3V Scientific Publishing House
Trends in Ecological and Indoor Environmental Engineering

Mohammad Anwar et al. *TEIEE 2(1) 2024*

RESEARCH ARTICLE
https://dx.doi.org/10.62622/TEIEE.024.2.1.01-10

OPEN ACCESS
ISSN 2956-9761

ANALYSING THE RELATIONSHIP BETWEEN ENERGY USE FOR ECONOMIC DEVELOPMENT AND CO_2 EMISSIONS, CROP, AND LIVESTOCK PRODUCTION IN PAKISTAN BY USING THE EXTENDED STIRPAT MODEL

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Received: 31.01.2024; ***Accepted:*** 17.02.2024; ***Available online:*** 03.03.2024 ***Published:*** 30.03.2024

Cite this article: Anwar, M., Khan, T., Mureed, F., Ali, Z., Alam, F., & Ullah, W. (2024). Analysing the Relationship Between Energy Use for Economic Development and CO_2 Emissions, Crop, and Livestock Production in Pakistan by Using the Extended STIRPAT Model. *Trends in Ecological and Indoor Environment Engineering*, 2(1), 1–10.

Contemporary human-made activities are responsible for the emission of more than 30 billion tons of carbon dioxide (CO_2), a greenhouse gas, into the atmosphere. The current study's primary purpose is to examine the key elements that contribute to the elevated levels of the release of CO_2 into the environment in Pakistan. The research used Pakistan's annual data spanning from 1970 to 2020, along with the STIRPAT (Stochastic Impact by Regression on Population, Affluence, and Technology) model. The relationship between the emission of CO_2 into the atmosphere and other chosen factors is examined using the ARDL (Auto Regressive Distributive Lag) model and the ECM (Error Correction Model). These models help to establish the credibility of the acquired findings. The paired Granger causality analysis revealed the presence of unidirectional and bidirectional cause-and-effect relationships between the named variable parameters in the activity under investigation. Pakistan must prioritize tackling the fundamental challenges afflicting its farming industry, particularly those pertaining to the efficiency of its livestock and crop production. The novelty of this study comes in its investigation of the interaction between hitherto undiscovered macro-level properties and the emission of CO_2 into the environment of Pakistan. The findings may assist policymakers in formulating an environmental and agricultural strategy aimed at promoting the use of sophisticated low-carbon technology.

Keywords: carbon dioxide emissions; livestock production index; agricultural land; STIRPAT model; ARDL model.

INTRODUCTION

Changing of the climate is a substantial challenge for mankind in the 21st century, since it constitutes a worldwide environmental issue (Wang et al., 2017). The primary drivers of global climate change are elevated greenhouse gas levels (GHG levels) in the atmosphere, particularly carbon dioxide emissions resulting from the use of fossil fuels for energy, population growth, the agricultural sector, and greater economic development (Iwata & Okada, 2014). Contemporary anthropogenic activity leads to the emission of more than 30 billion tons of carbon dioxide (CO_2), GHG, into the atmosphere. The use of fossil fuels and natural resources has resulted in a substantial increase in the GHG release, necessitating global recognition and action. While the Earth's temperature has undergone a permanent change, it is primarily human activities that have been the primary drivers of the rise in CO_2 releases, especially in the last century (Bakır et al., 2022; Lott et al., 2017; Zhang et al., 2022). The alteration in land use, along with the combustion of fossil fuels, ranks as the second most significant factor contributing to the escalation of greenhouse gas emissions. Unsustainable land use leads to a rise in GHG release in the atmosphere (Yang et al., 2019).

Land use activities of various human origins contribute to the emission of carbon into the environment. Researchers conducted a comprehensive investigation of the underlying mechanics of these processes, investing a great amount of time and effort. Additional investigation is required in the domain of variable factors, which impact the rates at which carbon is released into the environment via land exploitation. The aim is to decrease these emission rates by implementing suitable interventions. Recent studies have primarily employed the land-use carbon pathway to examine the factors influencing carbon inputs resulting from urban land expansion and the conversion of agricultural land (Salam et al., 2023). These studies have also investigated the patterns of carbon emissions associated with urbanization, quantified the amount of carbon emissions generated through land use (Zhu et al., 2019), and explored the interplay between energy consumption, land utilization, and the release of carbon into the environment (Wang et al., 2017).

The agricultural sector has been shown to be very vulnerable to the impacts of global warming, particularly in terms of changes in crop yields and productivity. Numerous studies have examined these changes over the last thirty years. By the mid-20th century, the agricultural sector maintained its agricultural production to meet the needs of the growing population. The agricultural sector's escalating input utilization resulted in a rise in carbon emissions. Previous studies suggest that future food scarcity may arise as a result of the projected adverse effects of climate change on the worldwide agricultural supply chain. The references used are Attavanich and McCarl (2014) and Brown et al. (2017).

The energy industry in Pakistan accounts for 73.2% of GHG emissions, with forestry, agriculture, and land use directly contributing 18.4%. Pakistan's intended nationally determined contribution (INDC) indicates that the country had a significant increase of 123% in its greenhouse gas emissions from 1994 to 2015. Pakistan's carbon dioxide emissions are very low, amounting to about 0.2 million metric tons. However, the country is severely affected by the consequences of global warming. Pakistan has failed to effectively tackle this problem (Salam et al., 2021; Salam et al., 2022; Salam et al., 2023).

