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Does Environmental Pollution hurt Agricultural Productive Efficiency? A New Evidence using ARDL and Wavelet Coherence Approaches

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Abstract

Environmental change daunts the aptitude to ensure global food security. The greatest significant threat to world fronting is how to mitigate environmental pollution without sacrificing agricultural productivity. The sharp rise in carbon dioxide emissions and global warming is altering the agriculture productivity's patterns as its vulnerability can be sensed by farmers. The spillover impact of climatic changes predicted to be great but differs by area and crop. This research fulfills the unprecedented need of adopting robustness methods to quantify the impact of CO₂ emissions, agriculture labor, land, feeds, and fertilizers on agriculture productivity over five decades-long data structured in time-series. The fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS), wavelet transform coherence (WTC) method, and gradual shift causality, tools have been espoused to observe the dynamic linkage in the long-term and short-run. The ARDL bound test confirms long-term co-integrated relation among the indicators. Furthermore, there is evidence of positive association between agriculture productivity and regressors which is also supported by the wavelet coherence outcomes. The Gradual shift causality test present a uni-directional causal link from all determinants to agriculture productivity which illustrates that all the regressors can significantly predict agriculture productivity. So, policies need to be formulated to explore a practical expansion approach with efficient use of fertilizers and feeds at an optimum level, in addition to environmental protection by encouraging public and private investment in agricultural research.

Keywords: CO₂ emissions; Agricultural productivity; Fertilizers; Feeds; Wavelet coherence

1. Introduction

The current generation is facing enormous challenges by climate change that has very adverse socioeconomics and environmental impact. The whole world is witnessing unprecedented heat waves, cruel droughts, an increase in air pollution and CO₂ emissions. The relentless surge in greenhouse gases like fluorinated gases, methane (CH₄), nitrous oxide (N₂O), and carbon dioxide (CO₂) are affecting the pattern of rain and temperature and negatively influencing land resources and water (Alexandratos, Nikos; Bruinsma, 2012; Ali et al., 2017; Kurukulasuriya et al., 2006; Mendelsohn, 2014). All poses of these dangers are a severe threat to food security. No country has strong enough to counter these challenges in a quicker way. However, more widen impacts are touched in developing countries due to high vulnerabilities and incapacity to mitigate the threats (Parker et al., 2019). Currently, an immense challenge comes from the loss of natural environments to make room for farming. Rainfall trends around the countries have started to alter, and these shifts are expected to escalate over the next years. It means more prolonged cycles, often within the same areas, with heavy rain and more extended dry periods.

Similarly, scientific evaluation about the air quality, including pollution forecasts and future greenhouse gas sequestration, is an imperative new environmental science field that presents foremost challenges to regulatory authorities. It is becoming notoriously hard to normalize CO₂ emissions of gases and specific substances from agriculture as this segment concerns the most fundamental human needs, i.e., foods. The current proposal blends preliminary research with social and political overlays, spanning a vast spectrum of practices in a dynamic sector. Pakistan being an agriculture-based economy is affected the most because of straight contact with nature, ranked 8th in the world's primarily vulnerable country through climate change with the substantial difference in rainfall due to 2-

3° expected rise of temperature by 2050 (Ahmad and Afzal, 2020). For instance, tropospheric ozone (O_3) is particularly harmful to crop yields among different air pollutants. Ozone-induced crop fatalities, supposed to cost around US\$ 11.18 billion in the year 2000 (Ainsworth et al., 2012). Temperature change with negative intensity to be unfavorable for various crops (Proskurowski et al., 2008). These uncertain events prompt us with a critical resilience thought message that unpredictable climate changes cause a rapid impact on agriculture productivity. Changes in crop management can alleviate climate change's negative influence, primarily due to temperature increases on crop phenology. But the introduction of new cultivars and a longer growth cycle could significantly affect yield phenology and potentially increase under a warming trend (Abbas et al., 2017).

Experts have given more alternative methods to ease the procedures to obtain technological advancement and foreign direct investment (Ahmad et al., 2020). It is hard for mainly developing nations to adopt unconventional methods with financial and high-tech constraints. However, emerging countries are the ones that have a high economic dependency on agriculture production, such as Pakistan, India, and Bangladesh in South Asia. Although Pakistan is still self-sufficient presently in major staples – ranked 8th in wheat production, 5th in sugarcane, 10th in rice, and 4th in milk (UNICEF, 2018). In contrast, moving towards urbanization is a vast threat to a rise in population, an enormous number of cutting trees, and overcrowded places that negatively impact Pakistan's ecosystem. All these led to rising floods, soil erosion, air pollution, and greenhouse gases in the environment (Kousar and Shabbir, 2021).

The possible impacts are less pronounced; however, food and hunger insecurity in different areas are caused by climate change (Wheeler and Braun, 2013). Previous studies have established that this sector permits the development of various non-agriculture industries and may have a hostile effect on crop yields with climate change (Lobell et al., 2015). The link between environmental change and agricultural productivity is a meaningful area for researchers to assess for developing countries (Anjum, Zada, and Tareen, 2016). Though the requirement to determine this topic is exceptional as in the worst case, if the agricultural productivity does not equal the food demand, it might lead to costly buying and raise the rate of poverty and hunger worldwide (Ahmad et al., 2016; Godfray et al., 2010; Foley et al., 2013; Lashkari et al., 2012). Therefore, this research examines the impact of CO₂ emissions, agriculture labor, land, feeds, and fertilizers on Pakistan's agriculture productivity using data from 1961 to 2016. The robustness of methods portrays the high efficiency of results while examining the lag phase and coherence between time series function of frequency and time. The current study is different from the prior research by employing the novel wavelet coherence test. Some essential properties of the wavelet transform coherence: like capable of analyzing signals with functionality that differ over time, offers illustration on a diverse scale, and conveniently obtainable via filter bank. The literature-based knowledge indicates that not a single researcher had applied the wavelet coherence approach to analyze environmental data to enumerate agriculture productivity. The advantage of the wavelet coherence tests is that it can capture both correlation and causal linkage between series at different frequencies and time periods. Thus, the present study fills the gap in the ongoing literature. The practice of finding an intense relationship between climate change, CO₂ emission, and productivity in agriculture development presents new evidence both in tabular and visual forms. Besides the introductory part, the below portion of this research consists and organized as follows: a review of relevant studies section provides the particular literature and systematic review in tabular form. Data & methods section

contains a new approach series of methodology while finding & discussion parts present the outcomes in detail. Finally, the conclusion & policy implications fall in the last section.

2. Review of Relevant Studies

In terms of labor contribution, agriculture remains Pakistan's most important sector of the economy, and as such, the mainstream of the population relies directly or indirectly on it. The main crops like rice, wheat, maize, cotton, and sugarcane account for 21.73% in the agriculture sector and contributing 4.20% in GDP, while 11.53% accounts for other crops with a 2.23% share in GDP (Pakistan, 2020). Stages of crops guided by the prevailing weather conditions and reflected in the accumulation of rising degree days influence the field management methods, including selecting crops and improvements in sowing dates (Ahmad et al., 2017; Wajiha and Qadir, 2016).

Higher temperatures in the growing season may have a major effect on agricultural production and food security (DS and RL., 2009). Pakistan's climate is ideal for cultivating different crops, such as cotton, wheat, rice, corn, and sugar cane. Above all, the wheat crop is the primary due to high domestic demand and consumption (Dharmasiri, 2012). The synergies between environmental concerns and agriculture productivity are highlighted by various authors (Aragón et al., 2019; Di Gregorio et al., 2017; Liang et al., 2017; Ukhurebor et al., 2021). The impact of business activities involves industrial production that pollutes the air, water, and various crops. The examination of the impact of air pollution of industries on farming crops includes recognizing the roles of the dose-response between the accumulation of contaminants and the loss of agriculture. Multiple studies have quantified the dose-response, and some applied the method of field experiments.

Consequently, some authors stated the relationship between total factor productivity of agriculture and air pollution (Zhou et al., 2018). Air pollution diminishes labor productivity from the economic side, leading to disrupting some certain degree of productivity of yield's physiological and biochemical, instigating the nutrient attention in acid rain and soil degradation (Heck et al., 1988; Zivin and Neidell, 2018). Parker (2015) claimed that financial considerations are beneficial in mitigating national environmental issues. Rafindadi (2014) evaluated the relations in Asia-Pacific countries between CO₂ pollution, water supplies, and natural resources and concluded; those variables influence the country-wide environmental sustainability plan. Another author used the ARDL bounds test to determine the climate change impact on food crops from 1968 to 2014. The finding revealed CO₂ emission and land area negatively effecting cereal yield while average rainfall, energy consumption, and labor force have a positive impact on Turkey's production (Chandio et al., 2020). Schmidhuber (2007) proposed that climate change would directly affect economic growth, food supply, and prices after finding a strong relationship between CO₂ emission and crop yield. Likewise, several studies have been carried out on climate change and agriculture productivity for developing nations, particularly in agriculture-based economy, from the exhaustive evaluation on the implementation of econometrics in agriculture and environmental economics (Fan and Carroll, 2012; Ozturk, 2015; Rehman et al., 2019). For the audience's ease, an in-depth systematic review of additional literature has comprised in tabular form as follows.

