Effect of Climate Change and Selected Macroeconomic Variables on Food Security in South Africa

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Abstract. Ensuring a balanced and economically healthy environment is paramount for attaining zero hunger in Africa. This vision is threatened by climate change, a multivariate concept which impacts different sectors, most notably the agri-food sector. This study examined the effect of climate change and selected macroeconomic variables on food security in South Africa, focusing on developing relevant policy decisions to promote sustainable food systems in one of Africa's most industrialised economies. Time series data on South Africa, covering the period of 1990 to 2022, were sourced from the World Development Indicators database. The study applied the ADF unit root test to examine their stationarity properties. At the same time, the Autoregressive Distributed Lag approach to cointegration (ARDL) was used to investigate the long-run and short-run relationships of the selected climate and macroeconomic variables and food security in South Africa.

Results from the short-run dynamics revealed that past changes (lagged values) in CO2 emissions, food import index, and particulate emission damage significantly impact food security. The error correction term indicated a strong adjustment to the long-term equilibrium, suggesting that food security responds quickly to deviations from its long-term trend. The high R-squared and adjusted R-squared values indicated that the model explains a substantial portion of the variance in food security. The model's diagnostics revealed no significant issue of autocorrelation in the residuals. At the same time, the absence of an ARCH effect indicates that the variance of the residuals is constant over time, and conditional heteroskedasticity is equally not an issue in the fitted model.

Keywords: Climate change; Food security; ARDL; ECM; South Africa.

INTRODUCTION

Food security, a multidimensional concept encompassing the availability, accessibility, utilisation, and stability of food, is a global topical discourse [1]. Likewise, ensuring that all people have sufficient, safe, and nutritious food for daily dietary needs for a healthy life is also fundamental to human welfare, economic stability, and social peace [2]. However, [3] emphasised the complexity surrounding the ambitious target of food security attainment. Apart from environmental, industrial activities and climatic conditions, this complexity is also influenced by many factors, including economic policies and actions [4]. Globally, the attainment of zero hunger is currently at risk of climate change extreme events, environmental degradation, industrial pollution, and several macroeconomic policies. Climate change, driven by greenhouse gas emissions, alters the pattern, occurrence and intensity of weather conditions [4], creating unpredictable crop growing conditions and reducing yields and the reliability of food supplies across the food value chains, thereby impacting agricultural productivity [5].

The African continent is particularly susceptible to the negative consequences of the changing climate and industrial pollution due to its dependence on agriculture for livelihood and food security [6]. South Africa, as one of the most industrialised nations on the continent, represents a good case study for studying the interconnectivity of industrial-induced air pollution, particulate emissions, climate change, and food security.

The country's industrial activities across various regions, including mining, manufacturing, and energy production, contribute significantly to particulate and CO2 emissions [7-8]. Just like in many African nations, South Africa's agricultural sector is a strategic economic sector [8], and "keeping an economically healthy environment balance is necessary for growth and development in Africa, especially with the estimated population growth of 1.7 and 2.5 billion people by 2030 and 2050 respectively" [9]. South Africa's agricultural sector is diverse, with various crops grown and livestock reared in different climatic regions. Industrial activities in South Africa contribute to significant particulate emissions, with consequential effects not only limited to the agri-food sector but also felt in other sectors [7]. The emissions' local and regional environmental impacts damage air quality, soil health, and water resources [7]. The emissions can reduce air quality, harm human health, and impact agricultural productivity by contaminating soil and crops [10]. Therefore, this study explored the impacts of these environmental and economic factors on food security in South Africa, with a particular focus on their effects on food security. This can provide policy guidance to promote sustainable food systems in an industrialised economy such as South Africa, which is facing significant environmental challenges.

Literature review

Carbon dioxide (CO2) emission: Several literature have established that increased CO2 levels in the atmosphere can positively and negatively affect crop growth [6, 9, 11-13]. While higher CO2 concentrations can enhance photosynthesis and plant growth under certain conditions, the associated climatic changes, such as higher temperatures and altered precipitation patterns, often negate these benefits [11]. In South Africa, changes in precipitation can have severe consequences for agriculture, which relies heavily on consistent and predictable rainfall. Drought conditions can lead to water scarcity, affecting rainfed and irrigated crops, while excessive rainfall can cause flooding and soil erosion [7].

The impacts of CO2 emissions and other extreme events on agriculture have also been documented in other nations. In Bangladesh, [9] noted that rising temperatures and changing precipitation patterns negatively impact crop yields. Major staple crops like wheat, rice, and maise are particularly vulnerable to climate change-induced water scarcity and pest and disease. In the Midwest, known as the "Corn Belt," climate change has led to shifts in planting dates and growing seasons in the United States of America [14]. The monsoon rains, crucial for Indian agriculture, have become increasingly erratic due to climate change [15]. This has resulted in droughts and floods that significantly affect crop production, particularly for smallholder farmers who lack the resources to adapt to these rapid changes.