Hence, the fundamental current study purpose is to examine the key elements that lead to Pakistan's substantial carbon emissions. The application of the STIRPAT (Stochastic Impact by Regression on Population, Affluence, and Technology) ecology model is based on 50 years of time series data from 1970 to 2020. Moreover, it is crucial to take into account the many factors of the economy that might potentially promote degradation of environmental components, both in the short term and in the long term. The present study used an autoregressive distributive lag (ARDL) model to examine the impact of economic factors on CO release. The primary significance of the present research resides in three main positions:

1) The present research investigates the correlation between hitherto unexamined macro-level attributes and the emission of CO_2 into the environment of Pakistan;

2) The relationship between the emission of CO_2 into the environment and other chosen factors is examined using the autoregressive distributed lag ARDL model;

3) The results might assist policymakers in formulating an environmental and agricultural strategy to enhance modern crop production techniques and reduce CO_2 release in order to maintain an appropriate degree of environmental safety.

This study suggests rearranging agricultural production methods to favour more environment-friendly or eco-friendly measures procedures.

The research methodology comprises multiple stages: firstly, the presentation and description of illustrations for the materials and methods section, which includes defining the model and explaining the origin of the data; secondly, evaluating previous studies that demonstrate correlations between selected variables; and finally, providing a comprehensive presentation of results and commentary that encompasses unit root measurements, ARDL-based tests, descriptive analyses, as well as long-term and short-term estimates.

MATERIALS AND METHODS

Data description

This analysis uses Pakistan's yearly time series data covering the years 1970 through 2020. We selected a time span and restricted the variables available for the research, since getting the data was the primary obstacle. In order to fulfil the study's aims, the data sets for the selected variables were sourced from the Food and Agriculture Organization Corporate Statistical Database (www.fao.org) and World Development Indicators (http://data.worldbank.org).

Table 1. Data explanation and resources

Parameters	Designation	Name of dimension	Source
Carbon dioxide release	CO_2	tons · 10^3	www.fao.org
Agriculture land	AL	km^2	http://data.worldbank.org
Agricultural value-added	AVA	% of GDP	http://data.worldbank.org
Crop production index	CPI	(2004 – 200 = 100)	http://data.worldbank.org
Energy consumption	EC	kg*	http://data.worldbank.org
Gross domestic product	GDP	current US $	http://data.worldbank.org
Index of livestock production	LPI	(2004 – 200 = 100)	http://data.worldbank.org
Fields sown with grain crops	LCC	hectares	http://data.worldbank.org
Population	POP	total	http://data.worldbank.org

*kg of oil equivalent per capita

The model's technical attributes

The STIRPAT Model

Ehrlich & Holdren (1971) propose the IPAT model (I = PAT) as a means of measuring the impact of technogenic activities on the environment. According to IPAT, the three primary determinants of environmental effects are population, affluence, and technology. The limitation of the IPAT model is that it can only assess the effect of changing one element while assuming that the other variables remain unchanged. Scientists have proposed the stochastic regression model (STIRPAT) in studies (York et al., 2003a; York et al., 2003b).

$$I = a \cdot P^b \cdot A^c \cdot T^d \cdot \varepsilon, \qquad (1)$$

where I is a quantity that represents the environmental influence; a is the coefficient of the model; P is a number that represents population size; ε is stands for the mistake in this case; A is the number that determines wealth; b, c and d are the driving force exponentials' coefficients; T is the parameter that is in charge of the technology.

Following logarithmic calculations, the model is converted to:

$$LnI = Lna + b \cdot LnP + c \cdot LnA + d \cdot LnT + Ln\varepsilon, \qquad (2)$$

where the values b, c and d show how the dependent and independent variables' elasticity connections change. A change in environmental exposure b, c or d corresponds appropriately to every 1% change in P, A or T.

Model extension and variables

The STIRPAT model may be expanded to include variable parameters for cattle production index, population for carbon dioxide emissions, crop production index, energy consumption, GDP, acreage for producing grain crops, and agricultural land value-added.

$$\begin{aligned} LnCO_{2t} = {} & \gamma_0 + \gamma_1 \cdot LnAL_{t-i} + \gamma_2 \cdot LnAVA_{t-i} + \gamma_3 \cdot LnCPI_{t-i} + \\ & + \gamma_3 \cdot LnCPI_{t-i} + \gamma_4 \cdot LnEC_{t-i} + \gamma_5 \cdot LnGDP_{t-i} + \\ & + \gamma_6 \cdot LnLCC_{t-i} + \gamma_7 \cdot LnLPI_{t-i} + \gamma_8 \cdot LnPOP_{t-i} + \varepsilon_t. \end{aligned} \qquad (3)$$

For variables that are stable at a level I(0), some at a first difference I(1), and a mixture of both at level I(0) and first difference I(1), this study employed the autoregressive distributed lag (ARDL) bound technique (Pesaran et al., 2001). In the context of time-series data, a deceptive regression might occur. Researchers developed and used the co-integration technique to determine the long-term association of time series variables in order to prevent spurious regression (Nkoro & Uko, 2016). The prerequisites for co-integrated series are as follows. This study evaluated the long-term correlations between the simulated variables using the ARDL technique. Every variable quantity underwent conversion to its logged form (Ln):

$$CO_2 = f\,(AL, AVA, CPI, EC, GDP, LCC, LPI, POP), \tag{4}$$

$$\begin{aligned} LnCO_{2t} = {} & \gamma_0 + \gamma_1 \textstyle\sum_{i=1}^{k} \Delta LnAL_{t-i} + \gamma_2 \sum_{i=1}^{k} \Delta LnAVA_{t-i} + \gamma_3 \sum_{i=1}^{k} \Delta LnCPI_{t-i} + \gamma_4 \sum_{i=1}^{k} \Delta LnEC_{t-i} + \gamma_5 \sum_{i=1}^{k} \Delta LnGDP_{t-i} + \\ & + \gamma_6 \textstyle\sum_{i=1}^{k} \Delta LnLCC_{t-i} + \gamma_7 \sum_{i=1}^{k} \Delta LnLPI_{t-i} + \gamma_8 \sum_{i=1}^{k} \Delta LnPOP_{t-i} + \varphi_1 \sum_{i=1}^{k} \Delta LnAL_{t-i} + \varphi_2 \sum_{i=1}^{k} \Delta LnAVA_{t-i} + \\ & + \varphi_3 \textstyle\sum_{i=1}^{k} \Delta LnCPI_{t-i} + + \varphi_4 \sum_{i=1}^{k} \Delta LnEC_{t-i} + \varphi_5 \sum_{i=1}^{k} \Delta LnGDP_{t-i} + \varphi_6 \sum_{i=1}^{k} \Delta LnLLC_{t-i} + \varphi_7 \sum_{i=1}^{k} \Delta LnLPI_{t-i} + \\ & + \varphi_8 \textstyle\sum_{i=1}^{k} \Delta LnPOP_{t-i} + \varepsilon_t, \end{aligned} \tag{5}$$

