop production land, CO_2 emissions, and precipitation have a significant positive effect on crop production index as index of food security. Additionally, urbanization and mean temperature have detrimental effects. The findings from Dumitrescu and Hurlin causality tests indicated that crop land and precipitation have a unidirectional causal effect on food security, whereas energy consumption, CO_2 emissions, urbanization, and mean temperature have a bidirectional causal relationship with food security. These findings imply that while maintaining the level of agricultural production and increasing it, the climate effects and environmental aspects of production should not be overlooked.

Keywords: Energy consumption, CO_2 emissions, Precipitation, CS-ARDL.

1. Introduction

SDG2, the Second Sustainable Development Goal, has set the target of enhancing nutrition, attaining food security, eradicating hunger, and promoting sustainable agriculture by the year 2030. Conflict, climate variability, and economic downturns have hindered progress toward SDG2 over the last few years, and these factors are expected to worsen following COVID-19, which is now being exacerbated by the Ukraine-Russia crisis. Between 720 and 811 million people worldwide go to bed hungry every night, highlighting the serious consequences of current global crises (UNICEF, 2020). Moreover, the number of people experiencing extreme food insecurity has doubled since COVID-19, increasing from 135 million to 276 million (UN Secretary General, 2022). Following the World Health Organization, the likelihood of becoming undernourished increased to 9.9 percent in 2020 from 8.4 percent in 2019 (World Health Organization, 2021).

In 1996, the World Food Summit stated that food security is achieved when every individual has access to sufficient and safe food supply that sustains an active and healthy life (World Food Summit, 1996). In this regard, the Food and Agriculture Organization (FAO) identifies four fundamental dimensions of food security, contain physical food availability, food access, food utilization, and food stability (Webb et al., 2006 and CFS, 2009). Physical food availability is achieved when a sufficient amount of food is permanently available for all members of society. In this dimension of food security, the water, land and energy use determines the food production growth (Godfray et al., 2010). The agricultural sector plays a key role in this dimension of food security. Since the dawn of humanity, agriculture has provided food for humans and contributed to the improvement of human living standards.

While global institutions such as FAO, WFP (World Food Programme), and the IFAD (International Fund for Agricultural Development) play a significant role in achieving the second SDG, domestic strategies, such as increasing agricultural productivity and promoting sustainable food production, are the most effective means of achieving food security and global zero hunger. The increasing global population, projected to reach 11.2 billion by 2100, is driving a rising demand for food and agricultural products. As the population continues to grow and food production rises, it is imperative to prioritize and increase agricultural production to fulfill the increasing demand for food of human societies. Several recent studies, such as Lu et al. (2021) predicted that given current consumption patterns, food, water, and energy consumption would rise by 50%, 80%, and 60%, respectively, for a population of 10 billion by the year 2050. A variety of factors, including land degradation, water scarcity, and global warming, are threatening food production. To feed 11.2 billion people by 2100, global food production needs to rise more than 50%. Increased food production will also pose numerous environmental challenges (Searchinger et al., 2019).

Extensive research has explored the interplay of food security with various factors, including climate change (Schmidhuber and Tubiello, 2007; Campbell et al., 2016; Mokhtar et al., 2022; Pickson and Boateng, 2022; Kargar Dehbidi et al., 2022), CO_2 emissions (Chandio et al., 2020; Degife et al., 2021; Koondhar et al., 2021a; Affoh et al., 2022), fossil fuel consumption (Günther, 2001; Arizpe et al., 2011; Raeeni et al., 2019; Mahdavian et al., 2022; Boly and Sanou, 2022), renewable energy consumption (Mallick, 2022; Kaimal et al., 2022), population (Rehman et al., 2022), economic growth (Kargar Dehbidi et al., 2022), water resources (Abdullah et al., 2022), soil fertility (Gebrehiwot, 2022), agricultural land (Hossain et al., 2020), environmental deterioration (Qi et al., 2018), and urbanization (Wang, 2019) across diverse countries and regions. This research has employed a variety of econometric techniques and methods.