Table 1. Systematic Review

Authors	Aims	Country/Region	Data & Methods	Conclusion
Warsame et al. (2021)	Ascertain the measure the impression of, measured rainfall, temperature, climate change, and CO ₂ on crop production	Somalia	Time Series (1985 to 2016) ARDL bounds, Granger causality	The rise of crop production in the long run by rainfall during the decline in the short-run. No significant impact has found of CO ₂ on crop production
Aziz et al. (2020)	To evaluates the EKC between economic growth, forest area, agriculture production, renewable energy, and environmental degradation	Pakistan	Time Series (1990 to 2018) QARDL methodology	The short-run impact of agricultural production on Ecological footprints demonstrate statistically negative results
Koondhar et al. (2020)	To explore the link between energy consumption, air pollution, and the involvement of agriculture in GDP.	China	Time series (1998–2018) ARDL bounds model, CUSUM, and CUSUMSQ test.	A casual affiliation was found between air pollution and agriculture development. The exponential population growth has led to a slow reduction in capital to gratify the rising population's food need.
Rashid et al. (2020)	To inspect the influence on cotton productivity by climatic variations	Pakistan	Time Series (1981-2015) ARDL bounds testing	All determinants of climate have a substantial effect on cotton productivity. Whereas, All climate variables have a positive impact on crop productivity except temperature.
Sharmila Raisa et al. (2020)	To observe the nexus between agricultural output, air quality, consumption of fertilizer, and agriculture contribution to the domestic economy	Bangladesh	Time Series (1972 to 2019) ARDL model	A close correlation exists between air pollution and farm productivity, agricultural land usage, energy use, fertilizer use, and crop production.
Sharif et al. (2020)	To influentially investigate economic growth, transport, and tourism on CO ₂ emissions.	Malaysia	Time Series (1995Q1 to 2018Q4) QARDL Model	Economic development, transport, and globalization with CO ₂ are substantially positive, and tourism indicates a negative relationship.
Mehmood (2020)	To measure the relationship between CO ₂ emission and globalization	Singapore	Time Series (1970–2014) ARDL approach	Growing political globalization by 1% would increase pollution by 2.06% in the long run. The presence

				of environmental Kuznets curve exist in Singapore
Naseem et al. (2020)	To determine the asymmetrical effect of agriculture, food security, and fossil fuel consumption on CO2 emission	Pakistan	Time Series (1969 to 2018) Multiple-unit root (PP, KPSS, ADF, and Z&A). Asymmetrical ARDL correlation	The findings confirmed the adverse shocks, the atypical reaction of CO2 to agricultural value-added. Also, consumption of fossil fuels would further exacerbate environmental conditions
Ali et al. (2020)	To investigate the causal link between CO2, CO2S, energy consumption (EU), (FOF), (GDP), and net domestic credit (NDC).	Pakistan	Time Series (1971 to 2014) ARDL bound testing, ADF, and PP.	Outcome presents CO2S, EU, and GDP have a significant bonding with CO2 emissions while NDC and FOF are not substantial.
Burakov (2019)	To empirically review the relationship between CO2 emissions and determinants, mainly for agriculture.	Russia	Time Series (1990-2016) ARDL bound test and pairwise granger causality.	Existence of long-run relationship between CO2 emission and agriculture found. The statistical role of Environmental pollution has a small impact on agriculture yet. Moreover, it revealed uni-directional causality from agriculture production to CO2 emissions
Khan et al. (2019)	aim to report the asymmetrical effects of environmental regulation on CO2 emission	China	Time Series (1991–2015) Non-linear ARDL	Environmental regulations, Financial development are advantageous and decline the CO2 emission while growth in urban population enhanced.
Shoko et al. (2019)	Investigate whether the newly changing possibility of climate variability affects the maize yield	South Africa	Time Series (1970 to 2016) ARDL	Rainfall and temperature were found as essential factors of maize yield. Nevertheless, excessiveness could have the opposite effect.
Gokmenoglu et al. (2019)	To empirically measure the relation among CO2 emissions, consumption, and agriculture with the existence of EKC.	China	Time Series (1971–2014) Bounds test approach under ARDL.	Conclusion discloses the positive and significant results for energy consumption, real income. Agricultural development positively results with elastic impact while inelastic on CO2 emission as real

					income shows negative and inelastic air pollution.
Matthew et al. (2018)	To evaluate the long term impact of greenhouse gas emission on health outcomes	Nigeria	Time Series (1985-2016) ARDL		A 1% increase in GHGE may cut life hope by 0.0422%. In case this happens, the rate of mortality would be 146.6%.
Husnain et al. (2018)	Climate change impact on agriculture value-added are examined	60 Countries	Panel data (1999 to 2011) GEMs, IAMs, function models		A positive linkage of precipitation has shown up with agriculture. However, the temperature has a negative association with Agriculture.
Mahrous (2018)	Explore the relationship between global climate change and the production of cereals.	Egypt	Time Series (1971-2013) ARDL Approach		The adverse effect has calculated on cereal crop in the short-run from temperature and rainfall While in the long-run, some crop's yield might be beneficial in case of CO ₂ increases.
Asumadu-Sarkodie and Owusu (2016)	To investigate the long-run causal relationship between CO ₂ emissions and the agricultural development	Ghana	Time series (1961 to 2012) ARDL, VECM		Confirmation of a long-run relationship depicts from results and CO ₂ emission found to negatively affect coarse grain, bean, vegetable, livestock, and cocoa.

Note: ADF-augmented dickey fuller, PP-Phillips Perron, KPSS-Kwiatkowski-Phillips-Schmidt-Shin, ARDL- Autoregressive distributed lag, QARDL-Quantile autoregressive distributive lag, VECM-vector error correction model, GEM-general equilibrium model, IAM-integrated assessment model.

Most of the studies have examined the nexus of climate change and agricultural productivity through ARDL for developing countries recently, adding more (Ahsan et al., 2020; Attiaoui and Boufateh, 2019; Banday and Aneja, 2019; Janjua et al., 2014). As with the world's growing population, it is vital to accelerate agricultural production to match the essentials nutrition to feed the world (Weeks, 2015). However, many climatic and environmental issues, including air pollution, rapid climate change, and ecological degradation, affect agricultural productivity. It is indispensable to identify the in-depth dynamics relationship of these factors with agricultural productivity to provide food security and meet Pakistan's future food demand. To the best of comprehension, earlier studies have provided only simple relational evidence among certain factors and used numeric techniques to capture relations differently with frequencies and periods such as simple regression, ARDL, FMOL, and more. However, there has been no sign from existing literature demonstrating a dynamic linkage between climate change, CO₂ emissions, and agricultural productivity using the wavelet coherence technique. The wavelet method of analysis gives an in-depth association of

determinants within the timescale and frequency bands (Pla et al., 2020). The wavelet efficiency becomes an upsurge when it comes to interacting lead-lag relationship on time series used in non-linear; it simultaneously allows to measure the dynamic linkages and causality (Adebayo and Akinsola, 2020). Thus, the wavelet coherence technique takes into account break-in time series, and it could otherwise disrupt measurement parameters without considering it (Kirikkaleli and Gokmenoglu, 2020).

3. Materials and Methods

3.1 The conceptual underpinnings

This portion emphasizes the connotation and the climatic impact on agriculture productivity. According to think-tank German watch on global climate index report, Pakistan ranked 5th most vulnerable globally, vanished 9989 lives, \$3.8 billion economic suffering, and perceived 152 extreme weather events between 1999 to 2018 (Eckstein et al., 2020). However, these large scale effects have been remained and continue under great debate.

3.2 Data and Assessment Scheme

This article uses a time series yearly data of TFP and CO₂ emission, Agri-Land, Agri-Labor, Fertilizers, and Feeds spanning from 1961 to 2016 of Pakistan. The TFP is the dependent variable in the model, and the independent variables are CO₂ emission, Agri-Land, Agri-Labor, Fertilizers, and Feeds. The natural logarithm of the series has been taken to ensure the normality conforms. Table 2 depicts the source, unit, and description of the determinants. The study analysis flow is depicted in Figure 1. The economic function and econometric model are highlights in equations 1 and 2 as follows;

$$TFP_t = f(ALB_t, ALD_t, FD_t, CO_{2t}, FT_t) \quad [1]$$

$$TFP_t = \vartheta_0 + \vartheta_1 ALB_t + \vartheta_2 ALD_t + \vartheta_3 FD_t + \vartheta_4 CO_{2t} + \vartheta_5 FT_t + \varepsilon_t \quad [2]$$

In Equation 2, TFP denotes total factor productivity of agriculture that reflects agricultural efficiency; ALB, ALD, FD, FT, and CO₂ signifies agricultural labor, land, feed, fertilizer, and carbon dioxide emissions, respectively.

