Physical Education, Health and Social Sciences

https://journal-of-social-education.org

E-ISSN: 2958-5996
P-ISSN: 2958-5988

Assessing the Nexus: Climate, Energy, and Geo-Political Risks in Pakistan

Ishfaq Hussain [1], Atteq ur Rehman [2], Spogmay khan [3], Nadeem Raza [4]

[1] MS Scholar, School of Economics, International Institute of Islamic Economics, International Islamic University, H10 Islamabad. ishfaqhussainchitrali@gmail.com
ishfaq.mseco002294@student.iiu.edu.pk
[2] Department of economics, Comsats university Islamabad attequrrehman1888@gmail.com
[3] Department of Economics, School of Social Sciences and Humanities (S³H).
National University of Sciences and Technology (NUST), H12 Islamabad
spogmaykhan827@gmail.com
[4] Department of economics, Comsats university Islamabad nadeemecon@gmail.com

DOI: https://doi.org/10.63163/jpehss.v3i1.226

Abstract

In today's world, environmental degradation is one of the major problems experienced by all the nations. The primary and key objective of this study was to assess the nexus between EFP, GPR, MTEMP, REC and NREC using autoregressive distributive lag (ARDL) approach. The time series dataset comprises a period of 1990 to 2022, collected from the Global Footprint Network and World Bank (Open Dataset). The Augmented Dickey- Fuller (ADF) tests confirmed that the dataset was a combination of stationary and non-stationary variables. The results of a bound test of the ARDL models indicate that a long-term cointegration exists between the variables in the model. The study used EFP as a dependent variable while GPR, MEANT, REC and NREC are used as explanatory variables. A percent increase in GPR insignificantly improves EFP by 25.5% while a unit increase in REC improves EFP significantly by 0.063 units. A percent increase in MEANT and NREC significantly reduces EFP by 248% and 46.5% respectively. The ARDL model reveals the significant positive impact of REC on Pakistan's ecological footprint, emphasizing the need of sustainable production and consumption using renewable energy sources. Higher GPR discourage FDI, and domestic investment reducing the production and consumption of commodities leading to the improvement in environmental quality. Rising mean temperatures (MEANT) and non-renewable energy consumption (NREC) negatively affect the ecological footprint, highlighting climate change challenges and its severity due to the excessive use of fossil fuels. Recommendations include incentivizing eco-friendly practices, addressing temperature-related issues, and promoting renewable energy to steer Pakistan towards a sustainable future. Strengthening environmental regulations and fostering international collaborations are essential components of this comprehensive approach.

Keywords: Ecological footprint, Geo-political risk, renewable energy, non-renewable energy, temperature, Climate change, Pakistan.

Introduction

In recent years, the global landscape has witnessed transformative changes driven by rapid urbanization, industrialization, and robust economic growth (Krausmann et al.,2019). Concurrently, a growing global concern for environmental preservation and sustainability has emerged, particularly in the context of the ecological footprint, a critical metric quantifying human impact on the Earth (Wackernagel and Rees, 1996).

This era of change is further complicated by the escalating geopolitical risks (GPRs), encompassing elements such as terrorism, war, militarization, and international conflicts, posing formidable challenges to sustainability. The concept of the ecological footprint, as introduced by Wackernagel and Rees in the early 1990s, offers a comprehensive evaluation of environmental impact, including factors like carbon emissions, land use, and resource consumption (Wackernagel et al., 2018). Geopolitical risks present uncertainties rooted in global political, social, and economic factors, including international conflicts, trade tensions, political instability, and shifts in global governance. As developing nations navigate this intricate interplay between ecological sustainability and geopolitical risks, the focus shifts to Pakistan, a country facing a heap of environmental challenges and geopolitical complexities. Understanding how geopolitical risks influence Pakistan's ecological footprint is imperative for informed policymaking and sustainable development.