Particulate emissions: This consists of dust, soot, smoke, solid particles and liquid droplets suspended in the air, which originate from various sources, including wastes from industrial activities, vehicular exhaust, and energy production [12]. These emissions have detrimental effects on both human health and the environment [16-17]. Agriculture poses significant risks to crop growth and productivity, ultimately impacting food security. Particulate matter is more lethal globally, and agriculture is regarded to be at the most receiving end of the impacts of such air pollution [18]. In heavily industrialised nations of China, high levels of particulate pollution have been linked to substantial reductions in crop yields [19]. Similar observations have also been reported in India, where air pollution from industrial activities and vehicular emissions negatively impacts agricultural productivity [20]. Likewise, in South Africa, industrial hubs experience high levels of particulate emissions from mining and other industrial activities, with serious consequential effects on human existence [21].

Food imports and per capita income: South Africa exhibits a special case for the association between food imports, income per capita, and food security. While the country has a relatively robust economic infrastructure, food security is mainly driven by income and unemployment instead of agricultural production, even in the agrarian areas [22]. The distribution of wealth and reliance on food imports significantly influence its food security landscape. South Africa and other Southern African countries rely on food imports to meet the demands of its population, especially for certain staples and processed foods [23]. This reliance also introduces vulnerability to global market fluctuations, trade policies, and geopolitical events. Per capita, income is also a critical determinant of food security. Higher-income levels generally enhance individuals' ability to purchase a diverse range of food, ensuring nutritional adequacy [24]. In South Africa, however, there is significant income inequality, with a substantial portion of the population living below the poverty line [25]. Besides, almost half of the population's per capita income comes from transfers, either a poverty-related government transfer (child support grant or grant for aged people) or remittances, which are considered private transfers [26]. The authors noted that many remittances go to wealthier households, so any remarkable effect on food security growth is not anticipated, especially among the vulnerable population.

Theoretical underpinnings

This study draws from some theories. First, the theory of environmental degradation [27] suggests that increased CO2 levels exacerbate soil erosion, desertification, and water scarcity, further threatening agricultural outputs and food availability. Similarly, in line with dependency theory [28], a high reliance on food importation can predispose a country vulnerable to global market fluctuations and trade policies. A high food import index for South Africa indicates dependency on external food sources. Environmental and public health theories are particularly important regarding particulate matter emission damage. Environmental theory [29] posits that poor environmental health (air pollution and soil contamination) directly impacts food production capacity and, thus, food security. The public health theory also links environmental pollution to adverse human health outcomes. High particulate emissions can trigger respiratory and other health issues, reducing labour productivity and indirectly affecting food security.

METHODS

Data: The study employed a quantitative research design, using a time series dataset for South Africa, spanning 1990-2022. This design was chosen to understand the dynamic relationship between climatic variables, economic variables, and food security indicators. South African datasets on food security indicators (index), economic variables such as per capita income and food import index, and climatic variables, such as CO2 emissions and particulate emission damage, were all sourced from the World Development Indicators [30].

Analytical techniques: The study utilised autoregressive distributed lag (ARDL) to examine the effects of climate and macroeconomic variables on food security in South Africa. The first step was examining the selected variables' time series properties using the ADF unit root test. The Bounds testing analysis followed this. The choice of this test is premised on several considerations, which is also supported by [31]. Firstly, unlike most multivariate cointegration procedures applicable to larger scope, the ARDL approach to cointegration is suitable for studies with smaller sample sizes, such as the 33 observations used in this study. Secondly, "it is also applicable irrespective of if the regressors in the model are purely I(0), purely I(1), or mutually cointegrated, but the procedure will likely fail in the presence of I(2) series". Also, the "bounds test is simpler compared to other multivariate cointegration techniques [32], because it allows the cointegration relationship to be estimated by OLS once the model's lag order is identified." Benefitting from [33] and [34] procedures, this study also modelled the long-run relationship, indicated in equation (5) as a general Vector Autoregressive (VAR) model of order p, which is expressed as:

$$z_t = \beta t + \sum_{i=1}^{p} \phi_i z_{t-i} + \varepsilon_t \ , \qquad t = 1, 2, 3, ..., T \tag{1}$$

where co represents a (k+1)-vector of intercepts (drift) and β denotes a (k+1)-vector of trend coefficients, and the following "vector equilibrium correction model (VECM) was also derived, in line with [33] procedure:

$$\Delta z_t = c_0 + \beta t + \pi z_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta z_{t-i} + \varepsilon_t \ , \qquad t = 1, 2, 3, ..., T \tag{2}$$

where the (k+1)*(k+1) matrices

$$\Pi = I_{k+1} + \sum_{j=i+1}^{p} \psi_i \ , \ \Gamma_i = -\Pi = \sum_{j=i+1}^{p} \psi_i , i = 1 \ldots p-1$$

contain the long-run multipliers and short-run dynamic coefficients of the VECM; Z_t is the vector of variables y_t and x_t respectively; y_t is an I(1) dependent variable (Food security)", expressed as:

$$Food\ security = \beta_0 + \beta_1 CO2 + \beta_2 FII + \beta_3 PCI + \beta_4 PED + \varepsilon_t \tag{3}$$

This is a "vector matrix of 'forcing' I(0) and I(1) regressors as already defined with a multivariate identically and independently distributed (i.i.d) zero mean error vector and a homoskedastic process". Furthermore, let us assume a unique long-run association among the variables. The conditional VECM can be expressed as:

$$\Delta LFSD_i = \delta_0 + \delta_1 LCO2_{it-1} + + \delta_2 LFII_{t-1} + \delta_3 LPCI_{t-1} + +\delta_4 LPED_{jt-1} + \sum_{i=0}^{p} \varphi \Delta LCO2_{t-i} + +\sum_{j=0}^{q} w\Delta LFII_{t-1} + \sum_{m=0}^{q} \eta \Delta LPCI_{t-1} + +\sum_{n=0}^{q} \psi \Delta LPED_{jt-1} + \varepsilon , \quad (4)$$

where δi is the long run multipliers, c0 is the drift, and εt is the white noise errors.