Schmidhuber and Tubiello (2007) studied the impact of climate change on four dimensions of food security, finding a detrimental effect on all aspects. They noted that climate change's overall impact on food security is regionally and temporally variable, contingent upon a country's socioeconomic status when addressing climate change. Raeeni et al. (2019) employed time series econometric methods, including causality and cointegration tests, confirming significant relationship among energy consumption and agricultural products in Iran.

Also, Kargar Dehbidi et al. (2022) examined the effect of climate change (precipitation and temperature) on food security (food price volatility) in Iran's provinces, utilizing the Panel-Var econometrics approach. Empirical findings revealed a significant effect of climate change on food security, with temperature exerting a greater influence than precipitation. Onour (2019) employed the ARDL bounds test of cointegration to assess CO_2 emissions' impact on Sudan's crop yields, revealing a significant positive impact on cereal yield. A 1% increase in CO_2 emissions resulted in a 3% and 0.7% increase in cereal yield in short and long run, respectivly, a finding echoed by Degife et al. (2021) for maize yields in Ethiopia. Affoh et al. (2022) investigated CO_2 emissions' impact on food security sub-indices (food availability, accessibility, and utilization) using PMG, FMOLS, and DOLS models across 25 sub-Saharan African nations. They found that CO_2 emissions had no significant impact on food utilization but had a positive impact on food accessibility and availability. Regarding the effect of energy consumption on agricultural products, Numerous studies have looked at how CO_2 emissions in MENA nations are impacted by factors like energy use, crop production, and urbanization (Farhani and Rejeb, 2012; Arouri et al., 2012; Omri, 2013; Jebli and Youssef, 2017; Magazzino and Cerulli, 2019; Alharthi et al., 2021 and Omri and Saidi, 2022).

Nonetheless, according to the authors' analysis, there has not been a comprehensive study conducted as of yet that analyzes the impact of CO_2 emissions on crop production index within this region. Identifying this existing research gap highlights the necessity and significance of this research as follows. First, even with the evident importance of CO_2 emissions and other control variables in influencing crop yields, a comprehensive investigation spanning the MENA region has not been undertaken. By addressing this gap, the study contributes to a deeper understanding of the dynamics of food security in MENA countries. The in hand study's findings will elucidate the primary determinants of food insecurity, providing valuable insights for the achievement of SDG, particularly within the MENA region. Second, this study pioneers the examination of the food security-energy-climate change nexus in the MENA context, thus enhancing comprehension of the intricate challenges faced by MENA nations. Third, the study delves into the relationships among CO_2 emissions, fossil fuel consumption, cropland, urbanization, temperature, precipitation, and crop production as a food security indicator. This exploration is conducted using the second-generation panel CS-ARDL estimator across a panel of 18 MENA countries. Lastly, the integration of recent methodological advancements, including second-generation panel tests, further bolsters the study's findings, enhancing their robustness and accuracy.

2. Data, Model, and Econometrics Method

2.1. Data

According to the empirical study's goals and data availability, the data was collected from 1990 to 2019 for 18 MENA region countries. Table 1 illustrates the details of variables of econometrics model.

Table 1. Details of model's variables.

Variables	Definition	Unit of measurement
Crop Production Index (CP)	All agricultural production (except fodder) relative to the base period (2014-2016 = 100)	Unit less (Index)
Cropland (CPL)	Land used for the cultivation of crops	1000 ha
Urban Population (URB)	The share of urban to total population	Percent
Energy Consumption (EC)	Total energy consumption	Million tons of oil equivalent
CO_2 Emissions (CO_2)	Total CO_2 emissions by agri-food system component	Kilotons
Mean Temperature (MT)	Annual Mean Temperature	Centigrade
Precipitation (PRC)	Annual Mean Precipitation	Millimeter

Crop Production Index (CP), CO_2 emission (CO_2), Crop Land (CPL), and Mean Temperature (MT) are gathered from the FAO. Urban Population (URB), and Precipitation (PRC) were gathered from the World Bank. Also, the Energy Consumption (EC) data is gathered from Energy Information Administration (EIA).

