A Spatial panel Analysis of Carbon Emission and Food security

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Abstract

This study examines the influence of co2emission on food security proxied by food supply by spatial econometrics models from 2000 to 2014 globally. We also comprised the socio-economic variables in the model for the bias of variables. The global Moran's I and local spatial autocorrelation technique used for spatial dependence, and they suggested the spatial dependence exist in the cross-sectional units. Therefore, we used the spatial panel model to check the spatial spillover effect of co2emisson on food supply. The chosen spatial panel Durbin model outcomes showed that the co2emission, population growth, and unemployment rate have negatively decreased the given country's food supply level and its neighbour countries. Simultaneously, the GDP and arable land are beneficial for the given country and its adjacent countries. Moreover, the real coefficients, direct, indirect (spillover), and the total effects of the carbon emission indicated that the carbon emissions decrease food security levels in both of this country and its nearest neighbouring countries. Therefore, the carbon emissions level needs to be reduced to improve food production (in quality and quantity) and increase the food supply level.

Keywords: Food security, Co2emissions, spatial panel Durbin model, spatial dependence

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Introduction

The number of undernourished peoples significantly decreased over the last decades. However, in many countries, whether they are developed or developing countries, this problem still exists (Masron et al., 2020; Long et al., 2020; Fusco et al., 2020; FAO, 2020). The weres situation of undernourishment and food insecurity in developing countries (FAO, 2020). The food and agricultural organizations (FAO) showed that the number of undernourished people raised from 668 million in 2010 to 688 million in 2019 globally (FAO, 2020). The majority of these hungry people resides in Africa (250 million), Asia (381 million), Latin America and the Caribbean (48 million). Food insecurity has a significant impact on health, overall economic growth of the region, individual productivity, social peace, and general for learning (World Bank, 2006; Upton et al., 2016; and Adebayo et al., 2016). Therefore, food security issues are in many regions of the world. This problem could highlight the value of carbon emission conditions as a basis for food security.

Food considered global public goods that must be made accessible to all at any time (Hamilton et al., 2003). Such as, all humans have the right to sufficient food on a daily basis, and no one can be exempt. The food and agricultural organization (FAO) suggest that food availability is not only a matter of food to feed everyone. They argued that the safety and quality of food production and distribution and easy accessibility to food are also fundamental things. In response to this issue, the food security idea has been extended to include four features: food availability, food accessibility, food utilization, and food stability. Unfortunately, due to the unavailability of 124 countries food security indicators data, we are not able to use all these dimensions, but we can use the proxy for food security that is food supply (kcal/capita/day) . in many works of literature, the food supply used as a proxy for food security as (Pangaribowo et al., 2013; van Weezel, 2017; and Ogunniyi et al., 2020). Therefore, in this study, the food supply is utilized as a proxy for measuring food security in the selected countries.

Several studies have identified many significant causes of food security theoretically and empirically, such as climate change by theoretically Ecker and Breisinger (2012); Pangaribowo et al., (2013) and empirically KINDA and Badolo, (2014); BEN ZAIED and Zouabi (2015); Mahrous, (2019), argued that the climate change is the crucial factor affecting food security. Population growth by theoretically Malthus (1798) and empirically Brown (1981); Masters et al. (2013); and Godbers and Wall (2014) investigated that the population growth is the critical factor affecting food security negatively. Income in terms of GDP by theoretically Devereux (1993) and empirically Pingali (2007); Tadase et al. (2016) argued that good income increase the economic access to food by improving the households ability to purchase food relative rich and nutrient. Unemployment by theoretically Black et al., (2008); Pangaribowo et al., (2013) and empirically Loopstra and Tarasuks (2013); Etana and Tolosa (2017) stated that unemployments decrease the level of food security. And arable land by theoretically Neo-Malthusian theory and empirically by Liu et al. (2010); Schneider et al. (2011); and Smith (2013) claimed that without arable land the food production is impossible to secure. Further information about these control variables used in this study is available in the literature section.