Testing the cointegration relationship between food security and its independent variables involves some procedures. First, the estimation of the above equation using the ordinary least squares (OLS) method, and the null hypothesis is stated as:

H0: $\delta 1 = \delta 2 = \delta 3 = \delta 4 = 0$, against the alternative: Ha: $\delta 1$ or $\delta 2$ or $\delta 3$ or $\delta 4 \neq 0$.

According to [31], if the lower bound critical value is greater than the calculated F-statistic, the null hypothesis of no cointegration will be accepted. On the other hand, if the F-statistic exceeds the upper bound critical value, the null hypothesis will not be accepted, indicating a "steady-state equilibrium between the variables under consideration". Then, "the critical values for the F-tests are determined, with those for the I(0) series referred to as the upper bound critical values, and those for the I(1) series as the lower bound critical values".

Secondly, let us assume a unique long-run association among the variables. The conditional ARDL long-run model (FDS, q1, q2, q3, q4) for LFDSt is:

$$LFDS_{it} = C_0 + \sum_{x=0}^{q} \alpha_1 LCO2_{t-1} + + \sum_{j=0}^{q} \alpha_2 LFII_{t-1} + \sum_{m=0}^{q} \alpha_3 LPCI_{t-1} + +\sum_{n=0}^{q} \alpha_4 LPED_{jt-1} + \varepsilon \quad (5)$$

By Schwarz Bayesian criterion (SBC) and Akaike information criteria, the lag length in the ARDL model was selected, while in the final step, the short-run dynamic elasticities were derived by estimating an error correction model associated with the long-run estimates, which is also expressed as:

$$LFDS_{it} = \alpha + \sum_{i=0}^{p} \varphi \Delta LCO2_{t-i} + +\sum_{j=1}^{q} w\Delta FII_{t-l} + \sum_{m=1}^{q} \eta \Delta LPCI_{t-1} + , +\sum_{n=1}^{q} \psi \Delta LPED_{jt-s} + \lambda ECM_{t-1} \quad (6)$$

where φ, w, η, ψ *and* α represents the -run dynamic elasticities of the model's convergence to long-run equilibrium, while λ is the speed of adjustment; Δ indicates the first difference operator, and ECMt-1 is the one period lagged error correction term.

The coefficient measures the speed of adjustment to restore equilibrium following system shocks. The "general-to-specific modelling technique by [35] is employed to select the preferred ECM, and this involves initial estimation of the ECM with various lag lengths for the differenced terms, and then refining the model by removing lags with insignificant parameters." Importantly, some diagnostic tests must be passed to have a correctly specified ECM model and to ascertain the reliability of the results. These include the "Autoregressive LM test for residual serial correlation, the Autoregressive LM test for normality distribution of the residuals, the Jarque-Bera test for normality in data distribution, and the ARCH test for heteroskedasticity in errors".

Model specification: The null hypothesis of this empirical study is that climate change does not impact food security in South Africa. This hypothesis was estimated using the ARDL bounds testing approach to cointegration, which is shown later in the subsequent equation. The relationship of food security with some theoretically hypothesised variables used in this study is specified as follows:

$$Food\ security = \beta_0 + \beta_1 CO2 + \beta_2 FII + \beta_3 PCI + \beta_4 PED + \varepsilon_t \quad (7)$$

The linear relationship is now transformed into a log-linear form of the model, which provides more appealing results as against the simple linear form. Given this position, the transformed equation (1) is specified as:

$$LFDS = \beta_0 + \beta_1 LCO2 + \beta_2 LFII + + \beta_3 LPCI + \beta_4 LPED + \varepsilon_t \quad (8)$$

where LFDS – Food security; LCO2 – CO2 emissions; LFII – Food import index; LPCI – Per capita income; LPED – Particulate emission damage; ε – White noise.

RESULTS AND DISCUSSION

Description, unit of measurement, summary statistics and correlation matrix of variables. Table 1 highlights the descriptions and units of measurement of the variables extracted from the South African dataset downloaded from the World Development Indicators of the World Bank.

Table 2 provides descriptive statistics for the natural logarithms of the five variables: food security (LFDS), CO2 emissions (LCO2), food import index (LFII), per capita income (LPCI), and particulate emission damage (LPED) of South Africa. From the results, the data shows slight skewness and moderate kurtosis, mostly indicating platykurtic distributions. The variables generally exhibit low to moderate variability around their means. Normality tests suggest that the distributions do not significantly deviate from normality, enhancing the reliability of the statistical conclusions drawn from it. In conclusion, all the discussions have provided a foundational understanding of the distributional properties of the isolated variables used in the study, and it is noteworthy to stress that all the isolated variables have 33 observations, which indicates a balanced dataset across the five variables.