where Δ is the first-difference operator; $\gamma_0, \ldots, \gamma_8$ are the short-term dependence coefficients; $\varphi_1, \ldots, \varphi_8$ are elasticity coefficient; ε_t is remaining term.

After verifying the long-term relationship between the parameters to examine the short-term dependence, an error correction model (ECM) should be constructed using ARDL methods:

$$\begin{aligned} \Delta LnCO_{2_t} = {} & \gamma_0 + \gamma_1 \textstyle\sum_{i=1}^{k} \Delta LnAL_{t-i} + \gamma_2 \sum_{i=1}^{k} \Delta LnAVA_{t-i} + \gamma_3 \sum_{i=1}^{k} \Delta LnCPI_{t-i} + \gamma_4 \sum_{i=1}^{k} \Delta LnEC_{t-i} + \gamma_5 \sum_{i=1}^{k} \Delta LnGDP_{t-i} + \\ & + \gamma_6 \textstyle\sum_{i=1}^{k} \Delta LnLCC_{t-i} + \gamma_7 \sum_{i=1}^{k} \Delta LnLPI_{t-i} + \gamma_8 \sum_{i=1}^{k} \Delta LnPOP_{t-i} + \varphi\, ECM + \varepsilon_t \end{aligned} \tag{6}$$

RESULTS AND DISCUSSION

Descriptive statistics

Table 2 demonstrates that the variables $LnCO_2$, LnCPI, LnEC, LnGDP, LnLCC, LnLPI, and LnPOP have negative leftward tails, but variables like LnAL and LnAVA have positive rightward tails. The researchers use the Jarque-Bera (J-B) test to evaluate the normalcy. In the J-B test, the null hypothesis is that the data follows a normal distribution, whereas the alternative hypothesis is that the data does not follow a normal distribution. The residuals of all the variables exhibit normality, as shown by the J-B test, which reveals very insignificant results at a 5% significance level. Kurtosis may be categorized into three distinct states:

– mesokurtic – this is the natural dispersion when the kurtosis value is equal to three;

– leptokurtic – this is an arc with a peak when the positive kurtosis value is greater than three,

– platykurtic – this is an arc with a flattened value when the negative kurtosis value is less than three.

Table 2 shows that only LnAL has a kurtosis value larger than three, making it leptokurtic, while LnAVA is roughly mesokurtic with a kurtosis value almost equal to three. With a kurtosis value of less than three, the remaining research variables are all platykurtic.

Correlation analysis

The results in Table 3 indicate that CO_2 emissions have a positive and strong correlation with various variables. Specifically, CO_2 release are highly correlated with the crop production index (CPI) at 99.43%, energy consumption (EC) at 97.80%, gross domestic product (GDP) at 97.34%, livestock production index (LPI) at 98.57%, land under cereal crop (LCC) at 97.34%, and population (POP) at 99.65%. Simultaneously, the variable of agricultural value added (AVA) has a negative correlation. There is no association seen in agricultural land (AL).

Figure 1 illustrates the predictive analysis showing that, in Pakistan, all research variables, except for the values of variables related to farmland exploitation and added value of agriculture, exhibit an upward trend between 1970 and 2020.

Table 2. Variables and their respective meanings for the study of descriptive statistics

Parameter	LnAL	LnAVA	$LnCO_2$	LnCPI	LnEC	LnGDP	LnLCC	LnLPI	LnPOP
Mean	12.8003	3.2147	11.1559	4.1305	5.9256	24.8308	16.2942	3.7581	18.6665
Median	12.7990	3.1689	11.3417	4.2345	5.9983	24.8408	16.3135	3.8475	18.7220
Maximum	12.8612	3.5095	12.1998	4.7605	6.1347	26.5982	16.5036	4.8413	19.2597
Minimum	12.7716	3.0291	9.8213	3.3911	5.6342	22.5770	16.0336	2.7298	17.8980
SD	0.0183	0.1239	0.7557	0.4166	0.1609	1.1346	0.1239	0.6491	0.4260
Skewness	0.6531	0.9439	-0.3446	-0.3655	-0.5559	-0.0951	-0.4559	-0.0071	-0.3050
Kurtosis	3.8370	2.8544	1.7655	1.8166	1.7841	2.0083	2.2953	1.7922	1.7825
Jarque-Bera	5.2146	7.7676	4.3307	4.1919	5.8815	2.2094	2.8773	3.1610	4.0178
Probability	0.0737	0.0606	0.1147	0.1230	0.0528	0.3313	0.2373	0.2059	0.1341
Sum	665.612	167.166	580.108	214.785	308.129	1291.201	847.299	195.421	970.657
Obs	52	52	52	52	52	52	52	52	52

Table 3. Correlation analysis

Parameter	$LnCO_2$	LnCPI	LnEC	LnGDP	LnLCC	LnLPI	LnPOP	LnAL	LnAVA
$LnCO_2$									
LnCPI	0.9943								
LnEC	0.9780	0.9755							
LnGDP	0.9798	0.9768	0.9313						
LnLCC	0.9734	0.9789	0.9501	0.9729					
LnLPI	0.9857	0.9829	0.9432	0.9840	0.9650				
LnPOP	0.9965	0.9948	0.9721	0.9843	0.9753	0.9894			
LnAL	0.0667	0.0445	-0.0041	0.0984	0.0941	0.0618	0.0678		
LnAVA	-0.8736	-0.8630	-0.8854	-0.8396	-0.8712	-0.8286	-0.8621	-0.0009	

