Boosting Load Capacity: How Financial Outcomes and Institutional Quality Influence Environment?

Ayodele Oluwaseun

November 30, 2024

Boosting Load Capacity: How Financial Outcomes and Institutional Quality Influence Environment?

[1]Ayodele Oluwaseun

[1]Department of Environment and Forestry, Obafemi Awolowo University, Nigeria

Email: ayodele.okulu@gmail.com

Abstract

This study investigates the impact of financial accessibility, AI innovation, urbanization, and institutional quality on the load capacity factor in the United States from 1990 to 2019. A series of stationarity tests were conducted to detect the presence of unit root problems, revealing a mixed order of integration with no significant unit root issues. To explore the cointegration among variables, the ARDL bounds test was employed, confirming long-run cointegration. The ARDL model's short-run and long-run estimations demonstrate that the Load Capacity Curve hypothesis holds in the United States, with a U-shaped relationship between income and load capacity factor. The findings also indicate that financial accessibility, AI innovation, and institutional quality positively influence the load capacity factor in both the short and long run. Conversely, urbanization significantly reduces the load capacity factor over both time horizons. Furthermore, the study utilized alternative estimation approaches, including Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR), all of which validated the ARDL estimation results. Diagnostic tests confirmed the robustness of the model, showing that the variables are free from specification errors, serial correlation, and heteroscedasticity. These findings provide valuable insights for policymakers aiming to enhance load capacity through financial and technological advancements while considering the implications of urbanization.

Keywords: AI Innovation, Financial Accessibility, Institutional Quality, Load Capacity Factor,

1. Introduction

Ecological problems have been a central concern in environmental economics during the past few decades. Natural diversification has been endangered by contamination, widespread societal shifts, and loss of habitat (Rai and Singh 2020). Ecosystem issues like climate change, erosion of soil, air and water pollution, biodiversity loss, and the risk of global warming are being put on by a rising need for natural resources (Azam et al. 2023). The United States, one of the six superpowers and the most developed nation in the world, with 52 developed states, is the subject of our study's analysis of environmental deterioration. The USA is acknowledged as a primary source of carbon dioxide emissions worldwide, significantly impacting the total concentration of greenhouse gasses inside the environment. Between 1990 and 2022, pollution climbed as a result of economic growth in the 1990s, peaked in the early 2000s owing to changes in efficiency and policy, decreased in the 2010s as a result of rising usage of natural gas, and continued to be impacted by green energy and technological advancements in the 2020s (Dogan et al.,2024). After China, the United States of America (USA) continues to be the world's second-largest emitter of carbon dioxide (CO2) (Ozan et al.,2023). However, according to data from the US Environmental Protection Agency (2022), the US has seen a 7% decrease in greenhouse gas (GHG) emissions since 1990. Additionally, the US ranks 7th in the globe for GDP per capita and has the greatest GDP in the world (Khan et al.,2021). Despite the perception of the US financial system as deep and sophisticated, a lot of people still face barriers to access to finance. The truth is that 16.7 million Americans are unbanked, meaning that they do not have accessibility to a standard financial deposit account, and 50.9 million individuals in the US are under banked, having used Alternative Financial Services (AFS) (Karp and Nash-Stacey, 2015). Moreover, the application of Artificial Intelligence (AI) technologies has the potential to significantly transform waste management practices in marginalized communities and enhance environmental conditions in the USA (Nwokediegwu and Ugwuanyi,2024). These concerning statistics for the chosen criteria highlight the importance of the present investigation from a US perspective.

