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Revisiting the role of climate change on crop production: evidence from Mediterranean countries

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Abstract
The Mediterranean region is an important agricultural center and is expected to be most affected by climate change due to its location. In this study, the role of climate change on agriculture is examined for eight South European countries on the Mediterranean coast for the period of 1996–2016. Carbon dioxide emissions, temperature and precipitation values are used as the indicators of climate change while cereal production is taken as a proxy for agricultural production. Results of the panel vector autoregression approach reveal that an increase in the carbon dioxide emissions and temperature have a negative impact on the cereal production. However, this effect is statistically significant only in the initial periods. On the other hand, an increase in rainfall has a statistically significant positive effect on crop production only in one period. However, eventually this effect turns to negative as expected, since excessive rainfall has a negative effect on agriculture as much as drought. In conclusion, the importance of bringing the policies and strategies to the forefront in ensuring the sustainability of agriculture and minimizing the negative effects of climate change in the region are discussed.

Keywords Agricultural production · Carbon emissions · Mediterranean basin · Panel VAR

1 Introduction

Climate change scenarios include extreme temperatures and droughts, changes in precipitation regime, extreme weather events and high atmospheric CO_2 concentrations. The impact of climate change on sectors and decision-making units is different (Stern, 2007; World Tourism Organization, 2008; Dell et al., 2009; Galarraga & Markandya, 2009). Therefore, the agriculture sector, which is directly related to weather events and climate conditions, is expected to be affected the most by climate change (El-beltagy & Madkour, 2012; Tumbo et al., 2012).

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In the long-term, climate change can affect the quantity and quality of crops through various factors such as productivity, growth rates, photosynthesis and sweating rates, and the presence of moisture (Mahato, 2014; Aryal et al., 2020). At the same time, it is possible to explain the effects of greenhouse gas causing climate change on agriculture in three different ways. Firstly, increased atmospheric CO_2 concentration has a direct impact on the growth rate of crop plants and weeds. Secondly, CO_2-induced climate changes cause a change in temperatures and precipitation levels, that are directly related to plant and animal productivity. Finally, increased sea-levels lead to loss of agricultural land through flooding and increasing the salinity of groundwater in coastal areas (Mahato, 2014). Hence, climate change poses an important threat to food security, which is necessary for humanity to survive.

In recent years, with the increasing number of studies on the effects of global warming, the effects of climate change on agriculture are also discussed extensively in the literature. The impact of climate change on the agricultural sector varies by the countries and regions. Most studies found that climate change negatively affects agricultural production and farmers' income (Iglesias et al., 2011; Solaymani, 2018; Migliore et al., 2019; Kogo et al., 2021). However, some studies show that the effect of climate change on agriculture is uncertain or mixed depending on the adaptation capacity of affected location (Temidayo Gabriel, 2012; Bindi & Olesen, 2011; Hare et al., 2011; Iqbal & Siddique, 2015).

The Mediterranean region is an important agricultural center and is expected to be most affected by climate change due to its location (Blue, 2008; Lionello et al., 2014). This study aims to investigate the impact of climate change on the agricultural sector for eight South European countries on the Mediterranean coast with the panel VAR approach. The panel models are frequently used in investigating the relationship between climate change and sustainability (Li et al., 2021; Wang et al., 2022, 2023a, c, b). The panel VAR approach has some advantages over the traditional VAR approach. For instance, the traditional VAR takes all variables as endogenous, while panel-data allows for unobserved individual heterogeneity (Love & Zicchino, 2006). On the other hand, impulse-response functions are used to define how today's shocks will affect variables in the future and thus to make an effective policy assessment (Ankargren & Lyhagen, 2018). However, as is well known, the error variance-covariance matrix is not expected to be diagonal. Hence, to show the effect of shocks of the variables individually, the residuals of the model should be decomposed and become orthogonal (Love & Zicchino, 2006). In the study, data cover the period of 1996–2016. The findings of the study will be a guide in terms of preventing production losses in the agricultural sector, developing new strategies to adapt against climatic degradation and taking due precautions.