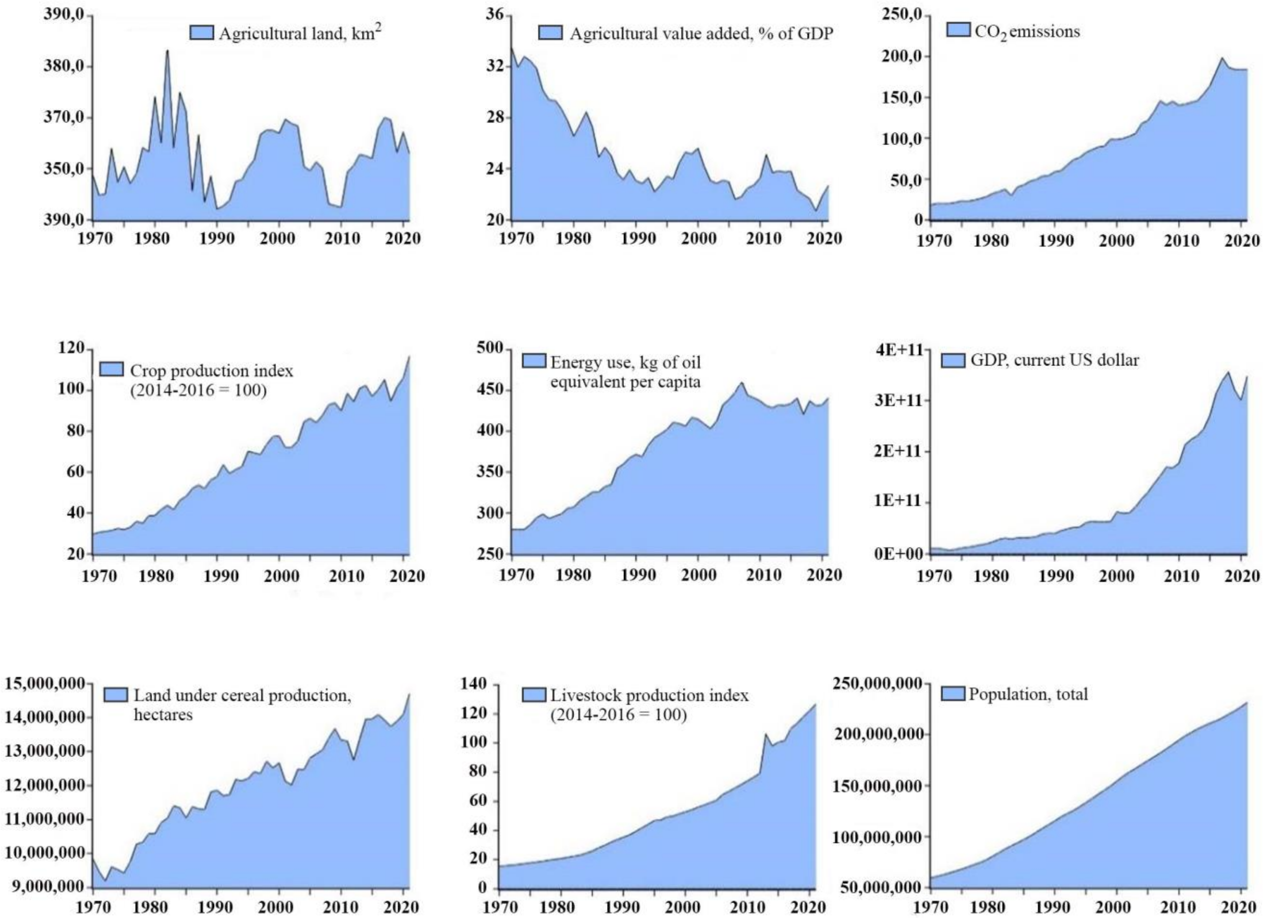

Figure 1. Displays the dataset trends for each variable, shown on separate plots

Results of the module root test

Table 3 presents the statistical analysis of the relationships between different parameters. From the analysis, a significant positive correlation can be seen between carbon dioxide emissions and the following factors: crop production index (CPI), energy consumption (EC), gross domestic product (GDP), livestock production index (LPI), land for growing grain crops (LCC), and population (POP). Conversely, the agricultural value added (AVA) variable has a negative association with ages (at%) of 99.43, 97.80, 97.34, 98.57, 97.34, and 99.65, respectively. There is no association seen in agricultural land (AL). In addition, the trend analysis, shown in Figure 1, indicates that all required parameters, except for areas designated for agricultural uses and added value of agriculture, demonstrate a consistent upward trend over the 50 years studied in Pakistan from 1970 to 2020 (Table 4).

Autoregressive distributed lag (ARDL) testing method

After doing the unit root test, the subsequent step should include the application of the ARDL bounds testing technique. This approach is used to ascertain the co-integration of variables prior to establishing their long-term and short-term relationships. The ARDL bounds testing technique relies on the AIC and SIC criteria, which are chosen for their favourable specifications. The calculated F-statistical value is shown in Table 5, with a value of 38.0988 at a significance level of 5%. The result surpasses both the lower and upper bounds, indicating that the ARDL model is suitable for this scenario. The data indicate the recognition of the alternative hypothesis, while denying the null hypothesis, which suggests the absence of it. Thus, the results support the alternative hypothesis by establishing a long-term relationship for all study variables using the ARDL bound test. Figure 2 displays the top 20 lags that are most likely to be achieved in the ARDL model. These lags were selected using the SIC (Schwarz, 1978) method. The research used the Schwarz Information Criterion (SIC) to choose the most suitable model [ARDL (4, 3, 4, 3, 4, 4, 4, 4)] for examining the long-term and short-term equilibrium connection between the variable values.