Our work utilized the load capacity factor, a crucial metric for evaluating how well a nation operates ecologically since it shows how human action damages our planet and how the environment makes up for it (Kartal et al.,2023). The majority of studies, however, have concentrated on carbon dioxide and ecological footprint, which largely address the demand side of environmental issues and run the risk of ignoring the supply side of these issues (Pata and Isik,2021). An LCF less than 1 jeopardizes ecological sustainability, whereas an LCF above 1 signifies biocapacity exceeding EF and sufficient natural resources for sustainability concerns. The literature on LCF is developing, although a thorough study of panel data has not yet been carried out (Pata and Samour,2023). Financial industry, commercial activity, population rates, modernization velocity, and usage of new technologies are the primary drivers of environmental pollution and greenhouse gas emissions that the USA must deal with due to its highly developed economy (Khan et al., 2019). The Fourth Industrial Revolution's central technology, artificial intelligence (AI), is progressively taking its place in propelling social progress and worldwide economic growth (Borges et al. 2021). Artificial intelligence (AI) has demonstrated enormous promise for preserving the environment (Kar et al., 2022; Marvin et al., 2022; Wang et al., 2023). It analyzes vast amounts of historical data to create effective prediction models, which improves the use of renewable energy. Furthermore, from a U.S. viewpoint, our analysis chooses financial accessibility, institutional quality, and AI innovation as fundamental policy variables in addition to the application of the advanced ARDL technique. According to these aspects, our study makes a substantial addition to the body of recent work. Global urbanization is speeding up; currently, 50% of people live in cities, and by 2025, that number is expected to rise to 60% (Pickett and others 2001). The United Nations reports that South America's urban population grew from 37% in 1960 to 82% in 2020 (Nations, 2018). Economic expansion results in the heavy use of power, natural assets, and production inputs, which initially pollutes the natural world and puts more strain on it (Nurgazina et al., 2022). However, it is widely acknowledged in the finance-environment discourse that the finance sector plays a crucial role in mitigating pollution by providing appropriate ecological financing (Kirikkaleli et al., 2022). Numerous works suggests that the institutional framework of a country affects the amount of government spending and how much of it ultimately influences production growth. The size of the public sector may have a negative effect on GDP development in nations with poor governance (Khan et al.,2024). Enforcing laws, regulations, corruption control, and rights of ownership, all of which minimize greenhouse gas emissions while promoting more productive and efficient practices, requires strengthening institutions (Ali et al., 2019).

Our investigation significantly contributes to the existing literature in several key ways. Firstly, there has been no empirical research on the relationship between AI innovation, institutional quality, and the Load Capacity Factor (LCF) in USA, making this study unique. The study employs ARDL methodologies to analyze trends and key research areas related to AI, financial accessibility (FA), institutional quality (IQ), economic development, and urbanization in the context of the USA's LCF from 1990 to 2018. By focusing on LCF, this analysis offers new insights for scholars and makes a notable contribution to the field. In order to provide a more thorough study, a comprehensive environmental evaluation should include biocapacity alongside carbon dioxide (CO2) emissions and the ecological footprint (EF), which emphasizes the demand of natural assets, by humans (Pata et al., 2023). Consequently, the Load Capacity Factor (LCF), defined as the ratio of biocapacity to ecological footprint (EF), was suggested by Siche et al. (2010). By considering ecological variables from the viewpoints of supply and demand, this technique provides a more comprehensive evaluation (Pata, 2021). As the first thorough analysis of LCF literature, our study seeks to answer the following queries: What is the consequence of FA, IQ, and AI on LCF in the United States? What additional implications do GDP and urbanization have on LCF? Comprehending these variables might help lawmakers and strategists in encouraging ecologically conscious behavior. Our study additionally uses FMOLS, DOLS, and CCR methodologies to verify the robustness of its findings. The research findings are very enlightening for legislators in the United States as well as for those who work to attain the Sustainable Development Goals (SDGs), encourage green growth, and improve ecosystem quality.

The order of the remaining sections is as below: Literature reviews constitute the main topic of the second section. The third chapter presents the data, technique, and theoretical framework. The empirical results are presented and discussed in the fourth portion. The conclusion and recommendations for policy are given in the last part of the paper.

2. Literature Review

The impact of financial inclusion, ICT use, and GDP development on the Load Capacity Factor (LCF) has been explored in several empirical studies. While many analyses have employed the ARDL model, most have concentrated on the effects of financial globalization and green energy on the LCF. Research on ecological degradation within the U.S. context is still relatively new and has not been extensively studied. This investigation, however, builds on previous studies to inform the selection of variables and methodologies used in the analysis.