There is no empirical research according to our best understanding that Investigate co2emissions' impact on global food security by spatial panel data modelling. If so, there are limited empirical studies that examine the effects of co2emission on global food security and that too without spatial effects. Therefore, This study inspects the importance of spatial spillover in connecting co2emission and food security in 124 developed and non-developed countries from 2000 to 2014 and using spatial panel models to examine the relationship between the co2emission (and other socio-economic factors) and food security with spatial effects. Moreover, to examine the direct, indirect (spillover), and the total effect of carbon dioxide and other socio-economic variables: population growth, income, unemployment, and arable land.

In addition to the introduction, the rest of the study distributed into five section: section 2 cover the extant literature review on the topic; section 3 shows the methodology of the study; Section 4 reveal the results and discussion; and Section 5 conclude the study.

Literature Review

Malthus (1798) has found that if the population growth rate is high, food shortages may occur and thus decrease food security in the long-term. More specifically, if the number of humans grows faster than the food, such as products of agriculture and industries, food insecurity may occur. Hence the systematic analysis of Brown (1981). Tian et al. (2016) and Masters et al. (2013) found that speedy population growth is followed by increases demand for food, leading to the food's shortage. For example, many regions have significant increases in water and land uses due to rapid population growth (Masters et al., 2013). Likewise, in another study by Tian et al. (2016) found that higher population growth would significantly affect food provisions and lead to food conflict, mostly in Southeast Asia, Sub-Saharan Africa, Northern and Central South America. With the passing of time, Malthus theory revived in the form of NeoMalthusians. NeoMalthusians add only to the classical theory of Malthus that the agricultural land is the basic and vital source for food security incrementation. By empirically, Liu et al., (2010); and Schneider et al., (2011) has identified that arable land has a positive and statistically significant impact on food security. Liu et al. (2010) provide empirical evidence that agricultural land shortage is becoming due to industrialization like in china. Furthermore, Schneider et al., (2011) argued that arable land is the vital source for agricultural activities. Lack of arable land could lead to food shortage, resulting in the number of undernourishment people increasing. On the other side, Ahmad (2016) concludes that forest area is an important determinant for the incrementation of global food security. The third factor, income proxied by GDP, is the basic and crucial factor affecting food security, particularly play a vital role in food accessibility. In this context, Devereux (1993) and empirically Pingali (2007); Tadase et al. (2016) argued that good income increase the economic access to food by improving the households ability to purchase food relative rich and nutrient. Furthermore, unemployment is also a crucial factor affecting food security negatively (Pangaribowo et al., 2013). For instance, Etana and Tolossa (2017); and Loopstra and Tarasuk (2013) found that the foremost significant factor in developing economies that increase the level of food insecurity is the high unemployment ratio. This might be explained that with a high unemployment rate, residents of the country would have inefficient income to purchase food items.

Another group of scholars thinks about food security with biofuel and co2emission, thought this line is related to Subramaniam et al.,(2019) empirically detected the influence of biofuel and co2emission on food security for 51 developing countries during the period 2001-2016. The study used a generalized panel method of moments (GMM) technique for estimation. The outcome indicated that biofuel and co2emission decrease the level of food security in developing countries. And they argued that increasing the production of biofuels raises food prices and thus adds to malnourishment. Several scholars used the co2emission as a proxy for climate change, environmental degradation to check its effects on food production. Such as Abdullah et al., (2020); Masron et al., (2020), both scholars used co2emission as a control variable to check its effects on developing countries' food security. And both are argued that co2emission decreases the country's level of food production, resulting in the level of food insecurity increases and the number of hunger have arisen. Similarly, Rasul and Sharma (2016) indicated that environmental deterioration presents a major threat to food production as a result of changes in rainfall distribution, co2emission, high temperature, water availability, biodiversity and land resources (Dawson et al., 2016). Kinda and Badolo (2014) empirically indicated the impact of climatic change on food security for the 71 emerging economies during the period 1960-2008. The study used food supply and the proportion of undernourishment of people as an index for food security. They also included food price, land under the cereal production, arable land, and rainfall as explanatory variables in their model. Their findings show that the proportion of undernourishment people increases, and food supply reduced by climatic variability in developing countries. This negative effect is more significant in African sub-Saharan economies than in other emerging nations. The outcome of the study also showed that the negative effect of climate change is worsened in the occurrence of civil battles and is more significant for the nations that are exposed to food rates shock. Mahrous (2019) empirically examined the global climate changes and food security linkage in East-African-Community (EAC) for the period 2000-14. They employed pooled fixed-effect method for estimation purposes. Their results indicate that rain has a significant positive impact on food security. Besides, Some scholar finds out the positive impacts of co2emission on food security. Such as, Akbar et al. (2018) checked the effect of co2emission on the production of food from 1964 to 2015 using the ARDL method. They argued that the environmental changes due to the level of co2emission have no negative impacts on food production.