Lag selection criteria

In order to ascertain the relationship between the variables $LnCO_2$, LnAL, LnAVA, LnCPI, LnEC, LnGDP, LnLPI, LnLCC, and LnPOP, it is crucial to choose the appropriate lag order for these variables while doing the ARDL bound test. The Akaike Information Criterion (AIC) (Akaike, 1974) and the Schwarz Information Criterion (SIC) are two methods that may be used to choose the most suitable lag order. The AIC and SIC lag selection analysis indicated that lag 2 is the optimal choice for our model. Table 6 demonstrates that the ARDL bound test has superior performance when the lag is set to 2, as compared to lags 0 and 1. In addition, the stability vector autoregression (VAR) test graph, proposed by Pesaran (Pesaran & Pesaran, 1997), may also be used to verify the suitable lag length in the VAR methodology.

Figure 3 illustrates the presence of dotted-shaped patterns inside the circle, signifying the dependability and consistency of our suggested model.

Table 4. Unit root test results

Parameter	ADF at level		ADF at 1st difference		PP at level		PP at 1st difference	
	t-statistics	P-value (L)*	t-statistics	P-value (L)*	Adj. t-statistics	P-value (B)**	Adj. t-statistics	P-value (B)**
$LnCO_2$	-0.469493	0.9819 (1)	-9.532800	0.0000 (0)	-0.852571	0.9534 (3)	-10.61113	0.0000 (6)
LnCPI	-2.453074	0.3492 (0)	-6.244916	0.0000 (2)	-2.194469	0.4823 (3)	-22.22974	0.0000 (49)
LnEC	-1.191091	0.9003 (6)	-3.078889	0.0126 (5)	-8.241114	0.0000 (5)	-41.53061	0.0001 (45)
LnGDP	-2.627867	0.2703 (0)	-6.181680	0.0000 (0)	-2.627867	0.2703 (0)	-6.153130	0.0000 (7)
LnLCC	-2.831048	0.1934 (0)	-7.493669	0.0000 (0)	-2.901047	0.1708 (1)	-8.469927	0.0000 (7)
LnLPI	-3.007492	0.1403 (0)	-9.361288	0.0000 (0)	-2.875365	0.1788 (10)	-9.555818	0.0000 (5)
LnPOP	0.385434	0.9986 (2)	-3.783954	0.0259 (1)	1.588120	1.0000 (4)	-2.533819	0.3114 (6)
LnAL	-5.852187	0.0001 (7)	-14.01066	0.0000 (0)	-4.231035	0.0080 (4)	-13.04097	0.0000 (3)
LnAVA	-2.165204	0.4981 (0)	-7.003459	0.0000 (0)	-2.189878	0.4848 (1)	-7.003459	0.0000 (0)

*P-value (Lag); **P-value (Bandwidth)

Table 5. Unit root test results

Statistics	Indicator value	Weight,%	I(0)	I(1)
F-statistic (k)	38.0988 (8)	10	1.85	2.85
		5	2.11	3.15
		2.5	2.33	3.42
		1	2.62	3.77

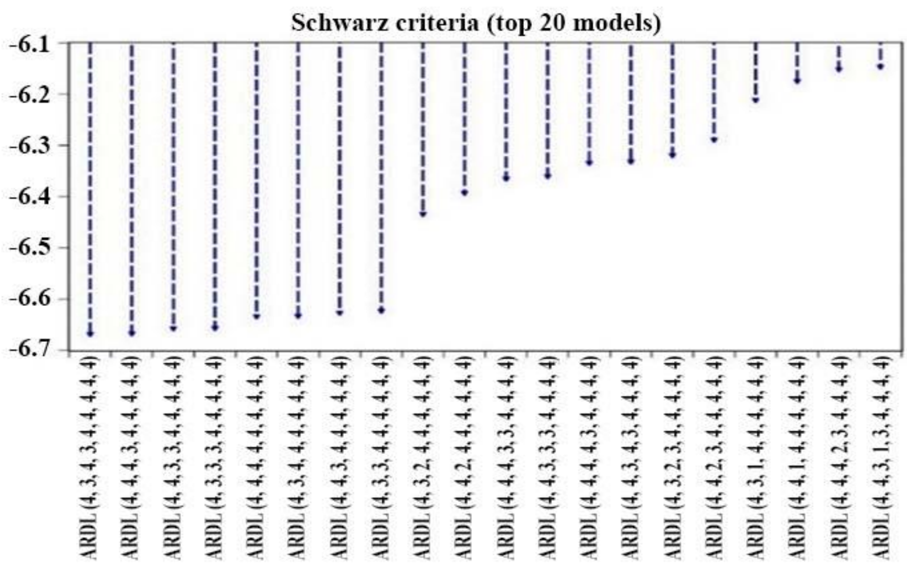

Figure 2. Criterion for selecting an ARDL model

Table 6. Lag selection criteria

Lag	LR**	FPE**	AIC**	SIC**	HQ**
0	NA	4.37E-23	-25.9440	-25.5999	-25.8130
1	673.629	5.69E-29	-39.5448	-36.1031*	-38.2342
2	147.847*	1.68e-29*	-41.0740*	-34.5349	-38.5839*

*The variable's model includes the number of past observations that are chosen based on a certain criteria; **LR – the test statistic for sequential modified likelihood ratio tests, with each test conducted at a significance level of 5%. FPE is for Final Prediction Error, AIC stands for Akaike Information Criterion, SIC stands for Schwarz Information Criterion, and HQ stands for Hannan-Quinn Information Criterion.