2.2. Model and Econometrics Method

According to the literature, the variables of model are selected. Hence, the empirical econometrics model can be expressed by equation (1).

$$CP_{it} = \alpha_0 + \alpha_1 CPL_{it} + \alpha_2 URB_{it} + \alpha_3 EC_{it} + \alpha_4 CO2_{it} + \alpha_5 MT_{it} + \alpha_6 PRC_{it} + \varepsilon_{it} \qquad (1)$$

Equation (2) indicates the ARDL approach, while the expanded form of equation (1) is shown in equation (3), taking into account the cross-sectional averages of the variables in the studied model (Chudik and Pesaran, 2015; Shao et al., 2021; Chien et al., 2022).

$$W_{i,t} = \sum_{i=1}^{P_w} \vartheta_{i,t}\, W_{i,t-1} + \sum_{i=0}^{P_x} \rho_{i,t}\, X_{i,t-1} + \varepsilon'_{i,t} \qquad (2)$$

$$W_{i,t} = \sum_{i=1}^{P_w} \vartheta_{i,t}\, W_{i,t-1} + \sum_{i=0}^{P_x} \rho_{i,t}\, X_{i,t-1} + \sum_{i=0}^{P_z} \beta_{i,t}\, \bar{Z}_{t-1} + \varepsilon_{i,t} \qquad (3)$$

Where, i denote the cross-section (18 MENA region countries) and t denote time period (1990 to 2019). W_{it} and $X_{i,\, t-1}$ indicate the dependent and independent variables respectively. Additionally, $\bar{Z}_{t-1}$ represents the average of sections to address cross-sectional dependence. P_w, P_x, and P_z, imply the lags. For the long-term estimation using CS-ARDL, the average mean group estimate is presented in equation (4). The short-term model is revealed in equation (5) as follows: (Adebayo et al., 2023; Li et al., 2023).

$$\hat{\pi}_{CS-ARDL,i} = \frac{\sum_{I=0}^{P_x} \hat{\rho}_{Ii}}{1 - \sum_{I=0} \hat{\theta}_{I,t}} \qquad (4)$$

$$\Delta W_{it} = \varphi_i \left[W_{i,t-1} - \pi_i X_{i,t-1} \right] - \sum_{i=0}^{P_w - 1} \theta_{i,t} \Delta_i W_{i,t-1} + \sum_{i=0}^{P_x} \rho_{i,t} \Delta_i X_{i,t-1} + \sum_{i=0}^{P_z} \beta_i \bar{Z}_t + \varepsilon_{i,t} \qquad (5)$$

Furthermore, all variables in the model, except for urbanization (percent), were converted to natural logarithms to reduce scale differences and improve estimation efficiency. Finally, the CS-ARDL equation for the variables in the present study is as follows:

$$\Delta lnCP_{i,t} = \theta_i + \sum_{i=1}^{P} \theta_{i,t} \Delta lnCP_{i,t-1} + \sum_{i=1}^{P} \theta_{i,t} \Delta lnCPL_{i,t} \sum_{i=1}^{P} \theta_{i,t} \Delta lnURB_{i,t} + \sum_{i=1}^{P} \theta_{i,t} \Delta lnEC_{i,t}$$
$$+ \sum_{i=1}^{P} \theta_{i,t} \Delta lnCO2_{i,t} + \sum_{i=1}^{P} \theta_{i,t} \Delta lnMT_{i,t} + \sum_{i=1}^{P} \theta_{i,t} \Delta lnPRC_{i,t}$$
$$+ \sum_{i=0}^{P} \beta_{i,t} \bar{Z}_{i,t-1} + \varepsilon_{i,t} \qquad (6)$$