Table 1 – Variables and sources of data [30]

Variables	Description	Unit of measurement	Sources
LFDS	Food Security	Food Prod. Index (2014-2016 = 100)	WDI, 2024
LCO2	CO2 Emission	Metric tons per capita	WDI, 2024
LFII	Food Import Index	% of merchandise imports	WDI, 2024
LPCI	Per Capita Income	Current US$	WDI, 2024
LPED	Particulate Emission Damage	% of GNI	WDI, 2024

Table 2 – Summary statistics (in logarithm form)

Variable	LFDS	LCO2	LFII	LPCI	LPED
Mean	4.386963	1.948780	1.809085	8.520290	-0.434
Median	4.366786	1.993197	1.852639	8.657488	-0.513
Maximum	4.738301	2.133770	2.128603	9.075327	0.331
Minimum	4.006424	1.743588	1.471233	7.904122	-0.946
Std. Dev.	0.222012	0.125649	0.191573	0.360937	0.429
Skewness	0.008827	-0.231290	-0.141348	-0.204	0.303
Kurtosis	1.749271	1.526104	2.063998	1.507	1.664
Jarque-Bera	2.151372	3.281232	1.314524	3.290	2.957
Probability	0.341064	0.193861	0.518268	0.192	0.227
Sum	144.7698	64.30975	59.69980	281.169	-14.337
Sum Sq. Dev.	1.577261	1.577261	1.174412	4.168	5.898
Observations	33	33	33	33	33

Further, Table 3 provides the correlation coefficients between the natural logarithms of the five variables indicated earlier. The correlation analysis revealed that carbon dioxide emissions, food import index, and per capita income are all positively correlated with food security. However, only particulate emission damage is negatively correlated with food security. This study also found a negative correlation between particulate emission damage and all other variables.

Table 3 – Correlation Matrix

Variable	LFDS	LCO2	LFII	LPCI	LPED
LFDS	1	0.65	0.39	0.81	-0.95
LCO2	0.65	1	-0.01	0.78	-0.75
LFII	0.39	-0.01	1	0.37	-0.36
LPCI	0.816	0.78	0.37	1	-0.88
LPED	-0.95	-0.75	-0.36	-0.88	1

Variance Inflation Factors and Unit Root Tests. Table 4 presents the results of the Variance Inflation Factor (VIF) test, which assesses multicollinearity among the variables included in the model. The results indicated no significant issue of multicollinearity among the variables of interest.

Table 4 – Results of Variance Inflation Factor Test for Multicollinearity

Variable	Coefficient Variance	Uncentered VIF	Centred VIF
LCO2	0.0305	987.777	3.965
LFII	0.0055	158.295	1.702
LPCI	0.0057	3524.717	6.122
LPED	0.0033	10.301	5.010
C	0.2925	2484.336	NA

Table 5 also presents the results of an Augmented Dickey-Fuller (ADF) test for the variables fitted in the model. This was used to determine whether it has a unit root, indicating non-stationarity or otherwise, which suggests stationarity. The result indicated that all the variables are stationary at the 1st difference form, except food security (LFDS), which appeared stationary in its level form and 1st difference form. This suggests that all the fitted variables do not exhibit a unit root issue and are not trend-stationary but rather stationary around a deterministic trend.

Table 5 – Unit Root Test Results

Variables	Augmented Dickey-Fuller Test Statistics			
	Level	Decision	1st Difference	Decision
LFDS	-5.8489	Stationary	-11.6606	Stationary
LCO2	-0.2237	Not Stationary	-5.8272	Stationary
LFII	-2.5370	Not Stationary	-7.7601	Stationary
LPCI	-1.5474	Not Stationary	-4.2501	Stationary
LPED	-0.6473	Not Stationary	-3.8760	Stationary

Cointegration Test using Autoregressive Distributed Lag (ARDL) Model / Bounds Testing Approach to Cointegration. Table 6 presents the results of a cointegration test using the ARDL model and the Bounds Testing Approach to examine a long-term relationship (cointegration) between the variables in the model. The null hypothesis is that of no relationship (no cointegration). From the results, the F-statistic (6.5416) is higher than the upper bound critical values (I(1)) at all conventional significance levels (10%, 5%, and 1%). Since this is so, we do not accept the null hypothesis of no levels relationship. Hence, there is evidence of a long-term cointegration relationship between the variables in the model.

Table 6 – Result of Cointegration Test using Autoregressive Distributed Lag (ARDL) Model / Bounds Testing Approach to Cointegration

F-Bounds Test Null hypothesis: No levels of relationship				
Test Statistic	Value	Significant	I(0)	I(1)
		Asymptotic: n = 1000		
F-statistic	6.5416	10%	2.2	3.09
k	4	5% 2.5% 1%	2.56 2.88 3.29	3.49 3.87 4.37
Actual Sample Size	30		Finite Sample: n = 30	
		10%	2.525	3.56
		5%	3.058	4.223
		1%	4.28	5.84

Estimated long-run coefficients from the ARDL Model. Table 7 presents the estimated long-run coefficients from an ARDL model. This model investigates the long-term relationship between the response variable (LFDS: food security) and the independent variables (LCO2: CO2 emissions, LFII: food import index, LPCI: per capita income, and LPED: particulate emission damage). From the results, the estimated long-run coefficient for CO2 emission is negative and not statistically significant, suggesting that an increase in CO2 emissions is associated with decreased food security in the long run. This result is in tandem with [6, 8, 11], who, in their separate studies, also reported a negative association of carbon emission with cereal yield, food security and agricultural economy growth in Ghana, South Africa and Anglophone countries, respectively. However, our result disagrees with [7], who found a positive and non-significant relationship between CO2 and agricultural production in a related study in South Africa.