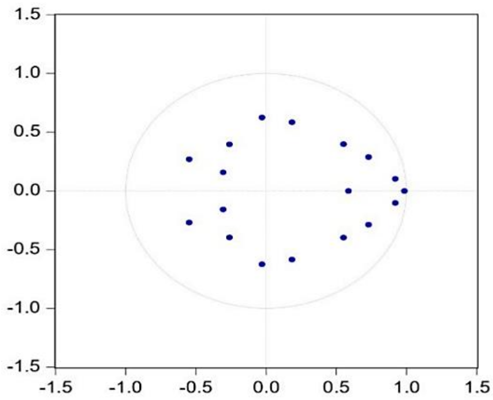

Figure 3. Evidence showcasing the dependability and consistency of the suggested model

ARDL Diagnostic and Stability tests

The independent residuals obtained from the fitted model were thoroughly investigated using various diagnostic and stability approaches to validate and verify the ARDL model. Residuals of a robust ARDL model must exhibit the required independence during diagnostic and stability checks. If this is not the case, the model should be adjusted before conducting further diagnostic and stability tests to confirm its statistical validity. By using this approach, the ARDL model achieves impartiality and resilience in order to derive accurate findings. The ARDL model's diagnostic test is shown in Table 7.

Table 7. Model diagnostic test results

Tests	Value	df	p-value
Heteroskedasticity: Breusch-Pagan-Godfrey			
F-statistic	1.3073	F (8, 42)	0.2499
Breusch-Godfrey Serial Correlation LM Test			
F-statistic	1.5934	F (10, 19)	0.1834
Jarque-Bera Test			
Jarque-Bera	2.5032	Probability	0.2860
Ramsey RESET Test			
F-statistic	1.467805	(1, 28)	0.2358

Table 7 displays many diagnostic tests used to verify the accuracy of the ARDL model. The following tests are used to detect heteroskedasticity: the Breusch-Godfrey serial correlation LM test, the Jarque-Bera test, and the Ramsey RESET test. We used the Breusch-Pagan-Godfrey Test statistics to assess the existence of ARDL residual heteroskedasticity. Table 7 shows that the ARDL residual test for heteroskedasticity does not reject the null hypothesis that there is no conditional heteroscedasticity at the 5% level of significance. Therefore, the residuals of the ARDL model do not exhibit conditional heteroskedasticity. The Breusch-Godfrey test statistic was used to assess the presence of serial correlation in the ARDL residuals. Table 7 does not provide evidence to reject the null hypothesis of no serial correlation at lag order h, with a significance level of 5%. This implies that, in lag order h, there is an absence of serial correlation. The Ramsey RESET Test data were used to measure the degree of functional misspecification of the ARDL model. Table 7 does not reject the null hypothesis's functional form at a significance level of 5%. Therefore, the ARDL model is currently in a functional condition. The Jarque-Bera statistics were used to assess the normal distribution of the ARDL residuals. Table 7 shows that the null hypothesis of a multidimensional normal distribution cannot be rejected at the 5% level of significance. Afzal et al. (2010) provide empirical data demonstrating that the residuals of the autoregressive distributed lag (ARDL) model conform to a multivariate normal distribution. This finding provides support for the null hypothesis at a significance level of 5%.

The research used the CUSUM and CUSUM of Squares residual tests to assess the structural stability of the equation in the ARDL model. Figure 4 depicts the CUSUM and CUSUM of Squares residual tests for the ARDL Model. Figure 4 illustrates that all the plots in the CUSUM and CUSUM of Squares residual tests are contained under the 5% significance level. This implies that the estimated equation parameters in the ARDL model are enduring and viable for confirmation, and they validate the evidence of the ARDL boundary test. Additionally, they establish the long-run and short-run causality, Granger-causality, and Cholesky method of dispersion decomposition as outlined in the paper by Granger (1988).

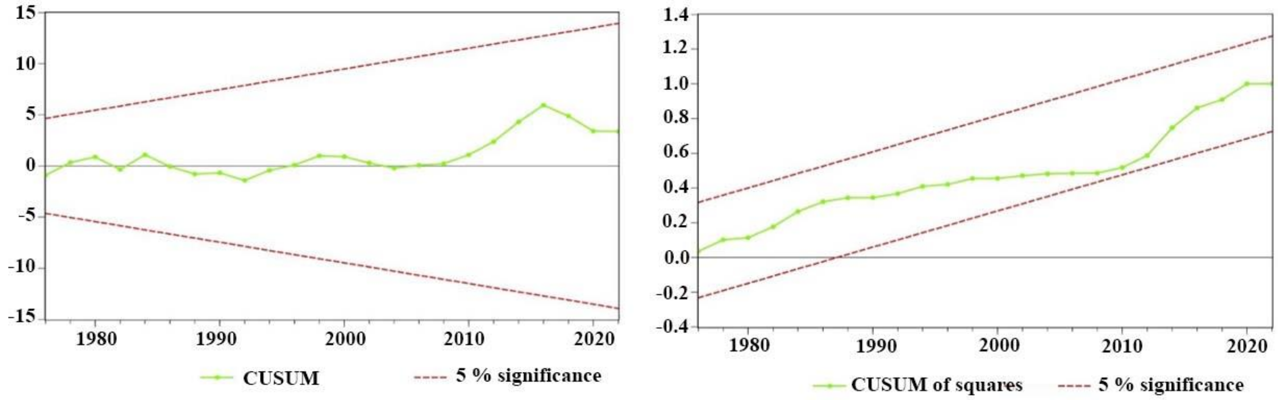

Figure 4. Test for stability

Co-integration test (Johansen test)

This study provides an overview of Johansen's method, as proposed by Johansen & Juselius (1990), for identifying the long-term correlation between different factors, including energy consumption, population size, land allocated for grain cultivation, farmland, agriculture value-added, carbon dioxide emissions, gross domestic product, and crop and livestock production indexes. Table 8 displays the results of the trace statistic test, revealing that four co-integration equations have a statistical significance level of 5%. Furthermore, the results of the maximum eigenvalue test also indicate the statistical importance of four co-integration equations at a 5% level. These data indicate a persistent correlation between the selected variables in this investigation.