2.1 GDP and Environment

Economic expansion is correlated with risks related to environmental pollution, air quality, and ecosystems (Awan et al.,2024). Growth in the economy motivates more carbon emissions, particularly when it is predicated on substantial energy usage and the use of fossil fuels to produce power (Nuta et al.,2024). Over the years, a great deal of inquiry has been done on the link between the environment and economic success. Further investigation on the correlation between the GDP and LCF in the USA needs to be done. Using data spanning from 1965 to 2017, Pata and Balsalobre-Lorente (2021) conducted a study in Turkey and identified an opposite relationship between the load capacity factor (LCF) and economic growth. In China, Ahmed et al. (2020) employed bootstrap causality analysis and the Bayer-Hanck cointegration test, and their results demonstrate environmental problems related to China's economic growth by illustrating how an increasing impact on the environment and pollution are brought on by GDP development. Similar findings were made by Pata and Isik (2021) in China and Majeed et al. (2021) in Pakistan, Agila et al.(2022) in South Korea, Shang et al.(2022) in ASEAN economies, Ridwan et al.(2024) in South Asian countries and Yang et al.(2024). A historical examination of the GDP growth of the G-7 countries concerning greenhouse gas emissions was carried out by Balcilar et al. (2018). They contend that environmental quality in Germany and the UK is not negatively impacted by economic expansion. Acar et al. (2023) disclosed an inverse U-shaped Environmental Kuznets Curve, which revealed that while initial economic growth contributed to more degradation of the environment, afterwards growth across a particular threshold led to increases in environmental quality. Using economic growth as a long-term economic instrument, Destek et al. (2020) gave policymakers fresh insights on how to improve the quality of our surroundings.

2.2 AI and Environment

Environmental degradation and the global warming problem are extremely complicated issues that need for cutting-edge and innovative remedies (Nishant et al., 2020). Since computers make it possible to monitor, analyze, communicate, and store information, they are essential for environmental protection. Artificial intelligence techniques can then be used to integrate and improve these duties (Cortes et al.,2000). Some academics have noted the possible environmental impacts of AI as relevant research progresses (like Kar et al. 2022; Vinuesa et al., 2020; Dhar, 2020). Dong et al. (2024) conducted an analysis of data from 267 Chinese cities between 2008 and 2019 and found that the use of AI minimizes carbon dioxide emissions by an average of 40,100 tons per unit increment. From 2012 to 2021, Chen and Jin (2023) conducted a study in Chinese A-share-listed industrial enterprises and discovered that the use of corporate AI technology has a favorable effect on reducing greenhouse gases.
According to Adnan et al. (2024), the application of artificial intelligence (AI) to environmental management more especially, its application to pollution has proven to be an important advance that has revolutionized environmental monitoring techniques. Additionally, the impact of artificial intelligence (AI) on the environment globally from 2010 to 2019 is examined by Wang et al. (2024) who demonstrate that AI significantly reduces ecological footprints.

2.3 Financial Accessibility and Environment

Much literature provides evidence that there is conflicting evidence linking finance and environmental concerns. On the one hand, financial accessibility gives businesses and green economies the availability of affordable and attractive financing schemes (Le et al., 2020). Conversely, industrial activities are rising in nations with relatively easy utilization of financial services and funds; as a result, emissions are high and the atmosphere is contaminated (Hasanov et al., 2021).Using the ARDL model, Raihan et al. (2024b) examined the link between financial accessibility and CO2 emissions in the G-7 region between 1990 and 2019. The results show that access to finance worsens environmental conditions and raises CO2 emissions. Moreover, Using AMG and CCEMG estimation as well as PMG for causality testing, Ali et al. (2022)

investigate the consequences of financial integration on the ecological impact in ECOWAS economies from 1990 to 2016. They revealed that the burden on the environment is increased by financial accessibility. Along the same principles, Hussain et al.(2022) in OECD countries, Vu et al.(2023) in MENA region, Anu et al. (2023) in developed and emerging areas, Fareed et al.(2022) in Eurozone, and Yurtkuran and Güneysu (2023) in Turkiye indicated that accessibility in finances is not good for the state of ecosystem. On the other hand, Saqib et al. (2023) investigated the implications of financial inclusion on the ecological footprint of developing nations between 1990 and 2019. Through the use of sophisticated panel estimate techniques, they demonstrated that monetary integration reduces environmental harm. Similar over view also represented by Feng et al.(2022) in China, Tamazian et al (2009) in BRIC countries and Zhong (2022) in China. Furthermore, Barut et al. (2023) described that financial accessibility did not affect contamination.