Table 2. Variables, Units and Sources

Symbol	Log-Symbol	Description	Units	Sources
TFP	LnTFP	Total agricultural factors productivity	Index	USDA
FD	LnFD	Sum of all sources of metabolizable energy (ME) used agricultural feeds	1000 Megacalories	USDA
FT	LnFT	Sum of N, P ₂ O ₅ , and K ₂ O fertilizers consumption.	Metric tons	USDA
ALB	LnALB	Total numbers of adults economically in agricultural activities	1000 persons	USDA
ALD	LnALD	Sum of rainfed cropland, irrigated cropland and permanent pasture area	1000 hectares	USDA
CO ₂	LnCO ₂	Carbon dioxide emission	Mt. tons per capita	WDI

*USDA- United States Department of Agriculture, **WDI- World Development Indicators

Figure 1. Flow Chart

3.3 Econometric Tools

3.3.1 Unit root tests

It is imperative to investigate series stationarity features before conducting further analysis. Thus the present research utilized conventional unit root tests (ADF and PP). The sensitivity to serial correlation in error terms and heteroscedasticity is the main distinction between ADF and PP tests. The Equations of ADF and PP explain as below;

ADF test:

$$\Delta Y_t = \beta \cdot D_t + \pi Y_{t-1} + \sum_{j=1}^p \sigma_j \Delta Y_{t-j} + \varepsilon_t \quad (3)$$

Whereby D_t depicts the deterministic term vector while the error term is represented by ε_t .

PP test:

$$\Delta Y_t = \beta \cdot D_t + \pi Y_{t-1} + \mu_t \quad (4)$$

The serial correlation and heteroscedasticity in the error terms are disregard in the PP test

As stated by Adebayo (2020), Kirikaleli & Adebayo (2020), and Alola et al. (2019), the conventional unit-root tests may present disingenuous outcomes if there is evidence of structural break(s) in series. Thus, the present study utilized Zivot & Andrews (ZA) unit root test introduced by Zivot to capture both stationarity features and a single break in series. The Equation of ZA exemplifies as follows:

$$\text{Model 1: } \Delta x_t = \varphi + \varphi x_{t-1} + \pi t + \delta DU_t + \sum_{j=1}^k d_j \Delta x_{t-j} + \mu_t, \quad (5)$$

$$\text{Model 2: } \Delta x_t = \varphi + \varphi x_{t-1} + \pi t + \gamma DT_t + \sum_{j=1}^k d_j \Delta x_{t-j} + \mu_t, \quad (6)$$

$$\text{Model 3: } \Delta x_t = \beta + \beta x_{t-1} + \beta t + \theta DU_t + \theta DT_t + \sum_{j=1}^k d_j \Delta x_{t-j} + \mu_t \quad (7)$$

Where DU_t depict dummy variable for mean shift occurring at each possible break-date (TB) while DT_t is the respective trend shift variable. Formally,

$$DU_t = \begin{cases} 1 & \dots \text{if } t > TB \\ 0 & \dots \text{if } t < TB \end{cases} \text{ and } DT_t = \begin{cases} t - TB & \dots \text{if } t > TB \\ 0 & \dots \text{if } t < TB \end{cases} \quad (8)$$

3.3.2 ARDL Approach

Auto-Regressive Distribution Lag Model (ARDL) developed by Pesaran and Shin (1998) and Pesaran et. al (2001) was used to capture the long-run co-integration association between the dependent and independent variables. Benefits of the ARDL bounds test over the other conventional or traditional co-integration techniques areas: (i) it can be used when there is a mixed order of integration; (ii) it incorporates both the short and long-run coefficients simultaneously; (iii) it is perfectly fit for small sample size; (iv) accommodating different lag length; (v) autocorrelation problem is removed. The calculated F-statistics are being compared to the lower and upper bound critical values. When the calculated F-statistics is below, the null hypothesis is not rejected; when the calculated F-

statistics is greater, the null hypothesis is rejected, which shows evidence of a long-run relationship among the variable. Equation (7) below explains the ARDL bounds model;

$$\begin{aligned}\Delta TPF_t = & \theta_0 + \sum_{i=1}^t \theta_1 \Delta TPF_{t-1} + \sum_{i=1}^t \theta_2 \Delta ALB_{t-i} + \sum_{i=1}^t \theta_3 \Delta ALD_{t-i} + \sum_{i=1}^t \theta_4 \Delta CO_{2t-i} + \sum_{i=1}^t \theta_5 \Delta FD_{t-i} \\ & + \sum_{i=1}^t \theta_6 \Delta FT_{t-i} + \beta_1 TPF_{t-1} + \beta_2 ALB_{t-1} + \beta_3 CO_{2t-1} + \beta_4 FD_{t-1} + \beta_6 FT_{t-1} \\ & + \varepsilon_t\end{aligned}\quad (8)$$

The null hypothesis and the alternative hypotheses are no co-integration and evidence of co-integration, respectively. We fail to accept the null hypothesis if the F-statistics is more than the lower and upper bond critical values. The alternative and null hypothesis are illustrated by Equations 8 and 9 correspondingly;

$$H_0 = \vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 \quad [9]$$

$$H_a \neq \vartheta_1 \neq \vartheta_2 \neq \vartheta_3 \neq \vartheta_4 \neq \vartheta_5 \neq \vartheta_6 \quad [10]$$

Where H_0 denotes the null hypothesis and H_a illustrates the alternative hypothesis.

After the long-run relationship is established, the ARDL model derives the error correction model (ECM). It was derived by estimating the model's short-run parameters by applying ECM. Hence, incorporating the ECM model into our short-run parameter of the ARDL model would result in Equation 10 as:

$$\begin{aligned}\Delta TPF_t = & \theta_0 + \sum_{i=1}^t \theta_1 \Delta TPF_{t-1} + \sum_{i=1}^t \theta_2 \Delta ALB_{t-i} + \sum_{i=1}^t \theta_3 \Delta ALD_{t-i} + \sum_{i=1}^t \theta_4 \Delta CO_{2t-i} + \sum_{i=1}^t \theta_5 \Delta FD_{t-i} \\ & + \sum_{i=1}^t \theta_6 \Delta FT_{t-i} + \beta_1 TPF_{t-1} + \beta_2 ALB_{t-1} + \beta_3 CO_{2t-1} + \beta_4 FD_{t-1} + \beta_6 FT_{t-1} + \omega ECT_{t-i} \\ & + \varepsilon_t\end{aligned}\quad (11)$$

Where: $\theta_{i=5}$ denote coefficients in the short run, ε_t represents the error term, $\beta_{i=5}$ mean coefficients, in the long run, t denotes the lags lengths, ECT_{t-i} denotes error correction term. It is showing the speed of adjustment from a short-run shock to the long-run equilibrium. ω represents ECM coefficients, which will be negative and significant.

3.3.3 Wavelet Approach

The wavelet approach is utilized in the current research to gather information about the time-frequency dependency between TFP and CO₂ emission, agri-land, agri-labor, fertilizers, and feeds in Pakistan using yearly data spanning from 1961 to 2016. Goupillaud et al. (1984) initiated the Morlet family. It is accepted that when time series variables are estimated and not stationary, the result will yield bias estimates if the conventional time-domain method is not employed. Additionally, in economics and finance, time-series data are prone to break (s); hence the traditional test of causality outcomes with parameters fixed are susceptible to surface (Adebayo and Odugbesan, 2020). Contrary to time-domain causality, the standalone frequency domain method major concern, also known as Fourier transform.