The above past studies are related to multiple crucial factors to food security. Unfortunately yet, no study finds out from the above past studies on spatial analysis of co2emission and food security. So, the purpose of this research work is going to investigate the effect of co2emission on food security in developed and developing countries with spatial effects.

Methodology and Data Specification

Data

As we discussed above, this research work aims to examine the impact of Co2emmission on global food security for 124 countries from 2000-2014 using spatial models. In our sample comprises those countries whose data are physically available. The dependent variable is food security, while the predictor variables are Co2emission, arable land, population growth, GDP per capita, and unemployment. Data of food security proxied by food supply (kcal/capita/day) collected from food agricultural and Organization (FAO) while Co2emission, population growth, arable land, GDP per capita, and unemployment obtained from world bank (WB). For further explanations of these variables, please visit table.1.

Table.1. Variables descriptions

Variables	Descriptions	Source
Food security	Food security measured through the food supply in terms of (kcal/capita/day).	FAOSTAT
Population growth	The annual percentage increase in population	World Bank
Co2emission	carbon dioxide emission per capita (in metric ton)	World Bank
Unemployment	The percentage of unemployed labour in the total workforce.	World Bank
Arable land	agricultural land as a percentage of the total land	World Bank
Gross domestic product	GDP per capita in constant (2010 US$)	World Bank

Source: FAO, (2020) and World Bank, (2020).

Methodology

Our main analysis is based on the spatial panel data technique. Originally, the spatial econometric model was used by Anselin in the context of crossectional data (Anselin 1988). Besides, several scholars used spatial models for the cross-sectional data (Rupasingha and Goetz, 2007; Elhorst, 2014a; Balta-Ozkan et al., 2015). Our study's importance is to consider the spatial effect of food security (that is, the given country's food supply depends on its nearest neighbour countries) for panel data. According to Elhorst (2003); Anselin et al. (2008); and Elhorst (2014), the spatial panel data model is a model of spacetime for panel data that is an expansion of the general nesting spatial models for cross-sectional data. There is three types of spatial panel data model are commonly utilized that are: spatial panel data model (SPDM), spatial-lag panel data model (SLPDM), and spatial-error panel data model (SEPDM). The general form of the SPDM given as follows (Elhorst, 2014b).

$$\boldsymbol{Y_t = al_N + \rho W Y_t + X_t \beta + W X_t \theta + \mu + \xi_{tlN} + u_t}\,; \qquad \boldsymbol{where,} \quad \boldsymbol{u_t = \lambda W u_t + \varepsilon_t} \qquad (\mathbf{1})$$

Here t represents time, and l_N indicated the $N * 1$ vector with the constant parameter a. Y denotes $N * 1$ the vector of the explained (food security) variable for each unit (country) $i(where\ i = 1,2,3, \ldots\ldots N)$. While the other side of the explained variable "X" indicating $(N * k)$ matrix of the explanatory variable. WX, WY, and Wu indicate spatial interaction among the independent variables, the dependent variable and the error terms of the different spatial unit respectively. $\lambda\ and\ \rho$ are the spatial autocorrelation coefficients indicating the strength of the model's spatial dependence. The coefficient, which is to calculate, is $\beta\ and\ \theta$ an associated $K * 1$ vector. W Denotes the spatial-weight matrix that captures the spatial correlation in our sample data. ξ Indicates time-period related effects. μ Represents the spatial specific effects or is an (N×1) vector of the intercept highlighting the effect of the excluded (omitted) individual-specific variable(s).