2.4 Institutional Quality and Environment

Natural resources, climate change, and the expansion of the economy are all greatly affected by institutional quality, which includes the rule of law, the efficiency of the administration, the quality of regulations, and stability in politics (Byaro et al., 2024). Therefore, ecological stability might be threatened by inadequate policies about these concerns. The relationship between institutional quality and environmental sustainability has been emphasized in several current studies (Hao et al., 2023; Ni et al., 2022; Borghi et al., 2023; Chhabra et al., 2023). From 1990 to 2019, Aydin et al. (2024) investigated the impact of institutional quality (IQ) on 10 European Union nations that invest the most in environmental technologies. They discovered that improved quality in institutions raises LCF in Germany and France and lowers LCF in Austria. Furthermore, it has been established that the LCC theory exclusively only applies to Spain. Zakaria and Bibi (2019), there will be a 0.114% reduction in pollution in South Asia for every 1% increase in the quality of institutions. According to Ali et al. (2019), in 47 developing nations, organizational excellence which includes measures of the legal system, bureaucratic superiority, and corruption control reduces emissions. Furthermore, Ni et al. (2022) investigate the role that institutional quality plays in raising the LCF of economies with high resource consumption, and the study's long-term findings support this claim. On the other hand, Dam et al. (2024) investigate how IQ affects LCF in OECD nations and find that, over time, institutional quality has a positive and significant consequence on degradation. Similarly, Findings by Anwar and Malik (2022) and Farooq et al. (2023) further confirmed the idea that institutional excellence might reduce environmental degradation. Achuo et al. (2024) additionally highlights how important it is for policymakers to promote legislation by improving institutional quality to foster a sustainable environment.

2.5 Urbanization and Environment

The phenomena of urbanization have a significant impact on the sustainability of the environment. But through encouraging energy-efficient technology, urban agglomerations, and climate change awareness through marketing and education, URBA can also have a positive impact on environmental quality (Kocoglu et al., 2021). Scholars like Ahmad et al. (2019) indicate that China is very interested in green technology, suggesting that URBA has a favorable link with the ecosystem. Similarly, Chien et al. (2023) explored the impact of urbanization on carbon emissions in the G-7 member nations using the innovative moment's quantile regression model. They found that growing populations seem to reduce emissions in high-emission nations. Moreover, using the dynamic ARDL model, Danish and Hassan (2023) argued that urbanization in Pakistan contributes to pollution control. On the other hand, Raihan et al. (2022c) examined how urbanization has affected CO2 emissions in the USA between 1970 and 2022. Using the ARDL framework, they demonstrated that for every 1% increase in urbanization, CO2 emissions increased by 0.56% in the short term and 0.20% in the long run. Furthermore, Azam and Khan (2016) employed the least squares method to investigate how urbanization affects the environment in SAARC countries. The results disclosed that, while there was a negative correlation in Bangladesh and India, there was an opposite relationship in Sri Lanka and Pakistan between urbanization and environmental degradation. In a similar vein, Tanveer et al.(2024) in Pakistan, Azam and Qayyum (2016) in USA, Alola et al. (2024) in Nordic region and Voumik et al.(2023b) in Keneya also observed that urban growth is harmful for the environment. But, Xu et al. (2022) carried out research in Brazil and discovered that urbanization does not affect LCF by using the ARDL bound testing. At the same way, Sui et al. (2024) used the ECM model in China to demonstrate that, over time, the growth of urbanization will not deteriorate the ecological environment.

2.6 Literature Gap

There hasn't been a thorough examination of the hyperlinks between load capacity factor (LCF), financial accessibility (FA), artificial intelligence (AI) innovation, institutional quality (IQ), economic growth, and urbanization in the United States as a whole. While these components have been a focus of individual studies in the past, comprehensive assessments have been lacking, especially when it comes to the relationship in the context of the United States. By advancing energy efficiency, green technologies, and sustainable urban planning, the proper application of AI technologies might assist in minimizing climate change. Moreover, conservation efforts can be supported by financial accessibility, and efficient pollution-reduction strategies may be fostered by modern institutions. These three interconnected factors IQ, FA, and AI form an emerging area for investigation in the context of the United States. To fill the research discrepancies, our research incorporates strong statistical techniques such as ARDL, FMOLS, DOLS, and CCR. The investigation intends to assist lawmakers in formulating policies appropriate to the distinct environmental and macroeconomic dynamics of the USA promoting equitable growth by emphasizing LCF's role in preserving the environment.