Initially, cross-sectional dependency should be checked in the empirical panel data. Therefore, the Pesaran (2004) cross-section test (Pesaran CD test) is applied to examine the presence of cross-sectional dependency for all variables in the model. In the Pesaran CD test, the null hypothesis is the absence of cross-section dependence (Pesaran et al., 2008). Equation (7) presents the Pesaran CD test statistic (Pesaran, 2004).

$$CD = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ik} \tag{7}$$

Where T is the time period (20 years) and N denotes the cross-section (18 MENA region countries). Additionally, $\hat{\rho}_{ij}$ represents the correlation coefficient. According to the results of Pesaran CD test, the researchers could select the first or second generation unit root tests. The first generation unit root tests contain Levin, Lin and Chu (LLC) and Im, Pesaran and Shin (IPS) stationary test. The second generation unit root tests contain Cross-Sectionally Augmented IPS (CIPS) stationary test.

But, it is necessary to check the homogeneity of slope in all cross-sections, before estimating the econometric model. According to this, the Pesaran and Yamagata (2008) homogeneity test is used in the present study. The null and alternative hypothesis of the slope homogeneity test is homogenous and heterogeneous slopes of cross-section, respectively (Pesaran and Yamagata, 2008). The homogeneity of slope is checked by equation (8) and (9).

$$\tilde{\Delta}= \sqrt{N}(\frac{N^{-1}S\%-k}{\sqrt{2k}}) \tag{8}$$

$$\tilde{\Delta}_{\text{Adjusted}}= \sqrt{N}\left(\frac{N^{-1}S\%-k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right) \tag{9}$$

In this study, the Westerlund panel cointegration test as the second-generation cointegration test is used to select the appropriate econometrics estimation approach. Following Westerlund (2007), the panel cointegration is checked by equation (10) to (13).

$$G_a = \frac{1}{n}\sum_{i=1}^{n} \frac{\acute{\propto}_i}{SE(\acute{\propto}_i)} \tag{10}$$

$$G_t = \frac{1}{n}\sum_{i=1}^{n} \frac{T\acute{\propto}_i}{\acute{\propto}_i(1)} \tag{11}$$

$$P_a = T\,\acute{\propto} \quad (12)$$

$$P_t = \frac{\acute{\propto}}{SE(\acute{\propto})} \quad (13)$$

In this paper, the second-generation panel CS-ARDL estimator is utilized because of its advantages over other methods. Panel CS-ARDL provides robust, effective, and powerful estimation capabilities, even in the presence of non-stationarity, slope heterogeneity, misspecification bias, endogeneity bias, serial correlation of error terms, limited sample size, and cross-sectional dependency (Samargandi, 2019; Azam & Haseeb, 2021; Okunade et al., 2022; and Salman et al., 2022). Additionally, CS-ARDL can estimate both long and short-run relationships, simultaneously. Moreover, the lag of dependent and independent variables can be included in the econometric model (Chudik and Pesaran, 2015)

3. Empirical results and discussion

The descriptive statistics of all variables of the model is showed in Table 2.

Table 2. Descriptive statistics of variables for MENA countries.

Variables	LnCP	LnCPL	URB	LnEC	$LnCO_2$	LnMT	LnPRC
Mean	4.42	6.55	72.4	3.08	8.96	3.1	4.8
Median	4.49	7.54	76.02	2.96	8.84	3.13	4.75
Maximum	5.58	9.83	100	5.71	11.8	3.37	6.81
Country	UAE	IRI	KWT	IRI	IRI	BHR	LBN
Minimum	1.72	1.38	20.93	0.58	6.6	2.64	2.63
Country	KWT	BHR	YEM	MAR	YEM	LBN	QAT
Standard Deviation	0.41	2.47	18.7	1.08	1.15	0.16	0.8
Skewness	-1.55	-0.64	-0.64	0.45	0.48	-0.32	0.07
Kurtosis	9.94	2.17	2.8	2.56	2.55	2.12	2.47
Observations	540	540	540	540	540	540	540
Cross section	18	18	18	18	18	18	18

According to the results of table 2, the mean of LnCP is 4.42, while the mean of $LnCO_2$ is 8.96. Furthermore, the mean of LnEC is 3.08, whereas the mean of LnCPL is 6.55. Also, the mean of URB, LnMT, and LnPRC are 72.4, 3.1, and 4.8, respectively, in the MENA region. The highest values of standard deviation belong to the LnURB and the lowest values belong to the LnMT variable.