Moreover, when $\lambda = 0\ and\ \rho \neq 0, \theta \neq 0$. equation (1), can be expressed as a spatial Durbin panel data model (SDPDM) that can capture the spatial effects among explained and explanatory variables that is WY and WX with $\rho\ and\ \theta$ being the spatial autocorrelation coefficient. The equation expressed as follows.

$$\boldsymbol{Y_t = al_N + \rho WY_t + X_t\beta + WX_t\theta + \mu + \xi_{tlN} + \varepsilon_t} \quad (2)$$

When $\rho \neq 0 \ \ and \ \lambda = 0, \theta = 0$, equation (1), may be considered as SLPDM that only captures spatial interaction effect among the explained variable WY, with ρ being the spatial autocorrelation coefficient.

$$\boldsymbol{Y_t = al_N + \rho WY_t + X_t\beta + +\mu + \xi_{tlN} + \varepsilon_t} \quad (3)$$

Finally, when $\boldsymbol{\lambda} \neq 0 \ and \ \theta = 0, \rho = 0$, equation (1), could be considered as a SEPDM that only captures spatial interaction effect among the error term. The equation described as follows.

$$\boldsymbol{Y_t = al_N + X_t\beta + \mu + \xi_{tlN} + u_t} \quad ; \quad \boldsymbol{where}, \quad \boldsymbol{u_t = \lambda Wu_t + \varepsilon_t} \quad (4)$$

Elhorst (2014) suggested the tests that are the WALD test, likelihood ratio (LR) test, and the Lagrange multiplier (LM) test for the selection of the spatial panel data model from the above spatial panel models.

Model Selection and Spatial Effect Test

It is essential to investigate the spatial effects in our study before evaluating any spatial econometric model. Moran (1950); Ullah, (1998); and Elhorst (2010) recommended the global Moran's I test to detect the spatial dependence of the dependent (food security) variable. The formula for evaluating Moran's I index is.

$$I = \frac{n \sum_{i=1}^{n} \sum_{j}^{n} w_{ij} \, (x_j - \bar{x})(x_i - \bar{x})}{S^2 \sum_{i}^{n} \sum_{j}^{n} w_{ij}}$$

Where

$$S^2 = \frac{1}{n} \sum_i (x_i - \bar{x})^2$$

Where x_i and x_j show the food security rates of country$i$ and j, respectively. The mean represents , and variance represents S^2. The value ranges from minus one to plus one, i.e. -1 to +1. A negative value shows negative spatial dependence, and a positive value means positive spatial dependence or spatial autocorrelation. The random spatial pattern appears when the index equal to zero. A -1 and +1 represents a perfect dispersion and perfect correlation.

For model selection, Elhorst (2014) recommended the Lagrange multiplier (LM) test to determine whether to establish an SDPDM, SLPDM, or SEPDM. Two kinds of (LM) test Anselin (1988) performed the Classical Lagrange Multiplier test (CLM) and the Robust Lagrange Multiplier (RLM) test.

Result Discussions

Descriptive Statistics

Table.2. Descriptive statistics

Variables	Mean	Median	Std.Dev	Min	Max	Count
Food Security	2819.376	2801.5	476.7818	1777	3825	1860
GDP	13391.29	5436.52	17448.79	194.8731	91565.73	1860
Co2emission	4.839367	3.19789	5.60744	0.049001	36.09166	1860
Population Growth	1.416856	1.275304	1.451821	-3.84767	15.17708	1860
Arable Land	16.1466	12.02346	14.25643	0.084006	64.14688	1860
Unemployment	7.671338	6.479	5.057171	0.319	33.473	1860

Table.2 displays the selected variables descriptive statistics. The summary statistics of all these variables are constructed before the logarithm. So, the average value of food security is 2819.376 with 2801.5 and 476.7818 of median and standard deviation, respectively. Similarly, the mean value of GDP, Co2emission, Population Growth, Arable Land and Unemployment is 13391.29, 4.839367, 1.416856, 16.1466 and 7.671338, respectively. The table also highlights the minimum and maximum values of the studied variables.