In the pursuit of a sustainable future, the nexus between renewable and non-renewable energy consumption plays an important role in shaping ecological footprints (Saqib, 2022). Increased reliance on renewable energy emerges as a key driver in mitigating environmental impact, contributing to lower carbon emissions, reduced resource depletion, and a more sustainable ecological footprint (Bélaïd,and Youssef, 2017). Conversely, heavy dependence on non-renewable energy sources worsens environmental resources and contributing to climate change. Temperature, significantly linked to ecological footprints, experiences shift due to climate change, impacting ecosystems and natural resources. This temperature variability further influences factors such as weather, climate, water utilization, and agricultural practices, thereby shaping the ecological footprint. The complex relationship between renewable and non-renewable energy consumption, temperature changes, and their collective impact on ecological footprints underscores the challenges in achieving sustainability goals.

In this investigation, we employ Caldara and Lacoviello's introduced GPR index (2018), a proxy for assessing geopolitical events. The index is computed monthly through a particular analysis of content from 11 major newspapers. It stands out as a more robust metric, offering a consistent and comprehensive depiction of global events and conflicts.

Literature Review

Khurshid (2023) discovered the adverse effects of GPR, NREC, and trade liberalization on the environment sustainability from 1980 to 2021. The study emphasizes the need for Pakistan to prioritize disaster readiness, diplomatic efforts, and shift towards renewable energy for sustainable development. Husnain et al., (2022) examined the relationship between GPR and environmental degradation in E7 countries, revealing an Environmental Kuznets Curve. Increased renewable energy benefits environmental quality, while non-renewable energy worsens degradation. Surprisingly, GPR reduces both CO_2 emissions and ecological footprint. Anser et al., (2021) employ robust methodologies, including FMOLS and co-integration tests, to examine the impact of Geopolitical Risks (GPR), Economic Policy Uncertainty (EPU), and energy sources on ecological footprint. Findings reveal that GPR, and renewable energy reduce ecological footprint, while EPU and non-renewable energy usage increase ecological footprint. Chen et al., (2023) investigate the impact of geopolitical risk on energy consumption and CO2 emissions in BRICS economies using a NARDL method. The study finds that both positive and negative changes in geopolitical risk have a lasting negative effect on energy consumption in China, India, and Brazil. Furthermore, increasing geopolitical risk adversely influences CO2 emissions in South Africa and Russia, while reduced risk has diverse long-term effects on emissions in China, India, and South Africa. Answer et al., (2021) investigate the environmental implications of geopolitical risk corruption, and governance in BRICS countries (Brazil, Russia, India, China, and South Africa) from 1990 to 2018. Employing FMOLS, DOLS, and CS-ARDL methods, their findings reveal a positive correlation between GPR, corruption, political stability, energy consumption, and CO2 emissions, contributing to a better understanding of these indicators' impact on environmental quality. Hashmi et al., (2022) examine the connection between geopolitical risk (GPR) and global carbon emissions, emphasizing GPR's pivotal role as a significant determinant of carbon emissions worldwide. The study underscores the substantial impact of geopolitical factors on the environmental aspect of the global carbon footprint. Nathaniel et al (2020) investigated renewable energy , urbanization, and ecological footprint in Middle East and North African (MENA) regions using Augmented Mean Group algorithm for 1990 to 2016. They concluded that REC have no significant impact on environmental quality while NREC significantly contributes to environmental degradation.

Model Specification and Methodology

Pakistan's geographical position, with borders facing continuous threats and terrorism from Iran, Afghanistan, and India, significantly impacts its business environment and economy. Tensions with India create political and economic unrest, while the relationships with powerful nations like the USA and China influence Pakistan's diplomatic standing. The region's economic development is closely tied to regional peace and security, and international tensions further complicate Pakistan's diplomatic relations. Facing political turmoil, rising terrorism, economic challenges, and environmental crises, Pakistan is among the top 12 countries most vulnerable to climate changes. Overcoming internal obstacles and upgrading environmental efforts are essential for Pakistan's resilience in this complex geopolitical landscape.

As a result, the primary goal of the current study aims to figure out the relationship between EFP, GPR, MEANT, REC, and NREC.