3. Methodology

3.1 Data and Variables

The first table is a vital component of this research as it contains an in-depth review of all the factors investigated. The LCF data for the United States is derived from the Global Footprint Network (GFN), which is more appropriate than the other environmental proxies. The study additionally included a large number of independent variables, all of which were based on precisely the information obtained. The World Development Indicators (WDI) provided reliable figures on GDP, GDP squares, and urbanization. Our World in Data was designed to collect statistics regarding other important factors such as Artificial Intelligence innovation and institutional excellence. However, information concerning financial accessibility was collected from the IMF. As a result, through enhancing the availability and dependability of the study's approach, extensive proof ensures an explicit and integrated analysis.

Table 01: Source and Description of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
GDP^2	Square of Gross Domestic Product	$LGDP^2$	GDP per capita (current US$)	WDI

AI	Artificial Intelligence Innovation	LAI	Annual patent applications related to artificial intelligence	Our World in Data
FA	Financial Accessibility	LFA	Financial Institution Access Index	IMF
IQ	Institutional Quality	LIQ	Government Effectiveness, Estimate	Our World in Data
URBA	Urbanization	LURBA	Urban Population (% of population)	WDI

3.2 Theoretical Framework

In environmental studies, the load capacity curve (LCC) is a vital tool that sheds light on the complex linkages among ecological health, financial stability, and human development. This emphasizes the equilibrium or imbalance between the planet's ability to recover its resources and its use of human assets. The LCF provides an additional environmental evaluation by contrasting ecological footprint and biocapacity (Dogan and Pata, 2022). A more robust ecological footprint and higher load capacity factor (LCF) are indicators of a more salubrious ecosystem (Pata and Kartal, 2023). The LCF was utilized in several recent researches by Sun et al. (2024), Dai et al. (2023), and Yang et al. (2023) to validate the LCC hypothesis in the selected locations. Because of these important features, we used the LCF as a proxy for environmental damage in our analysis instead of the more usual CO2 emissions or ecological footprint.

The LCC is thought to be connected in a U-formation, with GDP serving as the primary drive. This link highlights the knowledge of how resource utilization expands in tandem with GDP growth and advances in individual affluence as an essential aspect of environmental sustainability (Degirmenci & Aydin, 2024). According to Ulucak et al. (2020), several industries alter manufacturing processes and greenhouse gases, financial growth exacerbates commercial polluting substances, and expanding economies are disadvantaged. We previously mentioned that there might be multiple links between factors such as GDP growth, private investment in artificial intelligence, technical innovation, urbanization, financial globalization, and load capacity factor. Now, equation (1) is developed for LCC theory to boost the comprehension of earlier studies.

$$Load\ Capacity\ Factor = f(GDP, GDP^2, Q_t) \qquad (1)$$

In this case, Q_t denotes other factors changing the LCF, while GDP stands for wealth in equation (1). The 2nd equation attempts to give a deeper knowledge of the LCF by including variables such as economic growth, AI innovation, financial accessibility, institutional quality, and urbanization.

$$LCF = f(GDP, GDP^2, AI, FA, IQ, URBA) \qquad (2)$$

The load capacity factor (LCF) is denoted in equation (2), while finance availability (FA), AI innovation (AI), quality of institutions (IQ), and urbanization (URBA) constitute distinctive concepts. The econometric explanation of equation (3) was stated previously.

$$LCF_{it} = \delta_0 + \delta_1 GDP_{it} + \delta_2 GDP^2{}_{it} + \delta_3 PAI_{it} + \delta_4 FGOB_{it} + \delta_5 TI_{it} + \delta_6 URBA_{it} \quad (3)$$

The next equation illustrates the logarithmic values of the factors, which makes statistical information less complicated to interpret and constitute conclusions upon. Moreover, logarithmic scales assist in managing information with different dimensions while tackling obstacles such as heteroscedasticity, which is particularly relevant when working on large datasets. In this case, the research's coefficients are displayed in the parameter range of δ_0 to δ_6 .