Contrary to the results from [36], where food import was shown to have a direct relationship with food security in some Arab countries, the food import index in South Africa has a non-significant inverse relationship with food security, suggesting that an increase in the food import index is associated with a decrease in food security in the long run. Similarly, per capita income has an inverse and statistically insignificant relationship with food security, suggesting that increased per capita income is associated with decreased food security in the long run. This finding negates what [6] reported in a related study where per capita income as an indicator of economic growth was positively and significantly associated with food security. The findings also indicated that particulate emission damage has an inverse and significant relationship with food security. This implies an increase in particulate emission damage is strongly associated with a decrease in food security in the long run, and this relationship is statistically significant at the 1% level, which is in tandem with [13], who shared a similar view in a related study. For the constant term, which is positive and highly significant, this indicates that when all explanatory variables are zero, the expected level of food security is 4.8118.

Concerning the error correction term (EC) as represented by the equation in the second panel of Table 7, this term suggests the speed at which deviations from the long-term equilibrium are corrected in the short run. Among the fitted explanatory variables, only LPED has a statistically significant impact on food security in the long run, suggesting that only the impact of particulate emission damage is supported by strong statistical evidence, which reinforces the need to intensify efforts to improve food production by prioritising the reduction of particulate emission damage, given its significant negative impact. This further emphasises the importance of addressing environmental pollution to enhance food security in the country.

Table 7 – Estimated ARDL Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCO2	-0.1866	0.2063	-0.90	0.3792
LFII	-0.0669	0.0696	-0.96	0.3508
LPCI	-0.0148	0.0784	-0.18	0.8522
LPED	-0.5553	0.0660	-8.41***	0.0000
C	4.8118	0.5230	9.19***	0.0000
EC = LFDS – (-0.1866*LCO2 – 0.0669*LFII – 0.0149*LPCI – 0.5553*LPED + 4.8119				

Notes: *** significant at 1% probability level

Autoregressive Distributed Lag Model's Short-run Error Correction Regression. Table 8 presents the results of the Autoregressive Distributed Lag (ARDL) model's short-run error correction regression estimates. The essence is understanding the short-term dynamics and how quickly the food security can return to equilibrium after a shock. Given the estimates in the first panel of Table 8, a short-term increase in CO2 emissions does not lead to food security growth, as expected, and the relationship is statistically significant at a 10% level. This result completely agrees with [11], but it contrasts with the submission of [8]. Also, in agreement with [7], the previous period's change in CO2 emissions has a significant (5% level) positive impact on food security growth. For the food import index a short-term increase in the food import index is not associated with food security growth, and the relationship is also statistically significant at a 1% level.

In comparison, the previous period's change in the food import index directly and significantly impacted food security growth at a 1% level. Meanwhile, the two-period lagged change in the food import index has a positive and significant impact on food security at a 5% level. This finding agrees with [36] on some of the results reported in a related study. The estimate of particulate emission damage also indicated that a short-term increase in particulate emission damage is associated with a significant (1% level) food security growth. In contrast, the previous period's change in particulate emission damage is not statistically significant. Likewise, the two-period lagged change in particulate emission damage has a positive and significant (1% level) impact on food security growth. These findings align with what [12] and [13] reported in their separate studies. Then, the EC term is negative and highly significant at the 1% level, suggesting a strong speed of adjustment back to the long-term equilibrium after a short-term shock. More specifically, approximately 95% of the deviation from the long-term equilibrium is corrected within one period, which is a good sign. The model's diagnostics in the second panel of Table 8 also revealed an R-squared value of 0.8461, which implies that the model explains a substantial portion (84.61%) of the variation in the dependent variable (LFDS: food security) while adjusting for the number of predictors (Adjusted R-squared). Then, a relatively low standard error of the regression indicates a good fit of the model to the data. At the same time, the estimated Durbin-Watson statistic value of 1.8044 suggests that this statistic is close to 2 and that there is no significant autocorrelation in the residuals.

Therefore, the short-run relationships indicate that changes in CO2 emissions, food import index, and particulate emission damage significantly impact food security. Specifically, these variables' past changes (lagged values) have significant effects. The EC term strongly adjusted to the long-term equilibrium, suggesting that food security responds quickly to deviations from its long-term trend.

Table 8 – ARDL Short Error Correction Regression Estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ΔLCO2	-0.2338	0.1214	-1.92	0.0720*
ΔLCO2(-1))	0.3153	0.1291	2.44	0.0266**
ΔLFII	-0.1702	0.0528	-3.21	0.0054***
ΔLFII(-1)	0.2126	0.0497	4.27	0.0006***
ΔLFII(-2)	0.1082	0.0468	2.31	0.0343**
ΔLPED	0.4097	0.1623	2.52	0.0226***
ΔLPED(-1)	-0.0904	0.2471	-0.36	0.7192
ΔLPED(-2)	0.7085	0.1663	4.25	0.0006***
ECM(-1)	-0.9490	0.1322	-7.17	0.0000***
R^2	0.8461	Mean dependent variable		0.024103
Adjusted R^2	0.7875	S.D. dependent variable		0.062696
S.E. of regression	0.0288	Akaike Information criterion		-4.006700
Sum squared residual	0.0175	Schwarz criterion		-3.586341
Log-likelihood	69.1005	Hannan-Quinn criterion		-3.872223
Durbin-Watson statistic	1.8044			

Notes: *** sig at 1% probability level; ** sig at 5% probability level; * p-value incompatible with t-bounds distribution.