Function form of the Model

$$\mathrm{EFP} = f\,(\mathrm{GPR}, \mathrm{MEANT}, \mathrm{NREC}, \mathrm{REC})$$

Ecological Footprint is the function of GPR, MEANT, NREC and REC.

Econometric Form of the Model

$$\ln\mathrm{EFP}_t = \beta_0 + \beta_1 \ln\mathrm{GPR}_t + \beta_2 \ln\mathrm{MEANT}_t + \beta_3 \ln\mathrm{NREC}_t + \beta_4 \mathrm{REC}_t \ \ldots.. (1)$$

Where lnEFP is log of ecological footprint, lnGPR is log of geo-political index, lnMEANT is a log of mean temperature, lnNREC is a log of non-renewable energy consumption and REC is the renewable energy consumption and t is the period i.e., 1990 to 2022.

The ARDL model was used to examine the symmetric influence of variables in both the short and long term. The following ARDL equation shows the linear relationship between the independent and dependent variables in the study,

$$\ln\mathrm{EFP}_t = \eta_0 + \sum_{i=1}^{q} \eta_1 (\ln\mathrm{EFP})_{t-1} + \sum_{i=1}^{q} \eta_2 (\ln\mathrm{GPR})_{t-1} + \sum_{i=1}^{q} \eta_3 (\ln\mathrm{MEANT})_{t-1} + \sum_{i=1}^{q} \eta_4 (\ln\mathrm{NREC})_{t-1} + \sum_{i=1}^{q} \eta_5 (\mathrm{REC})_{t-1} + \mu_t \ \ldots. (2)$$

Now we can re-specify the equation 2 and we will get Autoregressive Distributed Lag (ARDL) model equation.

$$\ln\mathrm{EFP}_t = \eta_0 + \sum_{i=1}^{q} \eta_1 (\ln\mathrm{EFP})_{t-1} + \sum_{i=1}^{q} \eta_2 (\ln\mathrm{GPR})_{t-1} + \sum_{i=1}^{q} \eta_3 (\ln\mathrm{MEANT})_{t-1} + \sum_{i=1}^{q} \eta_4 (\ln\mathrm{NREC})_{t-1} + \sum_{i=1}^{q} \eta_5 (\mathrm{REC})_{t-1} + \lambda_1 (\ln\mathrm{EFP})_{t-1} + \lambda_2 (\ln\mathrm{GPR})_{t-1} + \lambda_3 (\ln\mathrm{MEANT} + \lambda_4 (\ln\mathrm{NREC})_{t-1} + \lambda_5 (\mathrm{REC})_{t-1} + \mu_t \ \ldots. \textbf{(3)}$$

λ and η, shows long-term and short representation of variables respectively while n represents lag of the independent variables in the model.

Description of Variables

S. No	Variables	Symbol including log	Measurement Units	Source
1	Ecological Footprint	lnEFP	global hectares per capita	Global Footprint Networks
2	Geo-Political Index	lnGPR	Index	https://www.matteoiacoviello.com/gpr.htm
3	Temperature	lnMEANT	Mean Temperature (Celcius)	Climate Change Portal World Bank

4	Non-Renewable Energy Consumption	lnNREC	Fossil fuel energy consumption (% of total)	World Development Indicators
5	Renewable Energy Consumption	REC	(% of total final energy consumption)	World Development Indicators

Ecological Footprint (EFP) is the number of environmental resources necessary to produce the commodities that support an individual's lifestyle, and a nation's prosperity (Hayden, 2023). Geopolitical Risk (GPR) refers to the risks arising out of interactions between countries. These interactions include trade relationships, security partnerships, alliances, multinational climate initiatives, supply chains and territorial disputes (Caldara and Iacoviello, 2022). Mean temperature (MEANT) is the average air temperature throughout a specific area, typically a year, a month, or a day. Non-Renewable Energy Consumption (NREC) include coal, natural gas, oil, and nuclear energy. Once these resources are used up, they cannot be replaced. Renewable Energy Consumption (REC) includes energy consumption from all renewable resources: hydro, solid biofuels, wind, solar, liquid biofuels, and biogas, geothermal, marine, and waste.