Therefore, to abolish these issues in the estimations, the wavelet coherence technique is utilized in this research. Morlet wavelet equation is presented below;

$$\varpi(t)\pi^{-\frac{1}{4}}e^{-i\varpi t}e^{-\frac{1}{2}t^2} \quad (13)$$

where: ϖ is utilised on time series frequency that is limited; $p(t)$, $n = 0, 1, 2, 3, \dots, N-1$; i is $\sqrt{-1}$. The time series is transmuted into the time-frequency domain and transmits to the change of wavelets. ϖ Is converted and developing into $\varpi_{k,f}$. This formula can be seen below:

$$\varpi_{k,f}(t) = \frac{1}{\sqrt{h}}\varpi\left(\frac{t-k}{f}\right), \quad k, f \in \mathbb{R}, f \neq 0 \quad (14)$$

Where: k describes the time and place of whereas f denotes the frequency. Odugbesan and Adebayo (2020) stated that k and f are the main parameters in the wavelet approach. The CWT Equation is depicted as follows:

$$\varpi_p(k, f) = \int_{-\infty}^{\infty} p(t) \frac{1}{\sqrt{f}} \varpi\left(\frac{t-k}{f}\right) idt, \quad (15)$$

The revitalization of the time series variable $p(t)$ is depicted by the next equation and the coefficient ϖ .

$$p(t) = \frac{1}{C_{\varpi}} \int_0^{\infty} \left[\int_{-\infty}^{\infty} |\varpi_p(a, b)|^2 da \right] \quad (16)$$

The wavelet power spectrum (WPS) captures the time series of vulnerability. The wavelet power spectrum equation is summarized below;

$$WPS_p(k, f) = |FWP(k, f)|^2 \quad (17)$$

The time series cross wavelet transform (CWT) as follows:

$$W(ork, f) = W_p(k, f) \overline{W_q(k, f)} \quad (18)$$

The CWT of TFP and CO₂ emission, agri-land, agri-labor, agri-machinery, fertilizers, and feeds in Pakistan using yearly data spanning from 1961 to 2016 parameters are depicted by $W_p(k, f)$ and $W_q(k, f)$ correspondingly. The wavelet coherence square is illustrated by Equation 7:

$$R^2(k, f) = \frac{|S(f^{-1}W_{pq}(k, f))|^2}{S(f^{-1}|W_p(k, f)|^2) S(f^{-1}|W_q(k, f)|^2)} \quad (19)$$

The $R^2(k, f)$ reveals the intensity of the interaction without including the nature of this connection being recommended. Torrence and Compo (1998) initiated a suggestion of associated direction by wavering the two-time series by signifying deferrals. Equation 8 depicts the Phase difference:

$$\phi_{pq}(k, f) = \tan^{-1} \left(\frac{L \{ S(f^{-1}W_{pj}(k, f)) \}}{O \{ S(f^{-1}W_{pj}(k, f)) \}} \right) \quad (20)$$

Where, O is the real component operator, while L is the imaginary operator.

3.3.4 Gradual Shift Causality

Toda and Yamamoto (1995) established a framework, which is anchored on vector autoregressive (VAR) built by Sims (1980). In calculating the optimal lag length, $p + d_{\max}$ is added to the lag of $d_{\max}$, which is ascertained by the series maximum order of integration in the VAR framework. However, ignoring the structural shifts can cause the VAR model to be unreliable and contradictory (Enders and Jones, 2016; Figueiredo et al., 2012). To examine the causal linkage between TPF and CO₂ emission, agri-land, agri-labor, agri-machinery, fertilizers, and feeds, Nazlioglu (2016) developed the Gradual shift causality test, which captures the structural shifts in Granger causality analysis and including the gradual and smooth shift. It can also be called the "gradual-shift causality test." The Fourier Granger causality test was developed using single-frequency (SF) and cumulative frequencies (CF), respectively, known as Fourier approximation. The modified Wald test statistic (MWALT) is generated by adding the TY-VAR analysis and Fourier approximation.

4. Findings and Discussions

Table 3 provides an introductory summary of all the variables used in this study. In the context of skewness and kurtosis tests, all the listed variables are approving to normal distributed, which confirms the normality assumption of the classical regression model. The probability value of the Jarque-Bera test is the standard test to measure. It reveals that all included variables are normally distributed, excluding total factor productivity of agriculture.

Table 3. Summary Statistics

	ALD	ALB	FD	CO ₂	FT	TFP
Mean	63588.7	15041.1	13091488	0.6032	1932604	83.879
Median	64029.4	13333.4	11491535	0.5787	1833350	85.965
Max	72392.0	27299.0	29017578	0.9878	5040100	107.18
Min	52443.0	7800.81	3184831	0.3083	41200	55.984
Std. Dev.	5729.4	5694.15	7892547	0.2220	1441110	16.474
Skewness	-0.1798	0.65699	0.4623	0.2657	0.2848	-0.1256
Kurtosis	1.9057	2.2365	1.9071	1.6208	1.8278	1.3798
JB	3.0960	5.3887	4.7814	5.0975	3.9632	6.2722
Prob	0.2126	0.0675	0.0915	0.0781	0.1378	0.0434

In the first step, we grasp integrating the time series variables for this study. For this purpose, two traditional stationarity tests, such as ADF (Elliott et al., 1996) and PP (Phillips and Perron, 1988) have been utilized. The results of these unit root tests imitate in Table 4. The ADF test results show no static variable at the level, and only one variable is named total factor of agricultural productivity stationary at the first difference, i.e., I (I). Likewise, the PP test reveals that only agricultural land is stationary at the level, and CO₂ is found to be stationary at the first difference, i.e., I (I).

Further, we examined the ZA unit root test by considering the structural break of time to prevent us from the misleading results of traditional unit root tests. The findings of the ZA unit root test listed in Table 5. The findings

expose that only agricultural land stationary at level, i.e., I (0). However, all the named variables have proved to be stationary after taking the first difference, i.e., I (1). In the context of the unit root test, the literature has reported that when we found a mixture of variables' integration, it is crucial to test long-term and short-run associations using the ARDL approach (Rehman et al., 2019).

Table 4. Conventional Unit Root Test

	ADF		PP	
	I(0)	I(1)	I(0)	I(1)
ALD	-1.182685	-6.390745	-3.646136**	-11.37973
ALB	-0.9617	-6.1419*	-1.0193	-6.371459
CO2	-1.649877	-6.371325	-1.943352	-11.257*
FD	-2.472408	-9.905282	-2.260468	-14.80907
FT	-2.597811	-7.917391	-1.450333	-11.80757
TFP	-1.312312	-8.073653	-1.208724	-8.057872

Note: Significance level of 1% , 5% and 10% is depicted by *,** and ***

Table 5: ZA Unit root Test

	At Level I(0)		First Difference I(1)	
	Intercept & Trend	Break-Date	Intercept & Trend	Break-Date
ALD	-5.306**	1980	-7.570*	1982
ALB	-3.970	1985	-8.385**	1985
CO2	3.611	1980	-9.253*	1973
FD	-4.368	1991	-5.412**	1988
FT	-3.850	1977	-9.256*	1984
TFP	-3.830	1986	-5.279**	1992

Note: Significance level of 1%, 5%, and 10% are depicted by * and **

Table 6 lists the ARDL bounds test findings to co-integration at the 10%, 5%, and 1% significance levels. This model is used to measure the long-run equilibrium and the linkage between incorporated variables. The ARDL Bounds Test F-statistics has a value of 6.11 that reveals the long-run co-integration association between total agricultural factor productivity, CO₂ emissions, farmland and labor, fertilizer, and feed at the significance level of 1%. The ARDL test obtains a long-term and short-run relationship between the variables, following the bounds test results to co-integration, which confirms linkage and co-integration among all selected variables. In addition, we performed several post-diagnostic tests, and the results are list in Table 6. The finding unveils our proposed model's smartness to tackle heteroscedasticity problems, misspecification, and residuals normality. So, the P-values of all these tests reflect 0.11, 0.11, 0.50, and 0.68, respectively. Surely, there is also evidence of the structural break in Pakistan's agricultural

productivity determinants during the research period. However, the post estimation graphs demonstrate the stability of the long-term coefficient with short-term movement in both equations using the cumulative sum (CUSUM) and the cumulative sum of square (CUSUMSQ) diagram, which is shown in Figures 2 and 3, respectively. Both figures reflect that the long-term coefficient framework is stable at the 5% level of significance.

Table 6: ARDL Bounds Test

Model	F-statistics	Co-integration	χ^2 ARCH	χ^2 RESET	χ^2 Normality	χ^2 LM
	6.11*	Yes	2.41 (0.11)	1.60 (0.11)	1.35 (0.50)	0.79 (0.68)
		10%		5%		1%
F-statistics	2.26	3.35	2.62	3.79	3.41	4.68

Note * represent a 1% level of significance

Figure 2. Cumulative Sum Plot for Stability

Figure 3. Cumulative Sum of Square Plot for Stability

After verifying the co-integration among agricultural productivity and its determinants, we discover short- and long-term dynamic linkage of these variables using the ARDL approach and illustrate the results in Table 7. The long-term ARDL estimates show that feeds positively and significantly connect with agricultural productivity, as the estimated coefficient value and its probability are 0.2132 and 0.005, respectively. In other words, a 1% increase in feed leads to an upturn in the agricultural productivity of Pakistan by 0.21%. Similarly, fertilizers' findings also positively impact agricultural productivity at the 5% significance level. These outcomes confirm that a 1% increase in fertilizer would augment agricultural productivity by 0.07%, exposing the maximum use of feed and fertilizer to increase Pakistan's agricultural production. As expected, rapid population growth will double the global demand for livestock and other agricultural products by 2050.