As mentioned before, the cross-section dependence of variables must be checked before the stationary test (Westerlund, 2007; Salim et al., 2017; Shao et al., 2021; Tarazkar, et al., 2021; and Chien et al., 2022). The results of Pesaran CD test are reported in Table 3.

Table 3. Results of Pesaran CD test.

Variables	Pesaran CD test
LnCP	23.95***
LnCPL	0.801
URB	49.28***
LnEC	47.34***
$LnCO_2$	36.48***
LnMT	53.52***
LnPRC	14.14***

*** denote significance levels at 1%

The results of the Pesaran CD test strongly rejected the null hypothesis of no cross-section dependence for all variables in the model, except for LnCPL. Since all variables (except LnCPL) exhibit cross-sectional dependence, it is recommended to use the second-generation panel stationary test. Therefore, the CIPS panel stationary test is employed to check the stationary properties of all variables, except LCPL. In conformity with the results of the Pesaran CD test, the LLC and IPS tests are used for LnCPL. The results of the CIPS, IPS, and LLC panel stationary tests are presented in Table 4

Table 4. Results of first and second generation unit root tests.

Variables	CIPS test statistic (Level)	CIPS test statistic (First Differences)	Result
LnCP	-2.35**	-	I(0)
URB	-1.65	-2.16***	I(1)
LnEC	-1.19	-2.21***	I(1)
$LnCO_2$	-1.56	-1.94***	I(1)
LnMT	-2.41***	-	I(0)
LnPRC	-2.9***	-	I(0)
Variable	LLC test statistic (Level)	IPS test statistic (Level)	Result
LnCPL	-3.69***	-2.82***	I(0)

***, **, * denote significance levels at 1%, 5% and 10%, respectively.
Schwarz-Bayesian Information Criterion (SIC) has been used for optimal lag length selection.

Base on the findings of Table 4, the CIPS test statistics for LnCP, LnMT, and LnPRC are statistically significant at the 1% and 5%, respectively. This suggests that LnCP, LnMT, and LnPRC follow an I(0) process. Contrary, the null hypothesis of stationary is rejected for $LnCO_2$, LnEC, and URB at the level. Additionally, the CIPS test statistics for the first difference of $LnCO_2$, LnEC, and URB are statistically significant at the 1% level of significance. Hence, $LnCO_2$, LnEC, and URB follow an I(1) process. According to the last row of Table 4, the LLC and IPS stationary tests' statistics indicate that LnCPL is stationary at the level and follows an I(0) process. Therefore, all variables in the model follow either an I(1) or I(0) process, and none of them follow an I(2) process. In the next step, we investigate the slope homogeneity analysis. The results of the homogeneity test are presented in Table 5.

Table 5. Results of Pesaran and Yamagata (2008) slope homogeneity test.

Test-Statistic	Value	Prob.
$\tilde{\Delta}$	13.99***	0.00
$\tilde{\Delta}_{\text{Adjusted}}$	16.34***	0.00

Note: *** denotes significance levels at 1%.

According to both $\tilde{\Delta}$ and $\tilde{\Delta}_{\text{Adjusted}}$ tests, the null hypothesis of homogenous slope parameters is rejected at a 1% significance level, indicating the presence of slope heterogeneity across MENA region countries. The results of the slope homogeneity test recommend the use of a heterogeneous econometric panel regression method. In the next step, panel cointegration tests are conducted. Table 6 showed the results of the Westerlund panel cointegration test.

Table 6. Panel cointegration test (Westerlund)

Statistic	Value
Gt	-3.483***
Ga	-8.179
Pt	-12.631**
Pa	-11.99

Notes: ***, **, * Significant levels at 1%, 5% and 10% respectively.