Descriptive statistics:

To provide quantitative descriptions in a format that is reasonable, descriptive statistics are used. Descriptive statistics are a useful tool for characterizing the behavior of many variables.

Table 2: DescriptiveStatistics

	lnEFP	lnGPR	lnMEANT	lnNREC	REC
Mean	18.646	4.326	3.046	4.067	48.994
Median	18.694	4.319	3.051	4.083	47.930
Maximum	19.108	4.908	3.085	4.135	58.090
Minimum	18.182	3.681	2.987	3.957	42.100
Std. Dev.	0.254	0.267	0.024	0.044	4.129
Skewness	-0.195	-0.089	-0.533	-0.986	0.498
Kurtosis	2.104	3.140	2.723	3.364	2.459
Jarque-Bera	1.313	0.070	1.670	5.524	1.765
Probability	0.519	0.965	0.434	0.063	0.414

Table 2 shows descriptive stat which consists of tools measuring central tendency i.e., Mean, and Median, tools measuring dispersion i.e., Maximum, Minimum, and Standard Deviation, and tools measuring normality in the dataset i.e., Skewness, Kurtosis, and Jarque Bera test. lnEFP, lnGPR, lnMEANT and lnNREC are left skewed as the value of skewness is less than zero while REC is rightly skewed. lnGPR and lnNREC are Platykurtic while the other three variables are Leptokurtic in nature. JB probability is high for all the variables except lnNREC, and this implies OLS residuals are normally distributed.

ADF's Unit Root Test:

The Augmented Dickey Fuller (ADF) test is a statistical method used to determine if a time series data is stationary or not. Stationary data means that the statistical properties of the distribution, such as mean, variance, and covariance, remain constant over time. The ADF test checks for the presence of a unit root, which implies non-stationarity. If the p-value of the test is less than or equal to 5%, we reject the null hypothesis that a unit root exists and conclude that the series is non-stationary.

Table 3: Results of Augmented Ducky–Fuller unit root tests
With Constant and Trend

	I(0)	I(1)
lnEFP	0.883	0.000*
lnGPR	0.047*	0.000*
lnMEANT	0.036*	0.000*
lnNREC	0.132	0.000*
REC	0.363	0.001*

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%, and no * means Not Significant.

Table 3 implies that unit root has been assessed by using Augmented Dickey Fuller test. ADF test implies that lnGPR and lnMEANT are stationary at level and do not require differencing. LNEFP, LNNREC and REC become stationary at initial differencing.

Lag Length Criteria

The lag length criteria table helps determine the optimal number of lags for the model. The likelihood ratio (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz criterion (SC), and Hannan-Quinn (HQ) criterion are used for selection.

Table 4. Lag Length Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	117.005	NA	0.000	-7.226	-6.995	-7.151
1	207.529	146.007	0.000	-11.453	-10.06576*	-11.001
2	238.684	40.19984*	5.77e-12*	-11.85058*	-9.306	-11.02125*

Table 4 displays the results of determining the required leg length. Thus, it can be concluded that the as per AIC Criteria, and other lag length criterion optimum lag 2 is more appropriate as four information criteria are significant at lag 2.

Serial Correlation

Serial correlation occurs when residuals in a regression model are correlated over time, violating the assumption of independent errors. This can be caused by omitted variables, incorrect model specification, time-dependent data, or measurement errors.

Table 5: Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test			
F-statistic	2.840	Prob. F(2,3)	0.203
Obs*R-squared	18.976	Prob. Chi-Square(2)	0.1203

Table 5 shows that there is no serial correlation among the variables as probability value is greater than 5% significance level hence, we do not reject the null hypothesis and conclude that there is no serial correlation among the variables.

F-Bound Test

The Bound Test is used in ARDL models to determine whether a long-run relationship exists between variables. It compares the F-statistic with critical value bounds. If the F-statistic is above the upper bound, cointegration is confirmed, meaning a stable long-run relationship exists. If it is below the lower bound, there is no cointegration. If the value falls between the bounds, the result is inconclusive. If cointegration is found, both short-run and long-run effects can be analyzed.