According to the impulse-response analysis results, a shock in carbon emissions and mean temperature affects crop production negatively for a long period. Responses are statistically significant only in the initial periods. On the other hand, a shock in precipitation has an initial positive effect on crop production for a short period of time. But then, this effect turns negative and lasts for a longer period. Similar to the carbon emissions and mean temperature, the response is significant only in the first period. In addition, variance decomposition of the VAR model suggests that, carbon emissions, temperature and precipitation variables explain almost 45% of the crop production, when the tenth period is considered. These results show that climate change has a significant impact on crop production of the eight South European countries studied.

In the next section, the effects of climate change on the agricultural sector in the Mediterranean region are discussed. In Sect. 3, the data set and summary statistics are presented while in Sect. 4 the econometric methodology are introduced. Finally, the results of the econometric analysis are examined and discussed in Sect. 5. A conclusion ends the paper.

2 Climate change and its effects on agriculture in the Mediterranean region

The Mediterranean region is located in a transition zone between the mild and rainy climate of Central Europe and the arid climate of North Africa. Therefore, it is affected by interactions between middle latitude and tropical processes. For this reason, it is expected that the Mediterranean region will be significantly affected even by small changes in the climate. Indeed, the region has been subjected to major climate changes in the past centuries (Luterbacher et al., 2006) and has been identified as one of the most important "hot spots" in climate change projections. The term "hot spot" is defined as a region where the effects of climate change on the environment or various sectors are particularly evident. These points provide important information to explore and identify the main processes of regional climate change (Giorgi, 2006).

In the Mediterranean region, current yearly average temperatures are about 1.5 °C higher than the pre-industrial period (1880–1899) and the difference is slightly higher than the global trend (+1.1 °C). Besides, in the region, the average increase is 0.03 °C per year and is also above the trend (Cramer et al., 2019). It is expected that the air temperature, which displayed a positive trend in the past decades, will be above the average in the future. In addition to the increase in temperatures, a decrease in precipitation is also expected. For instance, an annual decrease of 39.1 (±5.1) mm in rainfall and an increase of 1.57 (±0.27) °C in temperatures are expected between 2000 and 2050 (Saadi et al., 2015). Rainfall in the summer is expected to decrease by 10–15% in France, northwestern Spain and the Balkans, and by 30% in Türkiye with a global temperature rise of 2 degrees (Cramer et al., 2019). According to another scenario that covers the period 1901–2100, by the end of the twenty-first century, the Mediterranean region will be 20% warmer than the global average. As of 2020, this rate is 36% (MedECC, 2020). Besides, this rate of excess warming will be about 50% higher than the global average during summers. As the average temperature increases globally, precipitation in the region will decrease by 4% (20 mm) (Lionello & Scarascia, 2018).

Studies have demonstrated that climate change has devastating effects on the ecosystems and agricultural production of the Mediterranean basin. For example, olive cultivation has great socio-economic importance for the Mediterranean region. Tanasijevic et al. (2014) investigated the effect of climate change on olive cultivation. They have predicted that the production of rain-fed olive groves will not be the same in 2050 and production will become almost impossible due to water stress. Ponti et al. (2014) have found that a 1.8 degree increase in temperature decreases olive yield, increases olive fly infestation and consequently decreases profitability in small olive farms. Those farms are critical for soil and biodiversity conservation and fire risk reduction in the area.

Fader et al. (2015) have investigated the extent of the impact of climate change will have on irrigation needs in the Mediterranean region by the 2080s. Products such as olives, grapes, cotton and sugar cane grown in the region consume more than average irrigation water per hectare. Algeria, Libya, Israel, Jordan, Lebanon, Syria, Serbia, Morocco, Tunisia and Spain are the countries that have the highest risk of water scarcity. Climate change alone increases gross irrigation needs between 4 and 18%.

These rates rise up to 22–74% when the increase in the population is also considered. However, with advanced irrigation technologies, the Mediterranean region saves up to 35% of water. Temperature increases cause inadequate cooling in some regions. This affects the sustainability and efficiency of products that require cooling temperatures, such as apples. Funes et al. (2016) have predicted that starting from the middle of the twenty-first century, apple varieties will experience delays in blooming dates and this ultimately affects apple production in the region (Funes et al., 2016).