The results from Table 6 confirm the presence of a long-run cointegration relationship. Therefore, the CS-ARDL approach is employed to examine the impact of independent variables on food security. The results of short and long run second-generation panel analysis are presented in Table 7.

Table 7. Results of panel CS-ARDL estimation.

Dependent Variable: LnCP	Coefficient	Standard error	t-statistics
Long-run Results			
LnCPL	0.72*	0.41	1.74
LnURB	-0.06	0.129	-0.52
LnEC	0.77***	0.28	2.69
LnCO_2	0.34**	0.14	2.4
LnMT	-4.58*	2.71	-1.69
LnPRC	0.21*	0.127	1.69
CSD-Statistics			-0.47
Short-run Results			
ΔLnCP (-1)	0.07	0.08	0.82
ΔLnCPL	-0.14	0.31	-0.47
ΔLnURB	-0.04	0.1	-0.43
ΔLnEC	0.55***	0.15	3.6
ΔLnCO_2	0.23**	0.09	2.48
ΔLnMT	-1.97**	0.88	-2.24
ΔLnPRC	0.16**	0.07	2.33
ΔLnEC (-1)	0.02	0.2	0.1
ΔLnCPL (-1)	0.64	0.43	1.48
ΔLnPRC (-1)	0.09*	0.04	1.92
ECM (-1)	-0.92***	0.08	-10.31

Notes: ***, **, * Significant levels at 1%, 5% and 10% respectively.

The empirical findings from CS-ARDL estimation presented that CO_2 is positively linked with the crop production as index of food security in both short and long run. The positive effect of CO_2 emissions on crop production is reported in some previous studies like Weyant et al. (2018), Onour (2019), Chandio et al., (2020), Koondhar et al., (2021a), and Affoh et al. (2022). The main reason for the positive impact of CO_2 on crop production is the positive effect of CO_2 emissions in the atmosphere on photosynthesis process and crop yield by increasing the plant growth. Indeed, a 1% increase in the CO_2 emission can increase crop production by 0.34% in the long run.

Also, crop production and energy consumption have a significant positive relationship in the short and long run. The positive correlation among food security and energy consumption is consistent with Raeeni et al., (2019), and Mahdavian et al., (2022). According to the long run coefficient a 1% rise in energy consumption can boost the amount of crop production by 0.77%. The direct relationship between energy and food security implies that the higher consumption of energy leads to more crops production. Most agricultural tools and equipment are powered by fossil fuels (Ur Rahman et al., 2019). Energy in the agricultural sector is mainly use for supplying energy to water motor pumps, green house equipment and agricultural machinery. Also, energy is used in the production process of intermediate inputs, such as fertilizers, pesticides, etc. production (Martinho, 2020). Therefore, in order to rise the amount of agricultural crops, it is needed to use more agricultural equipment, which leads to increase in energy consumption.

The linkage between cropland and crop production is significant and positive and with a 1% growth in cropland the crop production rise by 0.72%. This result is consistent with Nasrullah et al., (2021), Koondhar et al., (2021b), and Kargar Dehbidi et al., (2022). The negative link between urbanization and crop production is not statistically significant. The effect of climate change on crop production is survived by mean temperature and precipitation. The positive effect of precipitation on crop production is statistically significant in the short and long run. This result is in line with research by Kumar et al., (2021), Ogundari and Onyaeghala (2021), and Kargar Dehbidi et al., (2022). Hence, a 1% increase in precipitation causes a 0.21% increase in crop production. The estimated coefficient implies that with the rise in rainfall, the amount of available water resource boost and leads to higher production. In contrast, the temperature has a significant negative influence on crop production. Indeed, a 1% rise in temperature leads to a 4.58% decline in production. It is in line with Meshram et al., (2020), and Zhang et al., (2022). Higher temperatures can increase crop growth period and evapotranspiration and also reduce water availability. In general, the negative impacts of climate change primarily stem from elevated temperatures, heightened rates of evaporation and transpiration, as well as alterations in precipitation patterns, all of which have detrimental effects on crop growth. The results of the Dumitrescu and Hurlin panel causality test are reported in the following table.