Table 6: F-Bound Test

Test Statistic	Value	Significance	I(0)	I(1)
F-statistic	19.503	10%	2.200	3.090
k	4	5%	2.560	3.490
		2.50%	2.880	3.870
		1%	3.290	4.370

Table 6 shows the autoregressive distributive lag model co-integration—the bound test. F-statistic is greater than the critical values of upper bonds values at a 1%, 2.5%, 5% and 10% significant level. As a result, the null hypothesis of no cointegration is rejected, implying that ecological footprint, geo-political risk, urbanization, renewable and non-renewable energy consumptions have a long run co-integration.

Heteroskedasticity Test

The Heteroskedasticity Test checks whether the variance of errors in a regression model is constant. If the variance changes across observations, the model has heteroskedasticity, which can affect the reliability of standard errors and hypothesis tests. Common tests include the Breusch-Pagan and White tests. A high p-value indicates homoskedasticity (constant variance), while a low p-value suggests heteroskedasticity, requiring adjustments like robust standard errors.

Table 7: Heteroskedasticity Test

Breusch-Pagan-Godfrey			
F-statistic	0.963	Prob. F(23,5)	0.581
Obs*R-squared	23.658	Prob. Chi-Square(23)	0.423
Scaled explained SS	0.405	Prob. Chi-Square(23)	1

Table 7 shows that there is no heteroskedasticity in the data because the probability value is larger than the 5 % significance level.

Table 8: Specification Test

	Value	df	Probability
t-statistic	0.613293	4	0.5728
F-statistic	0.376128	(1, 4)	0.5728
Likelihood ratio	2.606232	1	0.1064

Table 8 represent RAMSEY RESET test, and the value of the Ramsey Regression Equation Specification Error Test (RESET) test confirms that our model is correctly specified as p-value of both t and F stat are larger than the significance level of 5%.

Estimation results

The ARDL (Autoregressive Distributed Lag) model is a regression technique used to analyze the relationship between variables in both the short run and long run. It is flexible as it can handle a mix of stationary and non-stationary variables. The model estimates how the dependent variable responds to changes in the independent variables over different time periods. In the short run, ARDL captures immediate effects, showing how changes in independent variables influence the dependent variable within a short time. In the long run, it identifies a stable relationship between variables, ensuring that temporary fluctuations do not affect the overall trend. The estimation involves selecting the optimal lag length, checking for cointegration, and interpreting both short-run adjustments and long-run equilibrium.

Short Run Estimations

Table 9: ARDL short run estimations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CointEq (-1) *	-0.679	0.044	15.298	0.000
LNEFP (-1) *	0.679	0.109	6.226	0.002
LNGPR (-1)	0.172	0.048	3.582	0.016
LNMEANT (-1)	-1.690	1.099	-1.538	0.048
LNNREC (-1)	-0.316	0.161	-1.958	0.075
REC (-1)	0.043	0.008	5.622	0.003
D(LNEFP (-1))	-1.043	0.137	-7.630	0.001
D(LNEFP (-2))	-0.208	0.111	-1.880	0.004
D(LNEFP (-3))	0.557	0.074	7.508	0.001
D (LNGPR)	-0.065	0.015	-4.331	0.008
D(LNGPR(-1))	0.041	0.031	1.329	0.001
D(LNGPR(-2))	0.138	0.024	5.879	0.002
D(LNGPR(-3))	0.170	0.017	9.747	0.000
D(LNMEANT)	1.315	0.220	5.980	0.002
D(LNMEANT(-1))	-1.079	0.782	-1.381	0.004
D(LNMEANT(-2))	-2.046	0.566	-3.617	0.015
D(LNMEANT(-3))	-1.184	0.323	-3.668	0.015
D(LNNREC)	0.976	0.151	6.451	0.001
D(LNNREC(-1))	2.099	0.226	9.295	0.065
D(LNNREC(-2))	0.509	0.239	2.132	0.066
D(REC)	-0.017	0.004	-4.575	0.006
D(REC(-1))	-0.023	0.006	-3.669	0.015
D(REC(-2))	-0.041	0.005	-7.513	0.001
D(REC(-3))	-0.014	0.004	-3.515	0.017