To sum up, climate change has many direct and indirect impacts on sustainable agriculture. Direct effects can be defined as a geographical and seasonal redistribution of climate resources for agriculture and changes in operating costs (heating-cooling, insurance premiums). Indirect costs are environmental changes related to climate issues such as water scarcity, loss of biodiversity, increase in vector-borne diseases and infrastructure damage. In addition to these effects, it is estimated that climate change will have negative effects on the agricultural competition with the increase in oil and chemical fertilizer prices, thus farmers with limited capital will be adversely affected by these higher costs (Bocci & Smanis, 2019).

3 Data set and summary statistics

There is a bi-directional relationship between agricultural production and climate change (Yasmeen et al., 2022). As a result of agricultural activities, a significant increase in greenhouse gas production occurs. On the other hand, as discussed in the previous section, climate change causes several negatives such as food security risks and decreased productivity in agriculture. Therefore, it is important to review and understand the extent of the effect of climate change on agricultural activities in the Mediterranean region. Eight Mediterranean countries (Albania, Croatia, France, Greece, Italy, Slovenia, Spain and Türkiye) in southern Europe are chosen for this study. Annual data set between 1996 and 2016 is used for the analysis and 2016 is the most recent year with data available. Crop (cereal as tonnes) production is added to the model as the dependent variable. Carbon emissions as million tonnes CO_2 (carbon), mean temperature (temp as Celsius) and mean precipitation (rain as millimeter) variables are used to represent climate change. Crop production is taken from the United Nation's Food and Agriculture Organization (FAO) (FAOSTAT, 2019). Yearly mean temperature, precipitation and CO_2 variables, on the other hand, are taken from the World Bank Climate Change Knowledge Portal and Global Carbon Atlas, respectively (Bank, 2019; Atlas, 2019). Finally, logarithmic transformations are applied to all variables.

Summary statistics of the variables are presented in Table 1. As can be seen from the table, Italy has the highest carbon emissions mean value, while Albania has the lowest. In addition, France and Italy have the highest carbon emissions values, while the countries with the lowest maximum values are Albania and Slovenia. The highest variation in carbon emissions belongs to Albania while Croatia, Slovenia and Türkiye experience the highest difference in temperature. Finally, France and Türkiye have the highest mean crop production.

Table 1 Summary statistics

Country	Variables	Mean	Median	SD	Min	Max
Albania	lncereal	13.28	13.31	0.148	13.1	13.46
	lnrain	4.416	4.41	0.159	4.09	4.68
	lntemp	2.503	2.51	0.04	2.41	2.55
	lncarbon	1.296	1.43	0.348	0.43	1.73
Croatia	lncereal	14.894	14.92	0.138	14.52	15.13
	lnrain	4.489	4.51	0.162	4.12	4.79
	lntemp	2.444	2.46	0.054	2.32	2.52
	lncarbon	3.023	3.03	0.11	2.86	3.21
France	lncereal	17.99	18	0.082	17.81	18.1
	lnrain	4.24	4.24	0.108	4.03	4.41
	lntemp	2.452	2.46	0.042	2.36	2.53
	lncarbon	5.974	6.01	0.083	5.81	6.06
Greece	lncereal	15.377	15.39	0.074	15.19	15.53
	lnrain	3.987	3.99	0.164	3.51	4.28
	lntemp	2.67	2.68	0.035	2.6	2.72
	lncarbon	4.576	4.59	0.139	4.27	4.74
Italy	lncereal	16.802	16.81	0.075	16.69	16.96
	lnrain	4.332	4.33	0.107	4.19	4.55
	lntemp	2.541	2.55	0.032	2.46	2.59
	lncarbon	6.086	6.13	0.117	5.85	6.21
Slovenia	lncereal	13.21	13.23	0.123	12.9	13.39
	lnrain	4.712	4.73	0.137	4.4	4.96
	lntemp	2.275	2.28	0.063	2.13	2.37
	lncarbon	2.77	2.79	0.072	2.61	2.9
Spain	lncereal	16.853	16.88	0.148	16.47	17.05
	lnrain	3.919	3.94	0.162	3.61	4.19
	lntemp	2.639	2.63	0.025	2.6	2.68
	lncarbon	5.706	5.69	0.13	5.53	5.91
Türkiye	lncereal	17.3	17.3	0.089	17.18	17.47
	lnrain	3.865	3.9	0.112	3.59	4.04
	lntemp	2.473	2.48	0.048	2.37	2.59
	lncarbon	5.623	5.64	0.227	5.3	5.99