.

$$LLCF_{it} = \delta_0 + \delta_1 LGDP_{it} + \delta_2 LGDP^2{}_{it} + \delta_3 LAI_{it} + \delta_4 LFA_{it} + \delta_5 LIQ_{it} + \delta_6 LURBA_{it} \ (4)$$

3.3 Empirical Methods

This study used the ARDL method for data assessment to explore the link between LCF and variables such as GDP, GDP2, AI innovation, FA, IQ, and URBA in the USA. Additionally, we used the FMOLS, DOLS, and CCR approaches to guarantee robustness. To ensure stationarity, the unit root tests (DF-GLS, ADF, and P-P) were conducted at the start of the inquiry. Because of the nature of the time series data, the ARDL bound test was then applied. The estimates for the short and long-term ARDL were then performed. Next, we undertook multiple diagnostic tests in addition to the pairwise granser causality analysis. After a rigorous process of evaluation, we managed to determine which econometric approach was the most precise and effective.

3.3.1 Unit Root Tests

The key to avoiding incorrect regression is to use a unit root test. The stationary nature of the regression factors is confirmed by differences and stationary processes (Raihan et al., 2022a). To identify non-stationary data that could lead to incorrect outcomes, they establish if a time series is stationary or non-stationary (Voumik and Ridwan, 2023). When a time series exhibits a stochastic trend that is, when it gradually deviates from its mean it is said to have a unit root (Polcyn et al.,2023). Many studies have recommended running multiple stationarity analyses to assess the sequence integration categorization because the efficiency of such tests varies depending on the sample size (Voumik et al.,2023a).The present research used the Dickey Fuller-Generalized Least Squares (Elliot et al., 1992), the Philips Perron (Philips and Perron, 1968), and the Augmented Dickey-Fuller (Dickey and Fuller, 1979) unit root tests to observe the stationarity within the data set. Due to its ability to control serial autocorrelation, the ADF technique has grown in favor (Dickey and Fuller, 1981). Compared to the Dickey-Fuller (DF) approach, the ADF technique is more dependable and appropriate for more complicated tasks (Fuller, 2009).

3.3.2 ARDL Methodology

The ARDL limits testing technique created by Pesaran et al. (2001) was used when variables exhibit stationarity. The ARDL model can be used to account for endogeneity by considering the variable's lag time (Raihan,2023). According to Raihan and Voumik (2022a), another benefit is that it can be deployed in any investigative series integration situation. Even with a small number of observations, the ARDL model remains feasible. As a result, the ARDL cointegration method offers precise and effective estimates of the variables' long-term relationship (Raihan and Voumik, 2022b). Moreover, scholars can effortlessly detect dynamic adjustment mechanisms by incorporating lagged terms of variables with ARDL (Raihan et al., 2024a). Therefore, the ARDL bounds analysis technique can be applied regardless of whether the basic returning system is in sequence to separate in I(2) and the cointegration order occurs at I(0) or I(1) (Raihan et al.,2022b). Equation (5) shows the bounds assessment for the ARDL in the following way.

$$\Delta \mathrm{LLCF_t} = \delta_0 + \rho_1 \mathrm{LLCF_{t-1}} + \rho_2\ \mathrm{LGDP_{t-1}} + \rho_3 \mathrm{L}GDP^2{}_{\mathrm{t-1}} + \rho_4 \mathrm{LAI_{t-1}} + \rho_5 \mathrm{LFA_{t-1}} + \rho_6 \mathrm{LIQ_{t-1}} + \rho_7 \mathrm{L}URBA_{\mathrm{t-1}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_1\ \Delta \mathrm{LLCF_{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_2\ \Delta \mathrm{LGDP_{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_3\ \Delta \mathrm{L}GDP^2{}_{\mathrm{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_4\ \Delta \mathrm{LAI_{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_4\ \Delta \mathrm{LFA_{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_4\ \Delta \mathrm{LIQ_{t-i}} + \sum_{\mathrm{i=1}}^{\mathrm{q}} \delta_4\ \Delta \mathrm{LURBA_{t-i}} + \varepsilon_{\mathrm{t}} \tag{5}$$

As demonstrated by Pesaran et al. (2001), the upper and lower bounds could be utilized as the essential values, against which a comparison of the F-statistics is possible. If the F-statistics reject the null hypothesis and are more than the maximum permitted value, they imply a long-term link between the variables. The test findings are ambiguous if they are between the lowest and maximum bounds (Raihan et al.,2023a). After long-term connections are established, the error correction model (ECM), introduced by Engel and Granger (1987), is applied to assess the Error Correction Term (ECT) and short-term correlations. We use Equation (6) for the long-term analysis of the ARDL.