Table 8. Results of Dumitrescu and Hurlin panel causality test.

Hypothesis	W-stat	Z-stat	Results
CP → CO_2	2.06^{***}	3.2	CP → CO_2
CO_2 → CP	6.49^{***}	16.49	CO_2 → CP
CP → CPL	1.33	1.01	CP $\nrightarrow$ CPL
CPL → CP	4.19^{***}	9.56	CPL → CP
CP → EC	8.07^{***}	21.23	CP → EC
EC → CP	2.33^{***}	4.00	EC → CP
CP → PRC	1.13	0.41	CP $\nrightarrow$ PRC
PRC → CP	2.02^{***}	3.06	PRC → CP
CP → MT	2.11^{***}	3.33	CP → MT
MT → CP	7.67^{***}	20.02	MT → CP
CP → URB	6.36^{***}	16.09	CP → URB
URB → CP	6.59^{***}	16.77	URB → CP

Note: *** denotes significance levels at 1%.

The empirical results from the employed causality tests revealed bidirectional causality between crop production (as an index of food security) and CO_2. It also established bidirectional causality between energy use and crop production. Table 8 reveals unidirectional causality from cropland to crop production and a two-way causality link between urbanization and crop production. The findings indicate a unidirectional causal relationship from precipitation to crop production, while a bidirectional causal relationship exists between mean temperature and crop production.

4. Conclusion and Policy Implications

Food security is one of the most essential multi-dimensional phenomena, consisting of food availability, food access, food utilization, and food stability. As a result, paying special attention to agriculture is one of the most important ways to improve food security. This sector has a most important role in the production and food security. Hence, in the present study, the factors affecting agricultural production as an index of food security are examined in the MENA countries. The dependent variable of the econometric model is the crop production index. Also, the independent variables contain CO_2 emission, cropland, precipitation, mean temperature, urban population, and energy consumption. The CS-ARDL model is used to analyze panel data for the MENA countries from 1990 to 2019.

The outcomes of the CS-ARDL approach implied that CO_2 is positively linked with the CP in the short and long run. This finding aligns with prior studies, including those by Weyant et al. (2018), Onour (2019), Chandio et al. (2020), Koondhar et al. (2021a), and Affoh et al. (2022). The linkage between crop production (CP) and energy consumption (EC) is positive in both short and long run which is consistent with Raeeni et al., (2019), and Mahdavian et al., (2022). This result revealed that rising energy consumption can build up crop production. Cropland directly affects production, so expanding the CPL will lead to a rise in production. This result aligns with the findings of Nasrullah et al. (2021) in South Korea, Koondhar et al. (2021b) in Pakistan, and Kargar Dehbidi et al. (2022) in Iran. The association between urbanization and crop production was insignificant. Also, the effect of temperature (MT) and precipitation (PRC) as climatic variables on production was negative and positive respectively, which is in line with the findings of Kumar et al. (2021), Ogundari and Onyaeghala (2021), and Kargar Dehbidi et al. (2022). The causality outcomes indicated a bidirectional causality between crop production (CP) and CO_2, between energy consumption (EC) and CP, and between urbanization (URB) and CP. Finally, the results implied that there is a one-way causality from precipitation (PRC) to crop production (CP), but the causality linkage between mean temperature (MT) and CP is bidirectional.

According to the empirical findings, policies must be implemented in order to create a production structure that is resistant to climate change, with a focus on minimizing pollution caused by input consumption in agricultural sectors and maintaining the foundations of sustainable development. For example, MENA countries should adopt climate-resilient agricultural practices to strengthen their farms against climate changes. They can grow drought-resistant crop varieties, practice agroforestry, and use innovative irrigation methods like drip irrigation.