The data covers the period 1996–2016. Cereal is crop (cereal) production, carbon is carbon dioxide emissions; temp is yearly mean temperature and rain is yearly mean precipitation. Finally, ln represents the logarithmic transformation

4 Methodology

In this section, we present and discuss the econometric methodology that we use in the empirical analysis. First, we introduce the second-generation panel unit root test that we use to determine the order of integration of variables along with the first-generation tests. Then we give information about the panel VAR, impulse-response and variance decomposition techniques.

4.1 Panel unit root test

In the econometric models, in order for the regression relationship between the variables to be significant, the variables must be stationary or have the same order of integration. Granger and Newbold (Granger & Newbold, 1974) state that a spurious relationship may arise if the non-stationary series are included in the model. Therefore, stationary variables should be used to avoid this inaccuracy. For this purpose, unit root analysis is applied to the variables. However, before that, it is investigated whether there is a cross-section dependency between the unit of the variables. Considering the cross-sectional dependency between the units will significantly affect the findings. Therefore, choosing the appropriate unit root tests that take the cross-sectional dependency into account is crucial. Otherwise, the analysis will give erroneous results (Pesaran, 2006). The null hypothesis in the test of cross-sectional dependence shows that there is no correlation between units in the panel. In other words, the cross-sectional independence assumes that all countries are equally affected by a shock to any of the units and that other countries are not affected by a macro-economic shock in any of the countries. In this study, cross-sectional dependency is investigated with the following tests: (Breusch & Pagan, 1980) Lagrange Multiplier test, (Pesaran, 2004) horizontal sectional dependency (CD) test, (Pesaran, 2004) scaled Lagrange Multiplier test and (Baltagi et al., 2012) bias correction Lagrange Multiplier tests.

Unit root tests are divided into two part as the first- and second-generation according to whether there is dependency between the cross-sections. Accordingly, in the case of correlation between the units, the implementation of the second-generation panel unit root tests will provide more consistent results. Pesaran (2007) proposes a unit root test based on standard unit root statistics over covariate-augmented Dickey–Fuller (CADF) regression in the presence of cross-section dependency between the units of the series. The CADF equation is obtained by adding the lagged values of the cross-section averages and the first differences of the cross-section averages to the standard ADF equation. Pesaran's (Pesaran, 2007) approach, on the other hand, is based on simple arithmetic averages of ADF statistics ($CADF_i$) expanded by individual cross-section averages. The CADF test gives robust results even when the cross-section (N) and time (T) size is relatively small. This test also can be used in situations where either $T > N$ or $T < N$. In addition, CIPS, which is the unit root test statistic for the overall panel, is calculated by taking the average of the unit root test statistics for each country, i.e., each cross-section with the CADF test. CIPS statistics is formulated as below (Pesaran, 2007):

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i \tag{1}$$

One of the main problem in short-run time series is the lack of statistical power of unit roots tests. However, Im et al. (2003), IPS hereafter, showed that this problem can be solved by applying panel unit root tests. For this reason, we also employ IPS test in the study. IPS test is one of the cross-sectional independence tests and allows for heterogeneity in the value of ρ_i under the alternative hypothesis. The IPS model, which does not have a time trend, although it allows individual effects, can be written as follows (Hurlin & Mignon, 2007):

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{z=1}^{p_i} \beta_{i,z} \Delta y_{i,t-z} + \epsilon_{i,t} \tag{2}$$

In Eq. (2), $i = 1, \dots, N$ and $t = 1, \dots, T$. The errors $\epsilon_{i,t}$ i.i.d. $(0, \sigma_{\epsilon_{i,t}})$ are assumed to be independent across the units of the sample. In the IPS panel unit root test, the null hypothesis states that every series in the panel contains a unit root. The alternative hypothesis allows some of the individual series (but not all of them) to have unit roots (Baltagi, 2005).