Meanwhile, the increasing use of fertilizers in crops and livestock feeds to meet growing demand is a significant reason for increased greenhouse gas (GHG) emissions. Only livestock has contributed 14.5% to global GHG emissions (Rojas-Downing et al., 2017). The drastic climate change is a significant threat to agricultural production, and mitigating this impact on agriculture has become a crucial challenge to save food for the coming generation. In this context, our feed and fertilizer coefficient values show better results for agricultural production in Pakistan; on the other hand, it would be alarming for environmental pollution. We need to develop serious policies to monitor and address feed and fertilizer use and limit it to acceptable food security levels and save the world from global warming. However, many scholars have researched to solve this problem and bring the real picture before the economies' policymakers (Appiah et al., 2018; Edoja et al., 2016). Experts believe that sustainable crop production is the only way to save the world from pollution and food security for the present and future generations.

Moreover, sustainable agricultural production can be achieved by discouraging weak farming practices that affect the environment (Asumadu-Sarkodie and Owusu, 2017; Manandhar et al., 2018). The estimated cost of agricultural labor and land is 0.130 and 0.3227, respectively, indicating a positive and significant linkage of these two vital factors with long-term agricultural productivity. Furthermore, these results mean that a 1% increase in farm labor and land results in a 0.13% and 0.32% increase in Pakistan's agricultural productivity. Interestingly, agricultural land's productive effect is larger than the agricultural labor, feed, and fertilizer used in agricultural activities, suitable for sustainable agriculture. Likewise, CO₂ estimated value is 0.1711, which reveals the positive and significant effect of environmental pollution on agricultural productivity. If we assume a 1% increase in Pakistan's CO₂ emissions, it increased agricultural productivity by 0.17%. This finding is in line with the results of (Manzoor Ahmad et al., 2021; Munir Ahmad et al., 2021; Khattak et al., 2020; Rehman et al., 2020). Furthermore, the term error correction term (ECT)'s negative coefficient value indicates the validity of short-term linkages between variables. As presented in Table 7, there is also a short-run linkage of agricultural productivity with agricultural feeds, fertilizers, labor, and land. Overall, the ARDL approach results show a long-term and short-run relationship between all variables of the study.

Table 7: ARDL Long and Short-run results

Variable	Coefficient	t-Statistic	Prob.
Long-Run Estimation			
FD	0.2132*	2.9435	0.005
FT	0.0666**	2.1115	0.041
ALB	0.4292***	1.9991	0.053
ALD	0.0193	0.0861	0.631
CO ₂	0.1711**	2.6699	0.011
Short-run Estimation			
FD	0.213*	3.4095	0.001
FT	0.036*	2.0024	0.052
ALB	0.130	0.7294	0.470
ALD	0.3227	1.1464	0.259
CO ₂	0.1711*	2.9224	0.006
ECT(-1)	-0.652*	-6.4635	0.000
R ²	0.99		
Adj R ²	0.98		

Note: 1%, 5% and 10% level of significance is depicted by *, **, and *** respectively

We further employed FMOLS and DOLS to measure the robustness of the outcome of long-term estimates of the ARDL approach. The results of these two tests clarify in table 8. As per the results, there is a positive and significant long-term relationship between agricultural productivity determinants, including feed, fertilizers, agricultural labor,

and carbon emissions. However, agricultural land exerts a positive but insignificant effect on agricultural efficiency in Pakistan.

Table 8. Robustness Check

Variable	FMOLS			DOLS		
	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
FD	0.2177*	5.1701	0.000	0.2132*	4.1017	0.000
FT	0.0692**	3.7263	0.000	0.0666*	2.9423	0.007
ALB	0.0430*	2.9561	0.005	0.5278*	3.8161	0.000
ALD	0.0790	0.6034	0.550	0.0193	0.1200	0.905
CO ₂	0.1654*	4.3717	0.000	0.1711*	3.7204	0.000
R ²		0.99			0.99	
Adj R ²		0.98			0.98	

Note: *, ** and *** depicts 1%, 5% and 10% respectively

The current research utilizes the wavelet transform coherence (WTC) approach to catching the causality and correlation between TPF and the regressors. This method is crafted from the domain of physics to obtain formerly undetected information. Therefore, the research investigates the connection in the short, medium, and long-run between TPF and its regressors. The cone of influence (COI) is the white where discussion is carried out in the WTC. The thick black contour delineates a level of significance, based on simulations of Monte Carlo. In Figures 4a-4e, 0-4, 4-8, and 8-16 manifests short, medium, and long-term relations correspondingly. The vertical and horizontal axis in the Figure depicts frequency and time. Blue and yellow colours represents low and high dependency between the series. In-phase (positive) and out-of-phase (negative) connections are described by rightward and leftward arrows respectively. The rightward-down (leftward-up) explains the first variable lead (cause) the second parameter while the rightward-up (leftward-down) depicts that second variable lead (cause) the first variable.

Figure 4a elucidates the WTC between TFP and Agric-Labor between 1961 and 2016 at different frequencies from 1965 to 1970. From 2000 to 2005, the arrows are rightward-up, illustrating the TFP and Agric-Labor's positive interconnection. Thus, this infers an increase in TFP accompanies in Agric-Labor. Furthermore, Agric-Labor lead (cause) TFP, which signifies that Agric-labour can predict certain variation in TFP. Figure 4b shows the WTC between TFP and Agric-Land from 1961 to 2016 in Pakistan. The majority of the arrows are rightward-up, proving a strong connection (dependency) at different frequencies from 1965-1970 and 2000-2005. Therefore, a piece of positive evidence has found the correlation between TFP and Agric-Land. Moreover, Agric-Land lead (cause) TFP during this period and presents Agric-land can predict TFP. Figure 4c depicts the WTC between TFP and CO₂ from 1961 to 2016 in Pakistan. The majority of the arrows are rightward-up, demonstrates a strong connection (dependency) at different frequencies from 1964-1975 and low and medium frequencies from 2000-2005. Also, CO₂ leads (cause) total factor productivity during this period and clarifies a strong predictor of TFP. Figure 4d paints the WTC between TFP and feeds from 1961 to 2016. Similarly, Figure 4e gives a picture of the WTC between TFP and fertilizer from 1961 to

2016. The majority of the arrows are rightward-up, indicating a strong connection (dependency) at different frequencies from 1965-1980 and low and medium frequencies from 1982-2010. Fertilizer lead (cause) TFP during this period, unfolding the fertilizers is a strong predictor of TFP. Hence, this concludes that fertilizer can predict significant variation in TFP.

Fig 4a: WTC Between TFP & AgricLabor

Fig 4b: WTC Between TFP & Agric-Land

Fig 4c: WTC between TFP & CO₂

Fig 4d: WTC Between TFP & Feed

Fig 4e WTC Between TFP & Fertilizer

Table 9: Gradual Shift Causality Test

Causality Path	Wald-stat	No of Fourier	P-Value	Decision
ALB → TFP	12.05439***	3	0.098784	Reject Ho
TFP → ALB	4.467524	3	0.724624	Do not Reject Ho
ALD → TFP	6.671819	2	0.463830	Do not Reject Ho
TFP → ALD	15.87455**	2	0.026288	Reject Ho
CO2 → TFP	13.58028**	3	0.059170	Reject Ho
TFP → CO2	7.180727	3	0.410308	Do not Reject Ho
FD → TFP	7.724252	2	0.357536	Do not Reject Ho
TFP → FD	3.816134	2	0.800695	Do not Reject Ho
FT → TFP	17.27995*	1	0.015678	Reject Ho
TFP → FT	8.566952	1	0.285259	Do not Reject Ho

Note: Significance level of 1% , 5% and 10% is depicted by *, ** and ***

Furthermore, we have utilized Toda-Yamamoto based Gradual Shift Causality technique to measure the uni-directional and bi-directional linkage between agricultural productivity and CO² emission, land, labor, fertilizers, and feeds. Their results, listed in Table 9, reveal a uni-directional causality from agricultural labor to agricultural productivity at the 10% significance level. Similarly, this test has found a one-way causality from factor productivity to agricultural land, from CO₂ to agricultural productivity, and from fertilizers to productivity. This further means that labor, CO₂, and fertilizers cause the agricultural productivity in Pakistan, while the factor productivity only causes

agricultural land. Besides, the findings of this causality test also support the graphical measures of the wavelet technique.