According to the ARDL short results lnGPR shows an insignificant positive relation, REC shows significant positive relation with lnEFP while lnMEANT and lnNREC have a significant negative impact on lnEFP. A percent and a unit increase in GPR and REC respectively lead to an increase of 17.2% and 0.043 units. A percent increase in MEANT and NREC reduces the lnEFP by 169% and 31.6% respectively.

The results of the ECM model show that the value of the ECM coefficient is negative and significant (−0.679). This value of ECM indicates that around 67.9% of deviations are adjusted per year. The ECM coefficient is quite a large value implying that the adjustment of short deviation around the long run time path is very quick.

Long run estimations

Table 10 : Long run estimations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Ln GPR	0.254	0.083	3.053	0.059*
Ln MEANT	-2.488	1.745	-1.426	0.021**
Ln NREC	-0.465	0.207	-2.245	0.048**
REC	0.063	0.007	9.494	0.000***

$$\mathrm{lnEFP_t} = 0.254\mathrm{lnGPR_t} - 2.488\mathrm{lnMEANT_t} - 0.465\mathrm{lnNREC_t} + 0.063\mathrm{REC_t}$$

A percent increase in GPR insignificantly improves EFP by 25.5% while a unit increase in REC significantly improves EFP by 0.063 units. A percent increase in MEANT and NREC reduces EFP significantly by 248% and 46.5% respectively.

Structural Stability

The CUSUM of Squares test visually assesses the dynamic stability of an autoregressive model. Using red and blue lines, it checks for systematic changes in model coefficients. If the blue line is between the red lines, the model is considered stable at a 5% significance level, indicating a good fit for the data. This test is crucial for maintaining stability in autoregressive models sensitive to factors like lag length and sample points. CUSUM of Squares (Figure 1) shows that blue line is placed between the red lines, this implies that the model is stable at a 5% significance level and model is a good fit.

Figure 1: Cumulative Sum of Squares of Recursive Residuals (CUSUM of Squares)

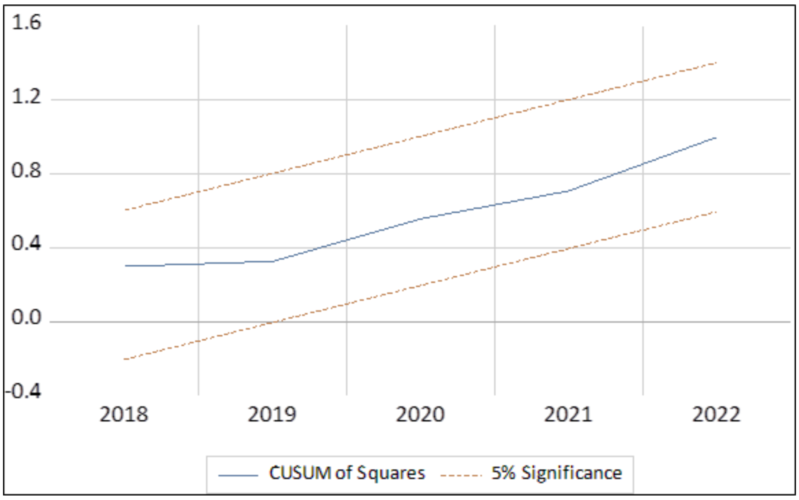

Table 1.9 shows the long run results of the ARDL model. All the variables have a significant impact on lnEFP except GPR. A percent increase in GPR lead to increase in EFP by 25.4%, GPR has significant positive impact in short run but long run its impact is not significant. In short run GPR causes instability within the economy but in long run the countries cater this with long term policies. Our results are consistent to those of Husnain et al., (2022), they stated that a one percent increase in GPR improves environmental sustainability by 0.10%. They added that higher GPR tend to fall in the production and consumption leading to the improvement in environmental quality. They concluded that GPR is one of the main determinants of investment in any country and higher GPR shows uncertainty in the economy leading to fall in the investment, and this have a positive impact on ecological footprint. Our results are not consistent to those of Nabila (2023), she concluded that GPR has a significant negative impact on environmental sustainability. She added that a unit increase in GPR deteriorate environmental sustainability by 0.234.