4.2 Panel VAR, impulse-response and variance decompositions analyses

The panel impulse-response and variance decomposition analyses which are based on the VAR model are presented. The panel VAR method works with the integration of the traditional VAR framework with the panel data set up. In the VAR model, popularized by Sims (1980) as an alternative to traditional simultaneous system equations, it is assumed that all variables are endogenous based on the autoregressive representation of the weak stationary process (Gebhard Kirchgässner, 2007). According to Sims, when there is true simultaneity between variables, there should be no distinction between endogenous and exogenous variables. "The VAR model is a generalization of the univariate autoregressive model and is used to capture the linear interdependencies in multiple time series. Its purpose is to describe the evolution of a set of k endogenous variables based on their own lags and the lags of the other variables in the model" (Lyhagen et al., 2015). In addition, all variables in the model are assumed to be stationary in order to avoid spurious relationships. Non-stationary variables need to be converted into stationary by taking differences (Gujarati & Porter, 2009). A first-order Panel VAR model is shown as follows (Love & Zicchino, 2006):

$$z_{it} = \Gamma_1 z_{it-1} + f_i + e_{it} \tag{3}$$

where z_{it} is a four-variables vector $\{cereal_{it}, rain_{it}, temp_{it}, carbon_{it}\}$ and $i = 1, ..., N$, $t = 1, ..., T$. The parameter f_i is the fixed-effect, e_{it} is idiosyncratic errors.

Impulse-response and variance decomposition analyses are used to get a deeper understanding of the relationships between the variables in the VAR model (Luetkepohl, 2007). The variance decomposition analysis reveals how the variables in the VAR model explain each other. In other words, it shows the change in the variables, which are explained by its own shocks and by other variables' shocks. If most of the changes in a variable are explained by its own shocks, then it can be said that the variable is exogenous (Enders, 2009). On the other hand, the impulse-response functions explain the response of one variable to innovations in another variable in the system while assuming that all other shocks are equal to zero. However, since the actual variance-covariance matrix of errors is not likely to be diagonal, it is necessary to decompose the residuals such that they are orthogonal to isolate the shocks to one of the variables in the system. The general layout is to make a specific ordering and allocate any correlation between the residuals of any two items to the first variable in the ordering. The identifying assumption is that the variables that came before in the sequence affect the following variables simultaneously along with a lag, while the subsequent variables affect the previous variables only with a lag. So, the variables that take place before in the system are more exogenous and the variables that take place after are more endogenous (Love & Zicchino, 2006). For this reason, in order to determine the responses of variables against shocks in the impulse-response functions correctly, the variables should be in the right order. To do so, the Cholesky-ordering is used. Finally, the impulse responses are functions of the estimated parameters and, hence, confidence intervals need to be presented. Thus, standard errors and confidence intervals of the impulse-response functions are produced by Monte Carlo simulations (Garita, 2011).

Table 2 Cross-sectional dependence results

BP LM	Pesaran CD	Pesaran LM	BC LM
33.934	3.707***	0.792	0.5923

Model is $lncereal = f(lnrain, lntemp, lncarbon)$, BP is Breusch-Pagan LM test, BC is Bias-Corrected scaled LM test. ***Indicates that the Null hypothesis is rejected at the 1% significance level

Table 3 Unit root test results

Variables	IPS	CIPS
lncereal	−2.783***	−3.799***
lnrain	−6.896***	−3.876***
lntemp	−4.445***	−5.583***
lncarbon	2.192	−0.521
dlncarbon	−3.864***	−4.823***

Maximum lag length is 1 for both tests. ***Indicates that the Null hypothesis is rejected at the 1% significance level

5 Findings

Before proceeding to the unit root analysis, it is investigated whether a cross-sectional dependence exists between the selected variables. For this, (Pesaran, 2004) cross-sectional dependence, (Breusch & Pagan, 1980) Lagrange Multiplier (LM) and (Pesaran, 2004) scaled Lagrange Multiplier tests are applied. In cross-sectional dependence tests, the null hypothesis suggests that there is no correlation between panel units. The test results are presented in Table 2 and the conclusions differ for different tests. Pesaran CD test, shows that there is cross-sectional dependency while others indicate the opposite. Considering all results, we decided to apply both the first- and second-generation unit root tests.