$$\Delta LLCF_t = \delta_0 + \sum_{i=1}^{q} \rho_1\ \Delta LLCF_{\mathrm{t-1}} + \sum_{i=1}^{q} \rho_2\ \Delta \mathrm{LGDP_{t-1}} + \sum_{i=1}^{q} \rho_3 \Delta GDP^2{}_{\mathrm{t-1}} + \sum_{i=1}^{q} \rho_4\ \Delta\ LAI_{t-1} + \sum_{i=1}^{q} \rho_5 \Delta \mathrm{LFA_{t-1}} + \sum_{i=1}^{q} \rho_6\ \Delta LIQ_{t-1} + \sum_{i=1}^{q} \rho_7\ \Delta LURBA_{t-1} + \theta ECM_{t-1} + \varepsilon_t \tag{6}$$

3.3.3 Robustness Check

It is essential to evaluate the responsiveness of long-run parameters obtained from the ARDL model through experiments before drawing any conclusions from a study. Consequently, to evaluate the dependability of the ARDL results derived from Eq. (5), this research used the FMOLS, DOLS, and CCR techniques. The FMOLS technique yields robust values and efficiently addresses measurement errors, serial correlation, endogeneity, bias from missing variables, and constrained sample size (Ahmad et al., 2024). It also considers the possibility of heterogeneity in the long-run parameters (Phillips and Hansen, 1990). In addition, in a model where the factors have distinct degrees of integration but are still cointegrated, the DOLS method takes a parametric approach to estimate a long-run connection (Stock and Watson, 1993). By combining data on the timing of each explanatory variable's measurement, this approximation eliminates the problems caused by shorter sample bias, endogeneity, and autocorrelation (Begum et al., 2020).Furthermore, the CCR is a regression model that can be applied to multivariate and single equation regression without requiring any modifications, hence guaranteeing the retention of efficiency (Park, 1992). Using the CCR modification, error terms in cointegrating models are separated from zero-regularity explanatory variables (Pattak et al.,2023).

3.3.4 Pairwise Granser Causality Test

Granger causality is a theory of statistics that assesses whether previous values of one variable provide useful information for predicting the other, to determine the causal relationship between the two variables (Rose and Paparas,2023). The Pair-wise Granger-causality test, which Granger (1969) developed was utilized in our work. A time series Y is said to be "Granger-caused" by another time series X if it may be leveraged to predict the latter's future (Raihan and Tuspekova, 2022a). These two variables' time series have a data length of T, and their values at time t are indicated by the variables Xt and Yt (t = 1,2,..., T), correspondingly. Nonetheless, the variables Xt and Yt may be shown in a bivariate autoregressive model.

$$X_t = \gamma_1 + \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=1}^{n} \mu_i X_{t-1} + e_t \quad (7)$$

$$Y_t = \gamma_2 + \sum_{i=1}^{n} \Omega_i Y_{t-1} + \sum_{i=1}^{n} ¥_i X_{t-i} + u_t \quad (8)$$

Here, the information criterion determines the "n" number of lags. The parameters used for the assessment were γ_1, γ_2, αi, Ωi, μi, and $¥_i$.

3.3.4 Diagnostic Test

To identify major problems that might have a direct effect on the precision of the predicted coefficients, a few diagnostic methods were employed, including the Lagrange Multiplier (LM) test, the Jarque-Bera test (Jarque and Bera, 1987), and the Breusch-Pagan-Godfrey test (Breusch and Pagan, 1979). The normality of the residuals is verified by the Jarque-Bera assessment. To make sure that errors do not correlate with time and result in skewed and deceptive calculations, the Lagrange Multiplier test looks for serial correlation in residuals. Heteroscedasticity can lead to estimates and standard errors that are incorrect when using the Breusch-Pagan-Godfrey test. Furthermore, we assess the coherence of the short-term beta coefficients in the ARDL method by comparing the repeated residuals to the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) examinations.