A percent increase in mean temperature has a significant negative impact of 248% on EFP, showing that GHGs emissions, industrialization, transportation, high energy consumption, deforestation increases the temperature of the world creating negative impact on the ecological footprint and environmental resources. Rise in temperature also lead to the scarcity of water and depletion of water resource making the future in threat. Pakistan is vulnerable to climactic changes, high fluctuations whether increase or decrease in climatic variables are not favorable to Pakistan. The negative consequences of elevated mean temperatures on ecological systems highlight the urgent need for global efforts to mitigate climate change and adapt to its unavoidable impacts for a more sustainable and balanced ecological future.

A percent increase in lnNREC reduces EFP by 46.5%, implying that the usage of non-renewable energy sources backed by gas, coal and oil products are vulnerable to the countries like Pakistan. Our results are consistent to those of Nabila (2023), she concluded that NREC have a significant negative impact on environmental sustainability. She added that a unit increase in NREC deteriorate environmental sustainability by 0.052 units. She stated that NREC can promote environmental degradation due to the increase in the production and energy consumption by using coal, natural gas, and oil products as all these sources significantly contributes to GHGs emissions. She further added that not only consumption of these sources like gas, coal and oil pollutes our environmental, but the extraction of these resources also pollutes our environment too. Our findings are consistent with Nathaniel and Khan (2020), they added that NREC are the source of environmental degradation in these ASEAN counties expect Philippines. Economic growth in these countries is not environment friendly. Dependence on non-renewable energy, like fossil fuels, poses significant challenges to ecological sustainability and increases the ecological footprint.

A unit increase in REC increase EFP by 0.063 units, our findings are supported by Adebayo and kirikkaleli (2021), they stated that increase in the consumption of renewable energy reduces CO2 emissions in short and medium terms. Our findings are consistent with Nathaniel and Khan (2020), they stated that renewable energy reduces environmental degradation in all the ASEAN countries. They advocated the ASEAN countries to make a structural shift from non-renewable to renewable energy consumption sources. The increasing adoption of renewable energy sources, such as solar, wind, and hydropower, is recognized as a pivotal strategy with positive ecological and economic impacts. This transition effectively combats climate change by reducing greenhouse gas emissions and concurrently improving economic efficiency. In essence, investing in renewable energy is not only an environmentally responsible choice but also a strategic move towards a more sustainable and resilient future.

Conclusion

The ARDL model paints a comprehensive picture of the intricate relationships among key variables influencing Pakistan's ecological footprint. Higher GPR discourage FDI, and domestic investment reducing the production and consumption of commodities leading to the improvement in environmental quality. The adverse effects of rising mean temperatures (MEANT) highlight the urgency for climate change mitigation, recognizing the interconnected challenges posed by GHG emissions, industrialization, and deforestation. Moreover, the substantial negative impact of non-renewable energy consumption (NREC) on ecological footprint emphasizes the importance of transitioning to renewable and cleaner energy sources. Conversely, the positive impact of renewable energy consumption (REC) on ecological footprint highlights the potential benefits of a strategic shift towards sustainable energy practices. The positive impact of green productivity (REC) suggests that fostering sustainable production and consumption practices can significantly enhance environmental sustainability.

The findings emphasize the need for policies favoring renewable energy and discouraging reliance on fossil fuels, aligning with global climate change mitigation goals. To achieve sustainable development, Pakistan should prioritize transitioning to green and renewable resources, supported by incentives for eco-friendly technologies. Recommendations include addressing rising temperatures through emission reduction, and adaptation of sustainable practices. Transitioning to renewable energy sources should be a policy priority, supported by dynamic research and development. These comprehensive strategies are essential for harmonizing economic growth with ecological well-being in Pakistan.