After revealing the cross-sectional dependency between the units, it is investigated whether the series contain unit root in order to avoid spurious regression. In panel studies, unit root tests are classified as first and second-generation panel unit root tests according to the presence of cross-sectional dependence. In panel data with cross-sectional dependence, first-generation unit root tests tend to reject the null hypothesis (Bhattacharya et al., 2016). In this case, the implementation of the second-generation unit root tests that take the cross-sectional dependence into account will provide robust results. We employ both the CIPS and IPS tests and report the results in Table 3. According to the tests, all series are stationary, except for the carbon series. The integration order of the carbon is I(1).

In the study, first, the appropriate lag length of the panel VAR model is determined for impulse-response and variance decomposition analyses.[1] According to the three model selection criteria of Andrews and Lu (2001), the preferred model is the first-order panel VAR model since it has the smallest MBIC, MAIC and MQIC. It is also found that the model does not reject Hansen's over identification restriction, therefore the model selection is appropriate. Before proceeding to the impulse-response and variance decomposition

[1] Stata codes of Abrigo and Love (2016) are used for panel impulse-response and variance decomposition analyses.

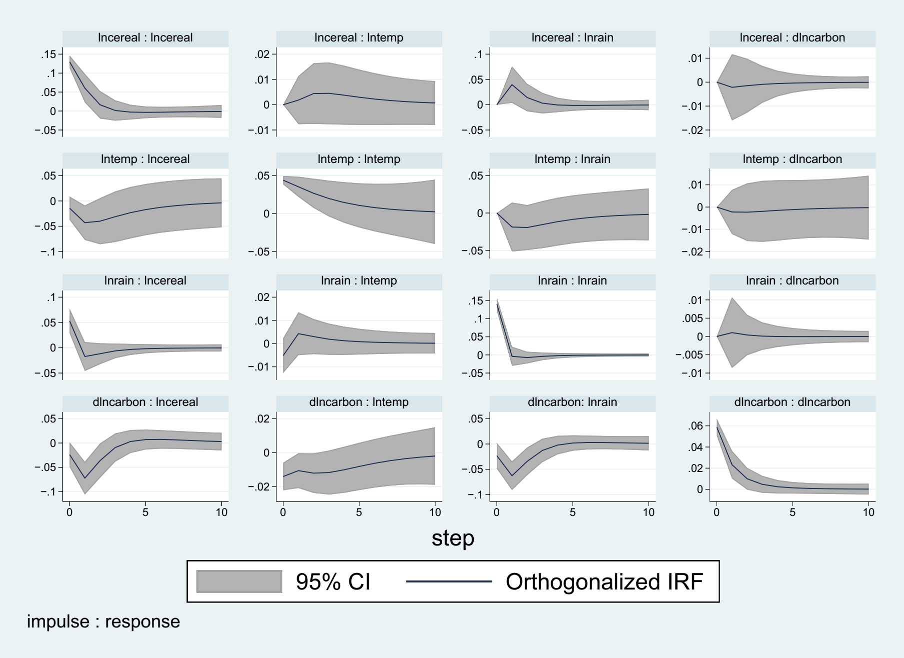

Fig. 1 The orthogonalized impulse-response functions

results, it is necessary to check the stability of the predicted VAR model. In order to test the stability of the panel VAR model, the moduli of the eigenvalues must remain within the unit circle, that is, less than one. In addition, a Monte Carlo simulation using 500 replicates is used to form confidence intervals. The predicted VAR model satisfies the stability condition according to the results of the stability test. For the Cholesky decomposition approach, the order of the variables is determined by the Granger causality analysis results.[2]