5. Conclusion and Policy Implications

This study mainly explores the real picture of the linkages between agricultural productivity and its determinants such as CO₂ emissions, agricultural lands, labor, feeds and fertilizers using the recent time-series data spanning from 1961 to 2016. In the first phase, the study examined the order of integration utilizing the ADF, PP, and ZA unit root tests and founds a mixture of level I (0) and the first difference I (I) data stationery. Since then, the ARDL bounds test has been employed, discovering the Cointegration relationship between the study variables at a 5% significance level. Meanwhile, the subsequent approach is ARDL with the error correction term, which we applied to capture the long-term and short-term linkages among agricultural productivity and the regressors. These findings exposed that the CO₂ emissions, agricultural land, labor, feed, and fertilizers have a positive and significant long-run impact on Pakistan's agricultural efficiency. Likewise, each regressors has a positive and considerable influence on productivity, excluding labor, as it has a positive but insignificant association with the outcome variable. Our findings' robustness has been verified utilizing the FMOLS and DOLS approach, which indicates our results almost robust and stable. The wavelet coherence technique has been employed as it has the advantage of capturing correlation and causality simultaneously at different levels of frequencies and periods. Subsequently, we applied the Toda-Yamamoto causality techniques to measure the long-term causality between agricultural productivity and all explanatory variables. This gradual shift causality test has the benefit of detecting causal linkage among factors even in the presence of structural breaks in series. In the context of the gradual shift causality test results, agricultural labor, CO₂ emissions, and fertilizers have a one-way relationship with agricultural productivity. In contrast, productivity has a uni-directional causal link with agricultural land.

Overall, this study has contributed to the current literature by proving that the determinants included have been validated because they have explained 99% agricultural productivity changes. It is proven that CO₂ emissions, land, labor, fertilizer, and feed have a positive and significant impact on agricultural performance in the long and short term. We make the following policy recommendations based on the experimental results of the study: (a) Considerably, Pakistan's most agriculture is semi-arid; in fact, it is vulnerable to climate change shocks. It needs the hours to strengthen Pakistan's agricultural sector to resilience against extreme weather such as heat, drought, cold, and floods to meet sustainable yield in agriculture, as it is observed that the summer season has been intensifying for the past decade. Furthermore, substantial investments and policies are needed to protect and strengthen production against pests and diseases. It has also increased, and farmers use more and more pesticides and bio-control. As a result, the environment deteriorated. Therefore, this is possible only when we encourage public, private investment, and public policy reforms in agricultural research, seed systems, agricultural input markets, and expansion to help farmers. (b) As our results show, Pakistan's agricultural land has a relatively low impact on long-term productivity. It might be due to multiple reasons such as soil salinity, waterlogging, lack of soil fertility, soil erosion, climate effects, and distribution of canal water inequality. These all problems and salinization of the soil severely deplete the soil's productivity and significantly reduce crop yields. In this context, some policy reforms and productive research are

desirable to create better ways to use fertilizers and water more efficiently to save Pakistan's future productivity. Furthermore, policies need to formulate to make better use of the largest network of canals as Pakistan has the most extensive canal roots that have the potential benefit to store water and generate renewable energy. These are the ones that can help protect and preserve the environment from the harmful waste of traditional semi-arid agriculture.

Declarations

1. Manuscript Compliance with Ethical Standard
2. There is no Conflict of Interest
3. Supplementary Data available-S1
4. Author's Contributions

Muhammad Ramzan- Main theme, data collection, Introduction, methodology, interpretations, conclusion and policy implications.

Hafiz Arslan Iqbal- Introduction and Literature Review

Tomiwa- Methodology and Data Analysis

References

- A, G., J, M., 1984. "Decomposition of Hardy Functions into Square Integrable Wavelets of Constant Shape." *J. Math. Anal.* 15, 723–736.
- Abbas, G., Ahmad, S., Ahmad, A., Nasim, W., Fatima, Z., Hussain, S., Rehman, M.H. ur, Khan, M.A., Hasanuzzaman, M., Fahad, S., Boote, K.J., Hoogenboom, G., 2017. Quantification the impacts of climate change and crop management on phenology of maize-based cropping system in Punjab, Pakistan. *Agric. For. Meteorol.* 247, 42–55. <https://doi.org/10.1016/j.agrformet.2017.07.012>
- Adebayo, T. S., 2020. Revisiting the EKC hypothesis in an emerging market: an application of ARDL-based bounds and wavelet coherence approaches. *SN Applied Sciences*, 2(12), 1-15.
- Adebayo, T.S., Akinsola, G.D., 2020. Investigating the causal linkage among economic growth, energy consumption and co2 emissions in thailand: An application of the wavelet coherence approach. *Int. J. Renew. Energy Dev.* 10, 17–26. <https://doi.org/10.14710/ijred.2021.32233>
- Adebayo, T.S., Odugbesan, J.A., 2020. Modeling CO2 emissions in South Africa: emapirical evidence from ARDL based bounds and wavelet coherence techniques. *Environ. Sci. Pollut. Res.* <https://doi.org/10.1007/s11356-020-11442-3>
- Ahmad, D., Afzal, M., 2020. Climate change adaptation impact on cash crop productivity and income in Punjab province of Pakistan. *Environ. Sci. Pollut. Res.* 27, 30767–30777. <https://doi.org/10.1007/s11356-020-09368-x>
- Ahmad Jan, S., Bibi, N., Khan Shinwari, Z., Ashiq Rabbani, M., Ullah, S., Qadir, A., Khan, N., 2017. Impact of salt, drought, heat and frost stresses on morpho-biochemical and physiological properties of Brassica species: An updated review. *J. Rural Dev. Agric.* 2, 1–10.
- Ahmad, Manzoor, Khan, Z., Rahman, Z.U., Khattak, S.I., Khan, Z.U., 2021. Can innovation shocks determine CO2 emissions (CO2e) in the OECD economies? A new perspective. *Econ. Innov. New Technol.* 30, 89–109. <https://doi.org/10.1080/10438599.2019.1684643>
- Ahmad, Munir, Rehman, A., Shah, S.A.A., Solangi, Y.A., Chandio, A.A., Jabeen, G., 2021. Stylized heterogeneous dynamic links among healthcare expenditures, land urbanization, and CO2 emissions across economic development levels. *Sci. Total Environ.* 753. <https://doi.org/10.1016/j.scitotenv.2020.142228>
- Ahmad, S., Nadeem, M., Abbas, G., Fatima, Z., Zeb Khan, R.J., Ahmed, M., Ahmad, A., Rasul, G., Azam Khan, M., 2016. Quantification of the effects of climate warming and crop management on sugarcane phenology. *Clim. Res.* 71, 47–61. <https://doi.org/10.3354/cr01419>
- Ahmad, S., Tariq, M., Hussain, T., Abbas, Q., Elham, H., Haider, I., Li, X., 2020. Does Chinese FDI, climate change, and CO2 emissions stimulate agricultural productivity? An empirical evidence from Pakistan. *Sustain.*

12. <https://doi.org/10.3390/SU12187485>

Ahsan, F., Chandio, A.A., Fang, W., 2020. Climate change impacts on cereal crops production in Pakistan. *Int. J. Clim. Chang. Strateg. Manag.* 12, 257–269. <https://doi.org/10.1108/ijccsm-04-2019-0020>

Ainsworth, E.A., Yendrek, C.R., Sitch, S., Collins, W.J., Emberson, L.D., 2012. The effects of tropospheric ozone on net primary productivity and implications for climate change. *Annu. Rev. Plant Biol.* 63, 637–661. <https://doi.org/10.1146/annurev-arplant-042110-103829>

Alam, A., Azam, M., Abdullah, A. Bin, Malik, I.A., Khan, A., Hamzah, T.A.A.T., Faridullah, Khan, M.M., Zahoor, H., Zaman, K., 2015. Environmental quality indicators and financial development in Malaysia: unity in diversity. *Environ. Sci. Pollut. Res.* 22, 8392–8404. <https://doi.org/10.1007/s11356-014-3982-5>

Alexandratos, Nikos ; Bruinsma, J.F., 2012. World Agriculture Towards 2030/2015: The 2012 Revision. ESA Work. Pap. No. 12-03. [https://doi.org/10.1016/S0264-8377\(03\)00047-4](https://doi.org/10.1016/S0264-8377(03)00047-4)

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., Din, I., 2017. Climate Change and Its Impact on the Yield of Major Food Crops: Evidence from Pakistan. *Foods* 6, 39. <https://doi.org/10.3390/foods6060039>

Ali, S., Ying, L., Anjum, R., Nazir, A., Shalmani, A., Shah, T., Shah, F., 2020. Analysis on the nexus of CO₂ emissions, energy use, net domestic credit, and GDP in Pakistan: an ARDL bound testing analysis. *Environ. Sci. Pollut. Res.* <https://doi.org/10.1007/s11356-020-10763-7>

Alola, A. A., Bekun, F. V., & Sarkodie, S. A. (2019). Dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on ecological footprint in Europe. *Science of the Total Environment*, 685, 702-709.

Anjum, A.S., Zada, R., Tareen, W.H., 2016. Organic farming: Hope for the sustainable livelihoods of future generations in Pakistan. *J. Rural Dev. Agric.* 1, 20–29.