Diagnostic Tests. Jarque-Bera normality test: Figure 1 presents the results of the Jarque-Bera normality test applied to the residuals of the fitted regression model, along with a histogram of the residuals. The p-value is 0.692411, which is much higher than common probability levels (p<0.01, p<0.05, p<0.10). This indicates that the study fails to reject the null hypothesis that the residuals are normally distributed. Then, the histogram appears to be symmetric with a central peak around zero, and with this visual assessment, one can infer that the residuals are approximately normally distributed. This is to say that the histogram, skewness, kurtosis, and Jarque-Bera tests suggest that the regression model residuals are approximately normally distributed. Then, the high p-value from the Jarque-Bera test also supports this conclusion.

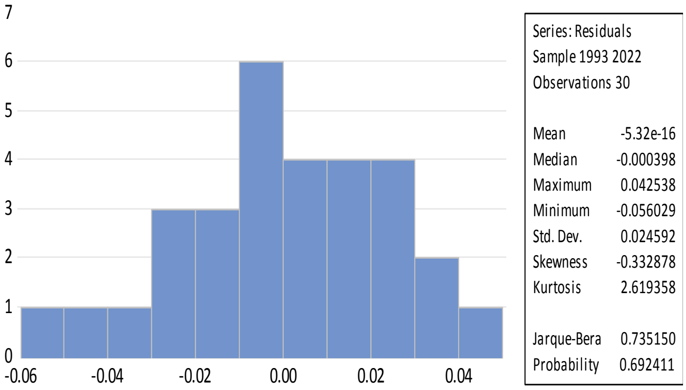

Figure 1 – Jarque Bera Normality Test

Diagnostic Tests. Bresusch-Godfrey (Lagrangian Multiplier- LM test): The Bresusch-Godfrey (Lagrange Multiplier) test for higher order serial correlation was used to check and detect the presence of serial correlation in the residuals of the fitted regression model, at up to 2 lags. The null hypothesis is that there is no serial correlation, and from the results in Table 9, there are higher p-values of F-statistic, which is 0.7610, and Chi-Square statistic, which is 0.5633, compared to the common significance levels ($p<0.01$, $p<0.05$, $p<0.10$). All these suggest that the model does not suffer from higher-order serial correlation as there is no significant evidence of such in the residuals of the fitted regression model. Hence, the study accepts the null hypothesis of no serial correlation at up to 2 lags. The absence of serial correlation implies that the model's residuals are independent, which is a desirable property, and this also enhances the reliability of the model's estimates and inferences.

Table 9 – Bresusch-Godfrey (Langrangean Multiplier Test) for Higher Order Serial Correlation (Ho: No serial correlation at up to 2 lags)

F-statistics	0.278509	Prob. $F(2, 14)$	0.7610
Obs*R^2	1.147937	Prob. Chi^2 (2)	0.5633

Diagnostic Tests. Autoregressive Conditional Heteroskedasticity (ARCH) test: The ARCH test detects the presence of heteroskedasticity, specifically conditional heteroskedasticity, in the residuals of a regression model. Conditional heteroskedasticity occurs when the variance of the residuals is dependent on past values. Given the results, the high p-values for both the F-statistic (0.6075) and the Chi-Square statistic (0.5920) suggest that there is no significant evidence of conditional heteroskedasticity in the residuals of the fitted regression model and that the model's residuals are homoskedastic. As a result, the study fails to reject the null hypothesis of no ARCH effect. Therefore, the absence of an ARCH effect indicates that the variance of the residuals is constant over time, which is also a desirable property, and this enhances the reliability of the model's standard errors and inferences.

Table 10 – Autoregressive Conditional Heteroskedasticity Test (Heteroskedastic Test: ARCH)

F-statistics	0.270053	Prob. $F(1, 27)$	0.6075
Obs*R^2	0.287184	Prob. Chi^2 (1)	0.5920

Cumulative Sum and Cumulative Sum of Squares test of model stability. Figure 2 presents the Cumulative Sum (CUSUM) model stability test, which assessed the stability of fitted regression coefficients over time. The test includes a plot of the CUSUM statistic against time and critical boundaries at a 5% significance level.