Global Moran's I Test Result

We utilized two types of test that global Moran and local Moran tests for the spatial dependence or the spatial autocorrelation in the cross-sectional units. The local Moran test is also known as local spatial autocorrelation. Both tests have revealed the results of spatial dependence.

For spatial dependence, two types of tests are conducted of these global Moran's I test result of the food security shown in the table.3, indicating that the positive spatial dependence in the world country-level food security in each year. It means that in our sample data have strong spatial dependence nor a negative or random spatial pattern. The different k-nearest neighbour (knn) weight indices used to describe the spatial relationship among countries. Because in our sample of countries have an island that why we used the 4-nearest neighbour (k-nearest neighbour method). Therefore, the global Moran's I test showed that food supply between countries is spatially dependent.

Table.3. Global Moran's I result

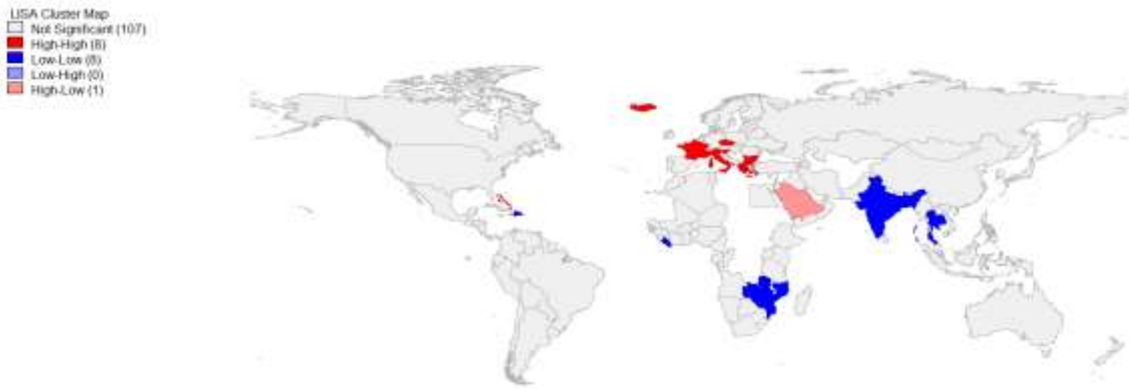
Years	Moran's I	P values
2ooo	0.6054	0.001
2oo1	0.6201	0.001
2oo2	0.6382	0.001
2oo3	0.6348	0.001
2oo4	0.6298	0.001
2oo5	0.6096	0.001
2oo6	0.5999	0.001
2oo7	0.5973	0.001
2oo8	0.6198	0.001
2oo9	0.6287	0.001
2o10	0.6145	0.001
2o11	0.5920	0.001
2o12	0.5724	0.001
2o13	0.5750	0.001
2o14	0.4642	0.001

Note: P-values < 0.01, Calculated by 999 Permutations.

Local Spatial-Autocorrelation Test Result

The outcomes of the local spatial-autocorrelation test are revealed in figure 1. The LISA map comprises four sets of observations: High-High, Low-Low, Low-High and High-Low. The High-High cluster shows the region with high-value surrounded by high-values, whiles the Low-Low cluster are thos e that have low-values and surrounded by low-values. Likewise, the rules apply to the Low-High and High-Low clusters. So, the local spatial autocorrelation also showed the spatial dependency between countries significantly. The local spatial autocorrelation is constructed based on the K4 spatial weight matrix. The findings are significant at the 5 percent level and support the occurrence of robust spatial dependence of global food security. Therefore, the global Moran's I, and local spatial autocorrelation result suggested that the spatial panel model is more reliable than other regression models to estimate the effect of co2emission on global food security.