Aragón, F.M., Oteiza, F., Rud, J.P., 2019. Climate change and agriculture: Subsistence farmers' response to extreme heat. *arXiv*. <https://doi.org/10.1257/pol.20190316>

Asumadu-Sarkodie, S., Owusu, P.A., 2017. Recent evidence of the relationship between carbon dioxide emissions, energy use, GDP, and population in Ghana: A linear regression approach. *Energy Sources, Part B Econ. Plan. Policy* 12, 495–503. <https://doi.org/10.1080/15567249.2016.1208304>

Asumadu-Sarkodie, S., Owusu, P.A., 2016. The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. *Environ. Sci. Pollut. Res.* 23, 10968–10982. <https://doi.org/10.1007/s11356-016-6252-x>

Attiaoui, I., Boufateh, T., 2019. Impacts of climate change on cereal farming in tunisia: A panel ARDL–PMG approach. *Environ. Sci. Pollut. Res.* 26, 13334–13345. <https://doi.org/10.1007/s11356-019-04867-y>

- Aziz, N., Sharif, A., Raza, A., Rong, K., 2020. Revisiting the role of forestry, agriculture, and renewable energy in testing environment Kuznets curve in Pakistan: evidence from Quantile ARDL approach. *Environ. Sci. Pollut. Res.* 27, 10115–10128. <https://doi.org/10.1007/s11356-020-07798-1>
- Banday, U.J., Aneja, R., 2019. Energy consumption, economic growth and CO₂ emissions: evidence from G7 countries. *World J. Sci. Technol. Sustain. Dev.* 16, 22–39. <https://doi.org/10.1108/wjstsd-01-2018-0007>
- Burakov, D., 2019. Does agriculture matter for environmental Kuznets curve in Russia: Evidence from the ARDL bounds tests approach. *Agris On-line Pap. Econ. Informatics* 11, 23–34. <https://doi.org/10.7160/aol.2019.110303>
- Chandio, A.A., Jiang, Y., Rehman, A., Rauf, A., 2020. Short and long-run impacts of climate change on agriculture: an empirical evidence from China. *Int. J. Clim. Chang. Strateg. Manag.* 12, 201–221. <https://doi.org/10.1108/IJCCSM-05-2019-0026>
- Dharmasiri, L.M., 2012. Measuring Agricultural Productivity Using the Average Productivity Index (API). *Sri Lanka J. Adv. Soc. Stud.* 1. <https://doi.org/10.4038/sljass.v1i2.4855>
- Di Gregorio, M., Nurrochmat, D.R., Paavola, J., Sari, I.M., Fatorelli, L., Pramova, E., Locatelli, B., Brockhaus, M., Kusumadewi, S.D., 2017. Climate policy integration in the land use sector: Mitigation, adaptation and sustainable development linkages. *Environ. Sci. Policy* 67, 35–43. <https://doi.org/10.1016/j.envsci.2016.11.004>
- DS, B., RL., N., 2009. Historical warnings of future food insecurity with unprecedented seasonal heat. *Science* (80-.). 323, 240–44.
- Eckstein, D., Künzel, V., Schäfer, L., 2020. Global climate risk index 2021 28.
- Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64, 813. <https://doi.org/10.2307/2171846>
- Enders, W., Jones, P., 2016. Grain prices, oil prices, and multiple smooth breaks in a VAR. *Stud. Nonlinear Dyn. Econom.* 20, 399–419. <https://doi.org/10.1515/snde-2014-0101>
- Fan, W., M. Carroll, C., 2012. Regional trend of climatic change in the USA. *World J. Sci. Technol. Sustain. Dev.* 9, 38–44. <https://doi.org/10.1108/20425941211223615>
- Figueiredo, F., Gomes, M.I., Henriques-Rodrigues, L., Miranda, M.C., 2012. A computational study of a quasi-PORT methodology for VaR based on second-order reduced-bias estimation. *J. Stat. Comput. Simul.* 82, 587–602. <https://doi.org/10.1080/00949655.2010.547196>
- Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food security: The challenge of feeding 9 billion people. *Science* (80-.). 327, 812–818. <https://doi.org/10.1126/science.1185383>

- Gokmenoglu, K.K., Taspinar, N., Kaakeh, M., 2019. Agriculture-induced environmental Kuznets curve: the case of China. *Environ. Sci. Pollut. Res.* 26, 37137–37151. <https://doi.org/10.1007/s11356-019-06685-8>
- Heck, W.W., Taylor, O.C., Tingley, D.T., 1988. Assessment of crop loss from air pollutants. *Assess. Crop loss from air Pollut.* <https://doi.org/10.2134/jeq1990.00472425001900040025x>
- Husnain, M.I.U., Subramanian, A., Haider, A., 2018. Robustness of geography as an instrument to assess impact of climate change on agriculture. *Int. J. Clim. Chang. Strateg. Manag.* 10, 654–669. <https://doi.org/10.1108/IJCCSM-03-2017-0049>
- JA. Foley, N.Ramankutty, K.A. Brauman, E.S. Cassidy, J.S. Gerber, M.J., 2013. Solutions for a cultivated planet.
- Janjua, P.Z., Samad, G., Khan, N., 2014. Climate change and wheat production in Pakistan: An autoregressive distributed lag approach. *NJAS - Wageningen J. Life Sci.* 68, 13–19. <https://doi.org/10.1016/j.njas.2013.11.002>
- Khan, Z., Sisi, Z., Siqun, Y., 2019. Environmental regulations an option: Asymmetry effect of environmental regulations on carbon emissions using non-linear ARDL. *Energy Sources, Part A Recover. Util. Environ. Eff.* 41, 137–155. <https://doi.org/10.1080/15567036.2018.1504145>
- Khattak, S.I., Ahmad, M., Khan, Z.U., Khan, A., 2020. Exploring the impact of innovation, renewable energy consumption, and income on CO₂ emissions: new evidence from the BRICS economies. *Environ. Sci. Pollut. Res.* 27, 13866–13881. <https://doi.org/10.1007/s11356-020-07876-4>
- Kirikaleli, D., & Adebayo, T. S., 2020. Do renewable energy consumption and financial development matter for environmental sustainability? New global evidence. *Sustainable Development*.
- Kirikaleli, D., Gokmenoglu, K.K., 2020. Sovereign credit risk and economic risk in Turkey: Empirical evidence from a wavelet coherence approach. *Borsa Istanbul Rev.* 20, 144–152. <https://doi.org/10.1016/j.bir.2019.06.003>
- Koondhar, M.A., Li, H., Wang, H., Bold, S., Kong, R., 2020. Looking back over the past two decades on the nexus between air pollution, energy consumption, and agricultural productivity in China: a qualitative analysis based on the ARDL bounds testing model. *Environ. Sci. Pollut. Res.* 27, 13575–13589. <https://doi.org/10.1007/s11356-019-07501-z>
- Kousar, S., Shabbir, A., 2021. Analysis of environmental degradation mechanism in the nexus among energy consumption and poverty in Pakistan. *Environ. Sci. Pollut. Res.* <https://doi.org/10.1007/s11356-020-12140-w>
- Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H.M., Fosu, K.Y., Gbetibouo, G., Jain, S., Mahamadou, A., Mano, R., Kabubo-Mariara, J., El-Marsafawy, S., Molua, E., Ouda, S., Ouedraogo, M., Séne, I., Maddison, D., Seo, S.N., Dinar, A., 2006. Will African agriculture survive climate change? *World Bank Econ. Rev.* 20, 367–388. <https://doi.org/10.1093/wber/lhl004>