Our analysis of the climate, energy, and geo-political risk nexus in Pakistan is limited by the availability of comprehensive panel data. We focus solely on Pakistan due to data constraints, limiting the generalizability of our findings to the broader regional context. Future research should consider a wider panel data approach, including neighboring nations, for a more holistic understanding of these intricate interlinkages in the geopolitical and environmental landscape.

References

Krausmann, F., Erb, K. H., Gingrich, S., Lauk, C., & Haberl, H. (2008). Global patterns of socioeconomic biomass flows in the year 2000: A comprehensive assessment of supply, consumption and constraints. Ecological economics, 65(3), 471-487.

Wackernagel, M., & Rees, W. (1998). Our ecological footprint: reducing human impact on the earth (Vol. 9). New society publishers

Wackernagel, M., Lin, D., Evans, M., Hanscom, L., Goldfinger, S., & Gambhir, R. (2018). National Footprint and Biocapacity Accounts 2018. Global Footprint Network.

Saqib, N. (2022). Nexus between the renewable and nonrenewable energy consumption and carbon footprints: evidence from Asian emerging economies. Environmental Science and Pollution Research, 29(38), 58326-58340.

Bélaïd, F., & Youssef, M. (2017). Environmental degradation, renewable and non-renewable electricity consumption, and economic growth: Assessing the evidence from Algeria. Energy policy, 102, 277-287.

Khurshid, N. (2023). Does the causality between environmental sustainability, non-renewable energy consumption, geopolitical risks, and trade liberalization matter for Pakistan? Evidence from VECM analysis. Heliyon, 9(11).

Husnain, M. I. U., Syed, Q. R., Bashir, A., & Khan, M. A. (2022). Do geopolitical risk and energy consumption contribute to environmental degradation? Evidence from E7 countries. Environmental Science and Pollution Research, 29(27), 41640-41652.

Anser, M. K., Apergis, N., & Syed, Q. R. (2021). Impact of economic policy uncertainty on CO 2 emissions: evidence from top ten carbon emitter countries. Environmental Science and Pollution Research, 28, 29369-29378.

Chen, Z., Gao, W., Zafar, Q., & Dördüncü, H. (2023). Natural resources extraction and geopolitical risk: Examining oil resources extraction in China. Resources Policy, 85, 103811.

Anser, M. K., Syed, Q. R., & Apergis, N. (2021). Does geopolitical risk escalate CO2 emissions? Evidence from the BRICS countries. Environmental Science and Pollution Research, 28(35), 48011-48021.

Hashmi, S. M., Bhowmik, R., Inglesi-Lotz, R., & Syed, Q. R. (2022). Investigating the Environmental Kuznets Curve hypothesis amidst geopolitical risk: Global evidence using bootstrap ARDL approach. Environmental Science and Pollution Research, 29(16), 24049-24062.

Nathaniel, S., Anyanwu, O., & Shah, M. (2020). Renewable energy, urbanization, and ecological footprint in the Middle East and North Africa region. Environmental science and pollution research, 27, 14601-14613.

Adebayo, T. S., & Kirikkaleli, D. (2021). Impact of renewable energy consumption, globalization, and technological innovation on environmental degradation in Japan: application of wavelet tools. Environment, Development and Sustainability, 23(11), 16057-16082.

Nathaniel, S., & Khan, S. A. R. (2020). The nexus between urbanization, renewable energy, trade, and ecological footprint in ASEAN countries. Journal of Cleaner Production, 272, 122709.

D. Caldara, M. Iacoviello, Measuring geopolitical risk, International Finance Discussion Papers 1222 (2018), https://doi.org/10.17016/IFDP.2018.1222

Hayden, A. (2023, September 10). ecological footprint. Encyclopedia Britannica. https://www.britannica.com/science/ecological-footprint

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. American Economic Review, 112(4), 1194-1225.