2000



2014

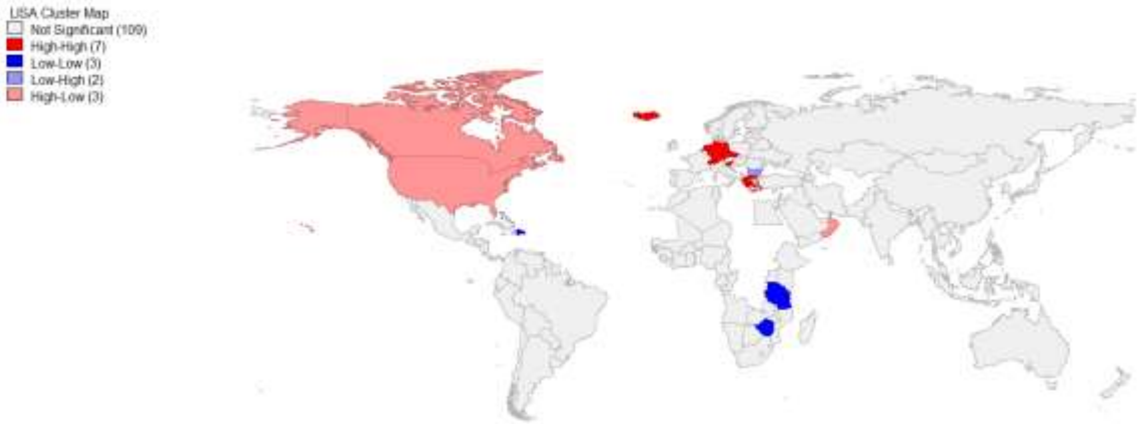


Figure. 1. LISA map of food security in 2000 and 2014

The Econometric Models' Results

Estimation Results of The Non-Spatial Panel Models

Table.4 shows the findings of the econometric panel model without considering the spatial effects. Firstly, the Non-spatial panel data model is estimated. Hausman's value represents that the random-effect hypothesis should be rejected at a 1% significance level. Therefore, we relied on the fixed effect model. Further, the findings of fixed-effects, time-period effects, and the combination of fixed-effects and time-period effects are shown in column (2), (3), and (4), respectively. It is evident from column 2 of table 4 that only population growth is insignificant while the other chosen variables are statistically significant at a 1% confidence level. Furthermore, all the selected variables in the time fixed-effect model are significant at a 1 % level. Likewise, in the double effect model, i.e. column (3), population growth and GDP have an insignificant contribution to our dependent variable.

Table .4. Estimation Results of the non-spatial panel data model

	Non-spatial fixed effects Models		
Determinants	individual effect	time effect	Double effect
Co2emission	-11.614***	-28.411***	-17.646***
Population growth	-0.533	-73.763***	-0.027
Arable land	12.700***	4.507***	8.505***
Unemployment	-9.013***	11.072***	-7.953***
GDP	0.0137***	0.011***	0.0008
Constant	114.65***	116.36**	165.23***
R^2	0.190	0.572	0.119
LM spatial lag	160.21***	172.11***	24.825****
LM spatial error	150.13***	100.4***	22.778***
Robust LM spatial lag	11.471***	73.331***	2.0509**
Robust LM spatial error	1.386**	1.6265	0.003
Hausman test	122.25**	122.128*	125.29***

Note: Significant codes: ***, **, and * indicate the 1 per-cent, 5 per-cent, and 10 per-cent significance level.

Although, the robust and the classic LM tests illustrate that the H_O: no spatially lagged dependent variable should be rejected at a 1 % level of significance. The results remain consistent in either case, including the individual, and/or time-specific fixed effects. For instance, the value of the LM Spatial lag test is 160.21 (p<0.000), 172.11 (p<0.000) and 24.825 (p<0.000) in column (2), (3) and (4), respectively. However, we may not reject the H_O: no spatial autocorrelation in the case of robust LM spatial lag of the double effect and robust LM spatial error of individual effects because his values are not significant at any level of significance. In short, the findings propose that the H_O: no spatial effect should be rejected in favour of the spatial-lag panel model.