Estimations of long and short term

The research sought to determine the long-term and short-term effects of different factors on the emission of CO_2 into the environment. Following the implementation of an ARDL bound test, the researchers discovered a significant and enduring relationship between the variables in both the short and long terms. The long-run coefficient values are shown in Table 9. The findings indicate that population, GDP, energy consumption, and agricultural output index have a positive and substantial influence on the emission of CO_2 into the environment. More precisely, a 1% rise in the agricultural production index, energy consumption, GDP, and population would result in a corresponding increase in CO_2 emissions of 0.9533%, 0.2551%, 0.0984%, and 1.2286%, respectively. While lacking statistical significance, the findings indicate a favourable correlation between cropland and acreage dedicated to producing grain crops, and the emission of CO_2 into the atmosphere. Furthermore, a just 1% rise in agricultural value-added would lead to a significant 0.7583% reduction in CO_2 emissions, given the negative and high coefficient of agricultural value-added. The livestock production index, the final study variable, had coefficients that were both negative and non-significant.

According to the ARDL bounds test approach, the empirical data suggests a temporary correlation between the variables. The coefficients for agricultural land, crop production index, energy consumption, GDP, and LPI exhibit positive values and are statistically significant at the 1% level. This implies that in the next years, Pakistan's agricultural area, crop production index, energy consumption, GDP, and livestock production index will all significantly contribute to a rise in the emission of CO_2 into the environment. According to Table 9, a 1% increase in cropland would result in a 1.7622% rise in CO2 emissions. Similarly, a 1% increase in energy expenditure, GDP, LPI, and crop production index will lead to a 0.5212%, 0.5187%, 0.3533%, and 0.5859% increase in CO_2 emissions, respectively. Initial estimates suggest that agricultural value added has a favourable effect on the emission of CO_2 into the environment, however this effect is not statistically significant. In addition, the findings demonstrated a notable inverse relationship between the area allocated for cultivating grain crops and the population. Specifically, a 1% rise in land utilized for producing grain crops and population resulted in a 1.3002% decline in carbon dioxide emissions and a 28.1776% drop in population. Short-term predictions provide an error correction model (ECM) that captures the co-integrated connection between the variables. The findings suggest that the disparities resulting from the shock experienced last year gradually approach the long-term equilibrium of this year by around 2.0816%. At the 1% significance level, the ECM coefficient (-1) has a statistically significant negative effect.

Table 8. Johansen test results

Hypothesized	Eigenvalue	Trace Statistic	0.05 Significant	Prob.**
None*	0.847684	295.1756	197.3709	0.0000
At most 1*	0.659747	201.0858	159.5297	0.0000
At most 2*	0.605272	147.1825	125.6154	0.0012
At most 3*	0.559744	100.7045	95.75366	0.0218
At most 4	0.399392	59.68456	69.81889	0.2452
At most 5	0.262030	34.19389	47.85613	0.4913
At most 6	0.197764	19.00131	29.79707	0.4928
At most 7	0.137991	7.983706	15.49471	0.4672
At most 8	0.011122	0.559233	3.841466	0.4546
Rank criterion of the unlimited cointegration (maximum eigenvalue)				
No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Significant	Prob.**
None*	0.847684	94.08979	58.43354	0.0000
At most 1*	0.659747	53.90331	52.36261	0.0345
At most 2*	0.605272	46.47796	46.23142	0.0470
At most 3*	0.559744	41.01998	40.07757	0.0391
At most 4	0.399392	25.49066	33.87687	0.3526
At most 5	0.262030	15.19259	27.58434	0.7328
At most 6	0.197764	11.01760	21.13162	0.6456
At most 7	0.137991	7.424473	14.26460	0.4402
At most 8	0.011122	0.559233	3.841466	0.4546

Max-eigenvalue test indicates co-integrating eqn(s) at the 0.05 level; *means the hypothesis is rejected at the 0.05 level; **means the hypothesis is rejected at the 0.01 level.

Table 9. Short and long term projections of Autoregressive Distributed Lag (ARDL) analysis