After estimating the VAR model, the Wald test is used to determine whether there is a causality among the variables. Accordingly, while carbon and temperature are the one-way Granger cause of cereal, bidirectional causality is found between rain and cereal. Based on variance decomposition results, when the tenth period is considered, the variable that explains the cereal most other than itself is carbon (20%). Carbon is followed by temperature (16%) and precipitation (9%) variables, respectively. These results show that the explanatory nature of these variables is relatively high since nearly half of the variation of cereal production is explained by these three variables. Figure 1 shows the impulse-response function graphics of the VAR model. In the figure, the gray band show confidence intervals at the 95% level. The first striking point is that, as seen in the graphic at the bottom left, carbon emissions have a negative effect on the cereal for four periods; from the fifth period the effect dies away. Carbon emissions lead to an increase in greenhouse gases that is one of the most important causes of climate change. However, this response is statistically significant only in the first three periods. As seen in the third row of the first column,

[2] The appropriate lag length, stability, causality and variance decomposition results of the panel VAR model is not reported in the study but can be obtained upon request.

precipitation has an initial positive and then a negative effect on cereal production. Only the first period response of the cereal is statistically significant. Finally, the second row of the first column shows that temperature has a negative effect on the cereal for almost entire period. Similarly, cereal's response to changes in temperature is statistically significant only in the second period. These results are in line with the projections of Iglesias et al. (2011).

Despite the rapid development of technology, the adaptation of various agricultural products to different conditions and developments in spraying and irrigation systems, agriculture is still the most vulnerable sector against climate change. The Mediterranean basin is adversely affected by both the loss of irrigation water and freshwater resources, forest fires and ecological imbalances due to desertification. With the high rate of population growth, energy demand is also increasing rapidly. Today, most of the energy demand in both industrial and daily life is met by fossil fuels. This increases CO_2 emissions and accelerates global warming. Besides, factors such as the destruction of forests and the migration from rural to urban areas, create many environmental and socio-economic problems. The worst effect of extreme weather events is the danger of losing agriculture's sustainability, thus sustainable development.

6 Conclusion

Agricultural production activities increase greenhouse gas which leads to a degradation in climate. On the other hand, climate change-related events cause reductions in agricultural production and the productivity of the industry. This mutual cause-effect relationship between climate change and agriculture is a highly debated issue in the literature.

In this study, the effect of climate change on agriculture is examined in the Mediterranean basin, one of the most affected regions by global warming. For this purpose, the eight South European countries on the Mediterranean coast (Albania, Croatia, France, Greece, Italy, Slovenia, Spain and Türkiye) are used with data covering with the period of 1996–2016. Cereal production is taken as the dependent variable. Carbon emissions, mean temperature and mean precipitation values represent the climate change in the model. The panel VAR model is applied for the analysis. The results of the impulse-response function show that an increase in temperature has a statistically significant effect in the period right after the increase. Then the effect dies out and is no longer statistically significant. The same holds for carbon but with a stronger effect in the first period after the increase. On the other hand, impulse of rain follows a different path from other variables. A positive shock in rain initially affects cereal production positively, however it is not statistically significant. After a period, this effect turns to negative and continues for at least two more periods until it converges to zero. To sum up, the overall findings point out that the climate change negatively affects cereal production in Mediterranean countries. Due to the relatively small sample size, some care should be taken when interpreting the impulse responses which shows in the relatively wide confidence bands. On the other hand, even if individual pointwise confidence intervals are wide, the general pattern can still be valid. However, implementation of policies and strategies to reduce the negative effects of climate change is vital to prevent agricultural losses in these countries.

The development of modern agricultural techniques and irrigation technologies will give contribution to efforts of preventing the reduction of agricultural production and yield in the Mediterranean region. To keep the impact of the climate change at the minimum level, the awareness of farmers should be raised. They should be trained to adapt to ever-changing climatic conditions, increase productivity and apply innovations. Also, they should be supported socio-economically to prevent migration from countryside to cities. The Mediterranean region has a great potential to produce clean energy sources such as solar and wind. To reduce the negative effects of climate change, the use of fossil fuels should be abandoned and the investments in the field of renewable energy should be increased. Finally, in order to improve the findings of this study, comparison of countries in the Mediterranean basin by using different econometric methods and considering larger data set is recommended.

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Data availibility The data set analyzed during the current study are available from the corresponding author on reasonable request. This does not apply to CO_2 which can be downloaded from http://www.globalcarbonatlas.org/en/CO2-emissions.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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