Estimation Results of The Spatial Panel Models

However, one needs to be cautious in employing the SLPDM when based on the LM tests' findings (LeSage and Pace, 2009). A more reliable method is to estimate the spatial Durbin panel model (SDPDM) and usage the estimation results to test whether the SDPDM can be simplified to the SLPDM or the spatial error panel data model (SEPDM). The appropriate way is to estimate both. The LR and the WALD tests show that hypotheses that the SDPDM is more reliable for further estimations than other models. In general, in the table.5 the two-way fixed-effect of SDPDM has a relatively higher value of goodness-of-fit than the non-spatial panel data models see table.4, especially for the two way SDPDM (column (4) of table 5). Therefore, the two-way fixed effect spatial panel Durbin model is selected from all other models.

Furthermore, in table.5 all the variables are significant in the double-effects or two-way fixed-effect spatial panel Durbin model but in the case of individual and time fixed-effect model nor all the variable are significant. Even the spatial lag coefficients of all variables greatly impact food security in the two-way fixed effect spatial panel Durbin model. So, all the coefficients of all variables and their spatial lag coefficients are statistically significant at the 1% level, except the spatial lag of the unemployment are significant at the 5% level. Such as all the real coefficients of the variables and their spatial lag coefficients significantly impact food security, indicating that all these variables have affected the given country's food security and affected its neighboring countries' food security. For instance, the real coefficient and the spatial lag coefficient of the co2 emission are negative effects on the given country's food security and its nearest neighbour countries food security, indicating that the food availability amount is decreased in the given country and its neighbour countries due to high carbon dioxide. This result is similar to the result of Eric and Kinda (2016), who found that climate change negatively affects food security in the given country and its neighbour countries. Eric and Kinda also stated that the population growth rate has both a direct and an indirect negative and significant effect on the availability of the food. In this context, our control variable population growth also negatively affects the given country food security and neighbouring countries. Besides that, the sign of the GDP and arable coefficient positively impact food security for both in the given country and its neighbour countries. The GDP outcomes are in line with the consequences of Ardakani et al. (2020), who found that the economic conditions in terms of GDP and food price index are positively and statistically significant effect on the given country food supply and its neighbour countries. In a simple way, the spatial lag coefficients result of all these variables indicating that these variables affect the nearest neighbour countries' food security of the given country. At the same time, the real coefficients of these variables indicate that these variables affect the given country's food security.

Table. 5. Estimation Result of spatial panel modes

	Spatial Durbin fixed effects model		
Determinants	Individual effect	Time effect	Double effect
Intercept	N/A	N/A	N/A
Co2emission	9.112***	2.923***	-12.374***
Population growth	2.610	-5.291***	-1.655***
Arable land	7.126***	4.505***	6.161***
Unemployment	-8.651***	4.332**	-7.744***
GDP	0.014***	0.007***	0.006***
W*fsindex	0.377***	0.324***	0.151***
W*co2emission	7.859***	-9.921***	-12.015***
W*population growth	-0.478	-7.047	-5.255***
W*arable land	5.087***	-2.844***	3.953***
W*unemployment	5.038***	2.603	-3.252**
W*GDP	-0.006***	0.001.	0.011***
R^2	0.60	0.62	0.63
Wald spatial lag/	85.247***	57.893***	47.765***
Wald spatial error	209.763***	98.761***	56.094***
LR spatial lag	77.897***	65.324***	47.989***
LR spatial error	188.987***	97.675***	45.897***

Note: Significant codes: ***, **, and * indicate the 1 per-cent, 5 per-cent, and 10 per-cent significance level.

Moreover, the model revealed substantial evidence for the presence of spatial dependence. Firstly, the spatial lag of the response variable, W*food security, is significantly positive. Secondly, the spatial lags of all the explanatory variables are significant. This another strong evidence for spatial dependence. After the estimation and discussions of the two-way fixed effect spatial panel Durbin model, it should be must to check the spatial effect of the two-way fixed spatial panel Durbin model.