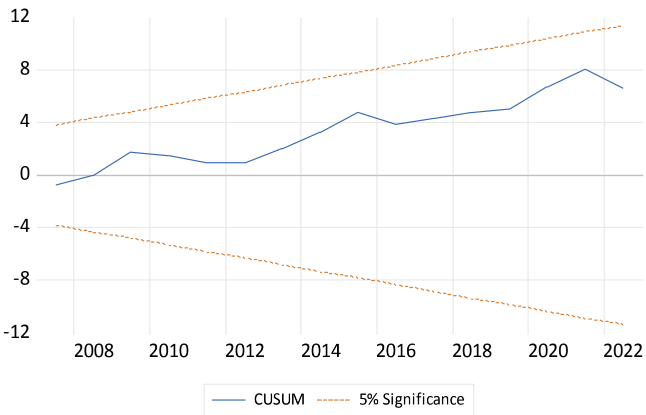

Figure 2 – CUSUM Test of Model Stability

The CUSUM blue line represents the cumulative sum of recursive residuals, which provides a visual indication of whether there have been any structural changes in the model parameters over time. On the other hand, the dashed orange lines represent the critical boundaries at a 5% significance level. The caveat is that the model parameters are stable over time if the CUSUM line stays within these boundaries. Still, if the CUSUM line crosses these boundaries, it suggests structural instability. Given the results, The CUSUM line remains within the 5% significance boundaries from 2009 to 2022. Hence, the study fails to reject the null hypothesis of parameter stability, suggesting that the regression model's coefficients are stable over time and no significant structural breaks exist. Therefore, the model's predictions and inferences are reliable, and the parameters have remained consistent over a certain period. Likewise, Figure 3 presents the Cumulative Sum of Squares (CUSUM of Squares) model stability test, which was used to assess the stability of the variance of the residuals in a regression model over time.

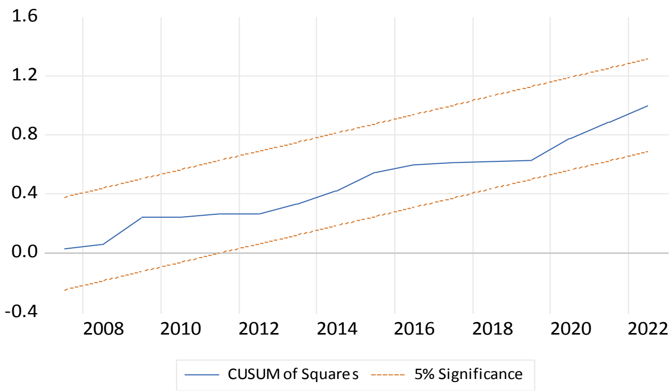

Figure 3 – CUSUM Square Test of Model Stability

Since the CUSUM of Squares line does not cross the critical boundaries, the study fails to reject the null hypothesis of variance stability. This implies that the model does not exhibit significant changes in the residual variance, and no major structural breaks affect the model's variance. The stability in the variance of residuals enhances the reliability of the model's predictions and inferences, confirming that the model remains consistent over time.

The research shed light on the multidimensional issue of food security in South Africa, emphasising the interplay between environmental factors, such as CO_2 emissions and particulate pollution, and economic conditions, represented by per capita income and the food import index. The study's results underlined the complex interdependencies between these variables and their collective impact on the nation's ability to ensure food security, particularly in climate change and economic vulnerability. The study's findings underscored environmental factors' significant role in food security, particularly climate change and air quality. One of the key findings relates to CO_2 emissions, which, while not statistically significant, showed a negative coefficient to food security. This implies that the increase in CO_2 emissions detrimentally impacts agricultural output and food availability. Rising CO_2 levels are a clear marker of climate change, which has long been associated with reduced agricultural productivity through increased temperatures, altered precipitation patterns, and more frequent extreme weather events such as droughts and floods. These changes disrupt the agricultural calendar, reduce crop yields, and impair the ability of South Africa's agricultural sector to meet the demands of a growing population.

Moreover, particulate emissions were found to have a substantial and statistically significant negative effect on food security, indicating the tangible and immediate harm caused by deteriorating air quality. The health impact of particulate pollution cannot be ignored either, as it affects the labour force's productivity, particularly in rural areas where agricultural activity is the primary source of employment. Poor air quality may also damage crops directly, either by impairing their growth or by making the land less arable over time due to the deposition of harmful substances. This underscores the urgent need for South Africa to address not just CO_2 emissions as part of a broader climate change strategy but also particulate matter pollution, which is primarily linked to industrial and transportation activities. These findings align with global research showing that environmental degradation, especially in the form of pollution, directly harms food security by disrupting both agricultural systems and the communities dependent on them.

Economic variables also played a critical role in shaping food security outcomes, with per capita income and the food import index (FII) being two of the primary indicators explored in this study. Interestingly, the coefficient for per capita income was negative, though statistically insignificant, suggesting that, while crucial, economic growth does not necessarily equate to improved food security. This highlights a broader structural issue within the South African economy: income inequality and unemployment. South Africa has one of the highest levels of income inequality in the world, which means that the benefits of economic growth are unevenly distributed. As a result, while per capita income may increase, it does not always translate into better access to food for most of the population, particularly those in impoverished and rural areas. Additionally, a reliance on market mechanisms alone to address food insecurity may not be sufficient, as higher incomes may lead to increased food prices if domestic supply does not keep pace with demand.

The food import index (FII) also displayed an insignificant negative coefficient, pointing to the vulnerability inherent in relying on food imports to meet domestic demand. While imports can fill short-term supply gaps, over-reliance on external food sources exposes South Africa to global market volatility, price shocks, and supply chain disruptions. Such vulnerabilities were highlighted during the COVID-19 pandemic, which saw disruptions in global trade and heightened food insecurity for many nations. South Africa's dependency on imported food could become increasingly problematic as climate change affects global agricultural production, leading to tighter food supplies and higher prices internationally. These findings emphasise the need for South Africa to strengthen its domestic agricultural sector to reduce dependency on imports and enhance self-sufficiency in food production.