Parameters	Coefficient	Std. Error	t-statistic	Prob.
Long-term projections [selected model: (4, 3, 4, 3, 4, 4, 4, 4, 4)]				
LnAL	0.931226	0.559909	1.663174	0.1572
LnAVA	-0.758314	0.179552	-4.223376	0.0083
LnCPI	0.953341	0.254643	3.743831	0.0134
LnEC	0.255103	0.127175	2.005917	0.0112
LnGDP	0.098383	0.056872	1.729908	0.0442
LnLCC	2.174394	0.516618	4.208902	0.0884
LnLPI	-0.349661	0.141434	-2.472249	0.0564
LnPOP	1.228602	0.246420	4.985810	0.0042
C	-51.27700	6.251928	-8.201790	0.0004
Short-run estimations [selected model: (4, 3, 4, 3, 4, 4, 4, 4, 4)]				
D(LnAL)	1.527037	0.127493	11.97744	0.0001
D(LnAL (-1))	1.443522	0.127364	11.33383	0.0001
D(LnAL (-2))	1.762162	0.114949	15.33001	0.0000
D(LnAVA)	-0.770452	0.042799	-18.00185	0.0000
D(LnAVA (-1))	-0.468241	0.043922	-10.66067	0.0001
D(LnAVA (-2))	-0.458567	0.051072	-8.978774	0.0003
D(LnAVA (-3))	0.077014	0.056137	1.371883	0.2285
D(LnCPI)	0.629818	0.035699	17.64266	0.0000
D(LnCPI (-1))	-0.708869	0.053248	-13.31255	0.0000
D(LnCPI (-2))	0.521352	0.047583	10.95676	0.0001
D(LnEC)	-0.019799	0.001112	-17.80511	0.0000
D(LnEC (-1))	0.517343	0.015759	32.82856	0.0000
D(LnEC (-2))	0.502535	0.015208	33.04359	0.0000
D(LnEC (-3))	0.518717	0.025063	20.69629	0.0000
D(LnGDP)	-0.087925	0.014847	-5.921986	0.0020
D(LnGDP (-1))	0.133525	0.012975	10.29132	0.0001
D(LnGDP (-2))	-0.049769	0.013417	-3.709497	0.0139
D(LnGDP (-3))	0.353307	0.015335	23.03917	0.0000
D(LnLCC)	2.188451	0.118250	18.50702	0.0000
D(LnLCC (-1))	-0.194013	0.084194	-2.304349	0.0694
D(LnLCC (-2))	-1.030181	0.074956	-13.74388	0.0000
D(LnLCC (-3))	-1.300215	0.073286	-17.74156	0.0000
D(LnLPI)	-0.328101	0.035220	-9.315748	0.0002
D(LnLPI (-1))	-0.522314	0.038822	-13.45396	0.0000
D(LnLPI (-2))	-0.755192	0.039404	-19.16550	0.0000
D(LnLPI (-3))	0.585923	0.044777	13.08526	0.0000
D(LnPOP)	-10.02819	0.817053	-12.27361	0.0001
D(LnPOP (-1))	6.922677	1.433761	4.828333	0.0048
D(LnPOP -2))	-0.683266	1.489273	-0.458791	0.6656
D(LnPOP (-3))	-28.17759	1.411688	-19.96021	0.0000
ECM (-1)*	-2.081664	0.063735	-32.66140	0.0000

EC = $LnCO_2$ - (0.9312*LnAL - 0.7583*LnAVA + 0.9533* LnCPI + 0.2551* LnEC + 0.0984* LnGDP + 2.1744* LnLCC - 0.3497*LnLPI + + 1.2286* LnPOP - 51.2770)

CONCLUSION

The major purpose of the present research was to examine the correlation between the emission of CO_2 into the environment and the key kinds of economic activities. Only a limited amount of study has investigated the potential influence of economics on CO_2 emissions in Pakistan using Dietz and Rosa's Stochastic Impacts by Regression on Population, Influence and Technology (STIRPAT) Model. However, these studies fail to include the cumulative impact of other significant sources of carbon dioxide emissions at the national level. The present study examines the correlation between GDP and CO_2 emissions, considering factors such as trade openness, industry value-added, total energy consumption, financial development, and urban population, in order to circumvent these limitations. It does this by using an enhanced iteration of the STIRPAT model.

The study used the STIRPAT model, a flexible ecological framework, to identify the key factors that influence carbon emissions in Pakistan. Due to the ongoing threat of carbon dioxide emissions, global leaders are devoting significant focus to the issue of climate change. The study examined the correlations among the following factors from 1970 to 2020 in Pakistan: agricultural land, land dedicated to cereal crops, population, energy consumption, GDP, crop and livestock production indices, and CO_2 emissions. The researchers conducted unit root tests using PP and ADF for each variable. The researchers determined the short and long-term relationships between each study variable using an autoregressive distributed lag (ARDL) bound approach. The results of both the long-term and short-term approximations indicated that the majority of research parameters exhibited a statistically significant positive correlation with the dependent variable, which is the emission of CO_2 into the environment. At a significance level of 1%, the F-statistic value was 38.0988, above the upper limit value. The long-term coefficient results demonstrated statistical significance for the index coefficients of agricultural production, population, energy consumption, and gross domestic product. The coefficients associated with farmland and land dedicated to grain crop cultivation had positive values, although they lacked statistical significance, indicating their unreliability. Moreover, the agricultural value-added coefficient exhibited a statistically significant and negative relationship, indicating that an increase in this factor would lead to a decrease in the emission of CO_2 into the environment. Based on short-term estimates, the coefficients for energy consumption, gross domestic product, agricultural land, the crop production index, and the livestock production index was all positive and statistically significant. This indicates that these factors play a crucial role in increasing the emission of carbon into the environment. The error correction model (ECM) exhibited a negative and very significant value of 1% according to the estimates of the short-run connections. This suggests that the long-term balance for this year reached around 2.0816% of the deviations caused by the shock compared to the previous year. The paired Granger causality analysis revealed the presence of both unidirectional and bidirectional causation between the specified variables in the study activity.

Our study is focused on Pakistan because to its growing population and energy limitations, which hinder the country's economic development and its ability to reduce emissions. The study's results suggest that Pakistan should prioritize addressing the fundamental issues plaguing its agricultural economy, particularly those related to the productivity of its livestock and crops. The study's conclusions may result in many legislative reforms that would ensure ongoing improvement.

Acknowledgements

We thank our respected reviewers for their valuable comments and suggestions that helped us to improve this paper.

Author's statements

Contributions

All authors contributed to the study's conception and design.

Conceptualization: M.A.; Data curation: M.A.; Formal analysis: M.A., T.K.; Investigation: T.K.; Methodology: T.K.; Software: F.M., F.A., W.U.; Visualization: T.K.; Writing – original draft: M.A.; Writing – review & editing: Z.A.

Declaration of conflicting interest

The authors declare no competing interests.

Financial interests

The authors declare they have no financial interests.

Funding

Not applicable.

Data availability statement

All the authors of this manuscript confirmed that the data supporting the findings of this study are available in the article. All the required data is available and easily accessible.

AI Disclosure

The authors declare that they did not use generative AI to assist you in writing this manuscript.

Ethical approval declarations

The authors declare that an ethical approvement was not needed.

Additional information

Publisher's note

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