Analysis of The Spatial Effect

The average direct effect, indirect effect, and total effects of all independent variables are present in table.6. The direct effects express the marginal effects of the changes in the independent variables of 1% on the same unit's dependent variable. The indirect effects are the marginal effects of the independent variables' changes in 1% on all neighbouring units' dependent variable value. At the same time, the total effect is the sum of direct and indirect effects.

Table.6 spatial effects of the spatial panel Durbin model

Independent variables	Direct effects	Indirect effects	Total effects
GDP	0.0122***	0.001**	0.013***
	(22.99)	(2.91)	(10.47)
Co2emission	-27.676***	-5.856***	-29.532***
	(16.48)	(-5.60)	(7.53)
Population growth	-70.975***	-6.988***	-77.963***
	(-12.8)	(-3.60)	(-6.09)
Arable land	3.882***	0.899	4.781***
	(7.06)	(0.84)	(2.96)
Unemployment	-11.368***	-2.690***	-14.058***
	(7.62)	(3.54)	(3.91)

NOTE: Statistics in the parentheses show t-values. significant codes: ***, **, and * indicate the 1 per-cent, 5 per-cent, and 10 per-cent significance level..

The average direct effect of the co2emissions is -22.99 (P=0.000). It indicates that a 1% rise in the level of the co2emission (for example, in the USA) leads to a 23% negative change in the USA's food security. Simultaneously, its indirect effect indicates that a 1% increase in the USA's level of co2emissions leads to a 5.9 % negative change in the nearest neighbour countries' food security of the USA. The total effect of the co2 emission is -29.99 (P=0.000). its indicates that a 1% increase in the level of co2emission, 29.53% decrease the level of food security in both of this country and its nearest neighbour countries. Similarly, effects of direct, indirect, and total for the population growth and unemployment rate. The direct effect of the GDP increases the level of food security in the given country. Its indirect effect also increases the level of food security in the neighbouring countries of the given country. While the arable land contributes to improving the given country's food supply but for its neighbouring countries may not be profitable. The total effect of the GDP and arable land result shows that the GDP and more agricultural land for food production of the given country increase the food supply level in both of this country and its neighbouring countries.

Conclusion

This study investigates the impact of co2emission and other socio-economic variables, i.e. unemployment rate, population growth and arable land, on global food security and using spatial panel Durbin model to examine the spatial effects of the co2emissions and other socio-economic variables on food security proxied by food supply (kcal/capita/day) for 124 developed and developing countries from 2000 to 2014. Before, we tested the spatial dependence using the global Moran's I and local spatial autocorrelation test. We thus found the spatial dependence of food supply between countries. After that, we finalized the spatial panel Durbin model from other spatial and non-spatial panel model based on R-square, LR-test, Wald-test, and LM-test. The finalized spatial panel Durbin model and its spatial effect result show that the co2emission has negatively played a crucial role in the decrementation of food security level in the given country and its neighbouring countries. The finalized regression model further argued that population growth and high-level of unemployment rate also negatively decrease the level of the food supply in both of this country and its nearest neighbouring countries. The other crucial factor to food security is the income coefficient result indicates that the high-income increase the access of people to healthy food and increase the food supply level in both of this country and its nearest neighbouring countries and *vice versa*. Therefore, the selected countries need to reduce carbon emissions and develop a low carbon to increase food production in quantity and quality and nutritious food and food supply. It is recommended that government through extension workers in the various states ensures farmers are aware of the effects of CO2 and to educate them on the different adaptation strategies in order to boost GDP and Food Security. Finally, policy-makers should implement policies that will stimulate increased GDP such as carbon sequestration, reduction in industrial activities that have been identified to be major sources of carbon and other greenhouse gas (GHG) emission which will not only boost agricultural productivity but also promote FS. Delaying action is costly and may ultimately lead to higher CO_2 concentrations, consequently producing additional damages to the economy as a result of higher temperatures, more acidic oceans, and other consequences of higher CO_2 concentrations. Future studies in this area may examine whether the relationship between co2emission and other socio-economic variables on global food security is nonlinear or time-varying since the current study is based on a Spatial panel model.

Conflict of Interest

Declaration of interest: none

Funding

We have not received any funding from any organizations.

Reference

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