This study's Autoregressive Distributed Lag (ARDL) model provided a critical outlook into the short- and long-term dynamics between environmental and economic variables and food security. The negative and statistically significant error correction term indicates a strong adjustment mechanism, suggesting that deviations from the long-term equilibrium are corrected rapidly. This means that while short-term shocks, such as sudden changes in CO2 emissions, food imports, or particulate pollution, may disrupt food security, there is a strong tendency for the system to revert to a long-term equilibrium. This finding is particularly important for policymaking, as it underscores the need for timely interventions to address short-term food security disruptions while focusing on long-term sustainability. In the short run, the significant coefficients for ΔLCO2 (changes in CO2 emissions), ΔLFII (changes in the food import index), and ΔLPED (changes in particulate emissions) in both current and lagged forms indicate that these variables have both immediate and delayed effects on food security. This suggests that fluctuations in environmental conditions and economic factors like food imports can have lingering impacts on food security beyond their initial occurrence. For instance, a sudden increase in CO2 emissions or particulate pollution may reduce agricultural productivity in the current season and affect future growing seasons by degrading soil quality or disrupting long-term planning in the agricultural sector. Similarly, short-term increases in food imports may ease food insecurity temporarily, but over-reliance on imports can exacerbate vulnerabilities in the long run. The results of this study highlight the urgent need for integrated policies that address both environmental sustainability and economic resilience to enhance food security in South Africa. Climate change mitigation measures should be prioritised, focusing on reducing CO2 and particulate emissions, improving air quality, and enhancing the resilience of agricultural systems to environmental shocks. At the same time, economic policies must be designed to reduce inequality, promote equitable access to food, and support domestic food production to reduce reliance on imports.

In conclusion, while both environmental and economic factors significantly impact food security in South Africa, the findings indicate that neither factor alone can fully address the challenges of food insecurity. The interplay between these variables and effective policy interventions will ultimately determine the country's ability to achieve sustainable food security. The significant short-run dynamics uncovered by the ARDL model further emphasise the need for immediate action to address environmental degradation and economic vulnerabilities while preparing for the long-term challenges posed by climate change and global economic shifts.

CONCLUSIONS

This study focussed on South Africa's food security by elucidating the interplay between environmental and economic factors. The findings underscore that climate change, evidenced by rising CO2 emissions and particulate pollution, has a detrimental effect on agricultural output and food availability, exacerbating food insecurity. Simultaneously, economic conditions, represented by per capita income and the food import index, also play a critical role. Higher per capita income correlates with better access to food, while reliance on food imports highlights vulnerabilities in the domestic food supply chain. These results emphasised the urgent need for integrated policies that address environmental sustainability and economic resilience to enhance food security in South Africa. Findings on the long-term impact of climate change and economic variables on food security revealed that CO2 emissions and the food import index have negative coefficients, suggesting a detrimental effect on food security. However, these results are not statistically significant. Per capita income also shows a negative but insignificant coefficient, indicating that economic growth alone does not guarantee food security.

In contrast, particulate emission damage has a significant negative effect, indicating that air quality deterioration significantly hampers food security. In addition, the ARDL model's short-run error correction regression estimates further reinforce the impact of environmental and economic factors on food security in South Africa. The negative and statistically significant coefficient of the error correction term (ECM) at -0.9490 indicates a strong adjustment mechanism towards long-term equilibrium, highlighting the importance of short-run dynamics in influencing food security. The significant coefficients for ΔLCO2, ΔLFII, and ΔLPED in current and lagged forms suggest that fluctuations in these variables have immediate and lagged effects on food security.

Given the findings highlighted, appropriate policy actions are important to build a more resilient food system in South Africa capable of withstanding the challenges posed by climate change and economic fluctuations. First, stringent regulations must be implemented to control CO2 emissions and particulate matter pollution, focusing on reducing short-term environmental damages that directly impact food security. Likewise, the promotion of clean energy projects and sustainable agricultural practices to mitigate the adverse effects of environmental degradation. In addition, reducing reliance on food imports will enhance domestic agricultural production capabilities. This can be achieved by reducing the dependency on imports by boosting local agricultural production and investments in infrastructure, technology, and training for farmers. Also, implementing economic policies that promote inclusive growth should be prioritised by ensuring that increases in per capita income translate into improved access to food for all socioeconomic groups. This could be achieved by providing adequate support to smallholder farmers and agribusinesses to enhance productivity and market access. While the provision of targeted subsidies or support to vulnerable populations can serve as buffers against the negative impacts of environmental changes and economic fluctuations, it is important for the government to raise awareness of the impacts of climate change on food security and the promotion of sustainable consumption patterns need to be prioritised.

Ethical Statement

The dataset used in this research was sourced from the World Development Indicators database of the World Bank. The dataset aligned with global research ethics and [37] 's Helsinki Declaration on a research protocol. The study also observed the University of Fort Hare Research Ethics Committee (UREC) 's protocol on research: "anonymity, informed consent, privacy, confidentiality, as well as professionalism". In addition, this research obtained ethical clearance with the number REC-270710-028-RA Level 01, with project number SEY001-22 (Project).

Conflict of Interest

The authors declared no conflict of interest.

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