- Lashkari, A., Alizadeh, A., Rezaei, E.E., Bannayan, M., 2012. Mitigation of climate change impacts on maize productivity in northeast of Iran: A simulation study. *Mitig. Adapt. Strateg. Glob. Chang.* 17, 1–16. <https://doi.org/10.1007/s11027-011-9305-y>
- Liang, X.Z., Wu, Y., Chambers, R.G., Schmoldt, D.L., Gao, W., Liu, C., Liu, Y.A., Sun, C., Kennedy, J.A., 2017. Determining climate effects on US total agricultural productivity. *Proc. Natl. Acad. Sci. U. S. A.* 114, E2285–E2292. <https://doi.org/10.1073/pnas.1615922114>
- Lobell, D.B., Hammer, G.L., Chenu, K., Zheng, B., Mclean, G., Chapman, S.C., 2015. The shifting influence of drought and heat stress for crops in northeast Australia. *Glob. Chang. Biol.* 21, 4115–4127. <https://doi.org/10.1111/gcb.13022>
- Mahrous W, 2018. Dynamic impacts of climate change on cereal yield in Egypt: An ARDL model. *Financ. Walaa Mahrous - J. Econ.*
- Manandhar, T., Prashad, B., Nath Pal, M., 2018. Risk Factors for Intrauterine Growth Restriction and Its Neonatal Outcome. *Gynecol. Obstet.* 08. <https://doi.org/10.4172/2161-0932.1000464>
- Matthew, O., Osabohien, R., Fagbemi, F., Fasina, A., 2018. Greenhouse gas emissions and health outcomes in Nigeria: Empirical insight from auto-regressive distribution lag technique. *Int. J. Energy Econ. Policy* 8, 43–50.
- Mehmood, U., 2020. Globalization-driven CO₂ emissions in Singapore: an application of ARDL approach. *Environ. Sci. Pollut. Res.* <https://doi.org/10.1007/s11356-020-11368-w>
- Mendelsohn, R., 2014. The impact of climate change on agriculture in Asia. *J. Integr. Agric.* 13, 660–665. [https://doi.org/10.1016/S2095-3119\(13\)60701-7](https://doi.org/10.1016/S2095-3119(13)60701-7)
- Naseem, S., Guang Ji, T., Kashif, U., 2020. Asymmetrical ARDL correlation between fossil fuel energy, food security, and carbon emission: providing fresh information from Pakistan. *Environ. Sci. Pollut. Res.* 27, 31369–31382. <https://doi.org/10.1007/s11356-020-09346-3>
- Nazlioglu, S., Gormus, N.A., Soytas, U., 2016. Oil prices and real estate investment trusts (REITs): Gradual-shift causality and volatility transmission analysis. *Energy Econ.* 60, 168–175. <https://doi.org/10.1016/j.eneco.2016.09.009>
- Odugbesan, J.A., Adebayo, T.S., 2020. The symmetrical and asymmetrical effects of foreign direct investment and financial development on carbon emission: evidence from Nigeria. *SN Appl. Sci.* 2. <https://doi.org/10.1007/s42452-020-03817-5>
- Ozturk, I., 2015. Measuring the impact of energy consumption and air quality indicators on climate change: evidence from the panel of UNFCCC classified countries. *Environ. Sci. Pollut. Res.* 22, 15459–15468. <https://doi.org/10.1007/s11356-015-4757-3>

- Pakistan, 2020. Pakistan Economic Survey 2019-20. Econ. Surv. Islam. Econ. Advis. Wing, Minist. Financ.
- Parker, L., Bourgoin, C., Martinez-Valle, A., Läderach, P., 2019. Vulnerability of the agricultural sector to climate change: The development of a pan-tropical Climate Risk Vulnerability Assessment to inform sub-national decision making. *PLoS One* 14. <https://doi.org/10.1371/journal.pone.0213641>
- Pesaran, M.H. and Shin, Y., 1998. An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. *Econom. Econ. Theory 20th Century Ragnar Frisch Centen. Symp.* 371–413.
- Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econom.* 16, 289–326. <https://doi.org/10.1002/jae.616>
- Phillips, P.C.B., Perron, P., 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75, 335. <https://doi.org/10.2307/2336182>
- Pla, C., Fernandez-Cortes, A., Cuezva, S., Galiana-Merino, J.J., Canãveras, J.C., Sanchez-Moral, S., Benavente, D., 2020. Insights on Climate-Driven Fluctuations of Cave 222Rn and CO₂ Concentrations Using Statistical and Wavelet Analyses. *Geofluids* 2020. <https://doi.org/10.1155/2020/8858295>
- Proskurowski, G., Lilley, M.D., Seewald, J.S., Früh-Green, G.L., Olson, E.J., Lupton, J.E., Sylva, S.P., Kelley, D.S., 2008. Prioritizing Climate Change Adaptation Needs for Food Security in 2030. *Science* (80-.). 319, 604–607.
- Rafindadi, A.A., Yusof, Z., Zaman, K., Kyophilavong, P., Akhmat, G., 2014. The relationship between air pollution, fossil fuel energy consumption, and water resources in the panel of selected Asia-Pacific countries. *Environ. Sci. Pollut. Res.* 21, 11395–11400. <https://doi.org/10.1007/s11356-014-3095-1>
- Rashid, M., Husnain, Z., Shakoor, U., ul Husnain, M.I., 2020. Impact of climate change on cotton production in Pakistan: An ARDL bound testing approach. *Sarhad J. Agric.* 36, 333–341. <https://doi.org/10.17582/JOURNAL.SJA/2020/36.1.333.341>
- Rehman, A., Ma, H., Irfan, M., Ahmad, M., 2020. Does carbon dioxide, methane, nitrous oxide, and GHG emissions influence the agriculture? Evidence from China. *Environ. Sci. Pollut. Res.* 27, 28768–28779. <https://doi.org/10.1007/s11356-020-08912-z>
- Rehman, A., Ozturk, I., Zhang, D., 2019. The causal connection between CO₂ emissions and agricultural productivity in Pakistan: Empirical evidence from an autoregressive distributed lag bounds testing approach. *Appl. Sci.* 9. <https://doi.org/10.3390/app9081692>
- Schmidhuber, J., Tubiello, F.N., 2007. Global food security under climate change. *Proc. Natl. Acad. Sci. U. S. A.* 104, 19703–19708. <https://doi.org/10.1073/pnas.0701976104>
- Sharif, A., Afshan, S., Chrea, S., Amel, A., Khan, S.A.R., 2020. The role of tourism, transportation and globalization in testing environmental Kuznets curve in Malaysia: new insights from quantile ARDL

- approach. *Environ. Sci. Pollut. Res.* 27, 25494–25509. <https://doi.org/10.1007/s11356-020-08782-5>
- Sharmila Raisa, T., Chowdhury, S., Professor, A., Rahman, M., 2020. A NEXUS AMONG AIR POLLUTION, ENERGY CONSUMPTION AND AGRICULTURAL PRODUCTIVITY IN BANGLADESH: AN ARDL MODEL WITH STRUCTURAL BREAK Analysis of some aspects that influence employees' performance in Bangladesh View project A NEXUS AMONG AIR POLLUTION, ENERGY CONSUMPTION AND AGRICULTURAL PRODUCTIVITY IN BANGLADESH: AN ARDL MODEL WITH STRUCTURAL BREAK. *Int. J. Manag. (IJM)* 11, 93–103. <https://doi.org/10.34218/IJM.11.7.2020.010>
- Shoko, R.R., Belete, A., Chaminuka, P., 2019. Maize Yield Sensitivity To Climate Variability in South Africa: Application of the Ardl-Ecm Approac. *J. Agribus. Rural Dev.* 54. <https://doi.org/10.17306/j.jard.2019.01201>
- Sims, C.A., 1980. Macroeconomics and Reality. *Econometrica* 48, 1. <https://doi.org/10.2307/1912017>
- Torrence, C., Compo, G.P., 1998. A Practical Guide to Wavelet Analysis. *Bull. Am. Meteorol. Soc.* 79, 61–78. [https://doi.org/10.1175/1520-0477\(1998\)079<0061:APGTWA>2.0.CO;2](https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2)
- Ukhurebor, K.E., Aigbe, U.O., Onyancha, R.B., Adetunji, C.O., 2021. Climate Change and Pesticides: Their Consequence on Microorganisms 83–113. https://doi.org/10.1007/978-981-15-7459-7_5
- UNICEF, 2018. National Nutrition Survey 2018: Key Finding Report. Gov. Pakistan UNICEF Pakistan 2018.
- Wajiha, I., Qadir, S., 2016. Roles of women in agriculture : A case study of rural Lahore, Pakistan. *J. Rural Dev. Agric.* 1, 1–11.
- Warsame, A.A., Sheik-Ali, I.A., Ali, A.O., Sarkodie, S.A., 2021. Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. *Environ. Sci. Pollut. Res.* <https://doi.org/10.1007/s11356-020-11739-3>
- Weeks, D.P.C.C.L.E.Y.N. to K. in 20, 2015. Sustainable Development Report 2020. Dk 53, 1689–1699.
- Wheeler, T., Von Braun, J., 2013. Climate change impacts on global food security. *Science* (80-.). 341, 508–513. <https://doi.org/10.1126/science.1239402>
- Y.Toda, H., Taku Yamamoto, 1995. Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. *J. Econom.* 66, 225–250.
- Zhou, L., Chen, X., Tian, X., 2018. The impact of fine particulate matter (PM_{2.5}) on China's agricultural production from 2001 to 2010. *J. Clean. Prod.* 178, 133–141. <https://doi.org/10.1016/j.jclepro.2017.12.204>
- Zivin, J.G., Neidell, M., 2018. Air pollution's hidden impacts. *Science* (80-.). 359, 39–40. <https://doi.org/10.1126/science.aap7711>
- Zivot, E., Andrews, D.W.K., 1992. Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *J. Bus. Econ. Stat.* 10, 251. <https://doi.org/10.2307/1391541>

Figures

Figure 1

Flow Chart

Figure 2

Cumulative Sum Plot for Stability

Figure 3

Cumulative Sum of Square Plot for Stability

Figure 4

a: WTC Between TFP & AgricLabor b: WTC Between TFP & Agric-Land c: WTC between TFP & CO₂ d: WTC Between TFP & Feed e WTC Between TFP & Fertilizer

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