Given that a substantial portion of pollution stemming from agricultural production is associated with energy consumption, the adoption of renewable energy sources, such as solar or wind power, for agricultural activities can markedly decrease carbon emissions attributed to energy use. Governments can facilitate this transition by offering financial incentives or subsidies for adopting renewable energy technologies.

Instead of chemical fertilizers and pesticides, using organic fertilizers and making producers aware of the benefits of using it is considered a suitable solution. Considering incentive policies such as guaranteed purchase of organic products, granting facilities to improve production infrastructure and imposing export subsidies on products which are produced with minimal emission of pollution and consumption of inputs can have positive effects on the production situation and food security. Increasing the mechanization of the production sector in the studied countries can also help to minimize post-harvest losses and enhance overall productivity. Processing and packaging agricultural products can not only reduce waste, but also provide farmers with economic opportunities.

In order to lessen the negative effects of climate change and enhance food security, cultivation patterns must be tailored to the geographical conditions of each region such as drought-resistant crops in arid regions or flood-resistant varieties in areas prone to heavy rainfall.

Also, creating a communication and commercial network based on comparative advantage, available water resources and climatic conditions can lead to increasing production stability, food security and reducing the effects of climate change. Collaborations between governments, private sector stakeholders, and research institutions can also drive innovation and promote sustainable agricultural practices.

The current study provides valuable insights into the factors affecting food security and agricultural production in the MENA region. However, due to limited data availability, it leaves a gap in testing the impact of climate change adaptation strategies, such as drip irrigation, conservation tillage, and various livelihood activities, on food security. Investigating the effectiveness of these strategies is crucial, as they offer practical approaches to mitigate the adverse effects of climate change particularly CO_2 emissions on food security. Future research in this area could offer a more comprehensive framework for policymakers and agricultural stakeholders seeking to increase food security, especially with the unpredictable climate conditions.

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امنیت غذایی، تغییر اقلیم و آلودگی محیط زیستی

در منطقه منا: شواهدی از نسل دوم تحلیل پنلی

چکیده:

امنیت غذایی بدلیل رشد جمعیت، موقعیت جغرافیایی و اقلیمی، یک مساله حیاتی در منطقه خاورمیانه و شمال آفریقا (منطقه منا) است. از دیگر سو بیشتر کشورهای واقع در این منطقه از منابع طبیعی فراوان با محوریت سوخت‌های فسیلی منفعت می‌برند. همچنین مسایل محیط زیستی، بویژه انتشار گازهای گلخانه‌ای ناشی از فعالیت‌های تولید و فشارهای ناشی از تغییرات اقلیمی اهمیت امنیت غذایی را برجسته

نموده است. در این مطالعه تاثیر تغییر اقلیم، آلودگی‌های محیط زیستی و سایر متغیرها بر امنیت غذایی در منطقه منا طی دوره 1990 الی 2019 مورد بررسی قرار گرفت. با توجه به وابستگی مقطعی نسل دوم برآوردگر پنلی CS-ARDL مورد استفاده قرار گرفت. نتایج نشان داد مصرف انرژی، سطح اراضی زراعی، انتشار گاز دی اکسید کربن و بارندگی تاثیر مثبت و معنی داری بر امنیت غذایی دارد. بعلاوه شهرنشینی و متوسط دما دارای تاثیر منفی هستند. نتایج آزمون علیت نشان داد که اراضی زراعی و بارندگی دارای رابطه علی یکطرفه با امنت غذایی بوده و مصرف انرژی، انتشار گاز دی اکسید کربن، شهرنشینی و متوسط دما دارای رابطه علی دوطرفه با امنیت غذایی هستند. نتایج حاکی از آن است که ضمن حفظ و افزایش تولید محصولات کشاورزی، باید به اثرات اقلیمی و تاثیرات محیطی زیستی تولید نیز توجه نمود.

کلمات کلیدی: مصرف انرژی، انتشار گاز دی اکسید کربن، بارندگی و CS-ARDL