4. Results and Discussion

4.1 Summary Statistics

The following section includes actual figures generated from predetermined estimating methods, whereas Table 02 highlights the statistical properties of the variables under consideration. Because every data point had the same amount of observations (32), the box delivers an extensive evaluation that includes key statistical measurements including mean, median, maximum, minimum, standard deviation, and probability value. Most variables had positive means, except LLCF and LFA, and LGDP2 had the highest mean. Furthermore, the standard deviations of all variables were low, indicating little change over time and a high concentration of data points around the mean. Besides, LLCF, LAI, LFA, and LIQ were positively skewed, while the rest of the variables were negatively skewed. To ensure that each factor in this investigation had a normal distribution, the Jarque-Bera normality test was executed.

Table 02: Summary statistics of the variables

Variables	LLCF	LGDP	LGDP2	LAI	LFA	LIQ	LURBA
Mean	-0.835416	10.64393	113.3917	7.505506	-0.129338	0.471661	4.377885
Median	-0.822656	10.71885	114.8942	7.157725	-0.13288	0.444502	4.382195
Maximum	-0.63269	11.15938	124.5318	9.724421	-0.065403	0.692247	4.417309
Minimum	-0.970971	10.08116	101.6297	6.320768	-0.183003	0.243055	4.32148
Std. Dev.	0.093945	0.318778	6.76113	1.035853	0.032861	0.110563	0.027091
Skewness	0.065531	-0.255693	-0.219087	1.155679	0.25722	0.257958	-0.500595
Kurtosis	1.965479	1.888894	1.876795	2.992345	1.75315	2.707801	2.252894
Jarque-Bera	1.449882	1.994763	1.938117	7.123243	2.425709	0.468734	2.08073
Probability	0.484353	0.368844	0.37944	0.028393	0.297347	0.791071	0.353326

Sum	-26.73331	340.6058	3628.534	240.1762	-4.138819	15.09316	140.0923
Sum Sq. Dev.	0.273596	3.150205	1417.099	33.26275	0.033476	0.378947	0.022751
Observations	32	32	32	32	32	32	32

4.2 Unit root test

Table 03 demonstrates the stationarity tests (ADF, DF-GLS, and P-P) for the log-transformed variables at both the level and first difference levels. The findings illustrate that financial accessibility, institutional quality, and urbanization are stationary at level I(0) form. On the contrary, LCF, GDP, GDP squared, and AI innovation were non-stationary at the level but became stationary after adjusting for the first difference (I(I)). Considering the heterogeneous order of integration, therefore, we can perform the analysis using the ARDL methodology in the next section.

Table 03: Results of Unit root test

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-0.588	-5.743***	-0.643	-5.432***	-1.576	-4.110***	I(1)
LGDP	-0.725	-4.148***	-0.359	-4.928***	-1.118	-3.731***	I(1)
$LGDP^2$	-0.416	-5.903***	-0.740	-4.863***	-1.241	-3.655**	I(1)
LAI	-2.061	-4.134***	-1.068	-3.671***	-2.341	-4.061***	I(1)
LFA	-3.871**	-4.071***	-3.703**	-4.021***	-3.771**	-4.052***	I(0)
LIQ	-4.052***	-5.007***	-3.054**	-4.090***	-3.342**	-3.770***	I(0)
LURBA	-4.115***	-7.043***	-7.654***	-8.453***	-3.065**	-4.432***	I(0)

4.3 ARDL Bound test

The current study used an ARDL limits test to establish co-integration across the chosen variables. Based on the outcomes of the ARDL bound assessment, the null hypothesis of no co-integration is rejected at the 1% significance threshold. The F-test statistic result of 8.345 reached the specified value. As a consequence, it is possible to argue that the parameters of the model have certain co-integrating interactions. Such characteristics encourage the framework to adapt fastest to a typical stochastic disturbance. Therefore, we can conclude that variations in all of the factors identified influence the load capacity factor (LCF) in the United States.

Table 04: Results of ARDL bound test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	8.34532	10%	1.99	2.94
K=6		5%	2.27	3.28
Asymptotic: n=1000		2.50%	2.55	3.61
		1%	2.88	3.99

4.4 ARDL Short-run and Long-run estimation

After the cointegration had been verified by the bound testing process, we might evaluate the long-term connection among those variables. Table 5 adopts the dynamic ARDL model to demonstrate the short- and long-term effects of LGDP, LGDP2, LAI, LFA, LIQ, and LURBA on LLCF in USA. According to the research, the US environment's load capacity appears to go up with GDP growth but falls with economic growth over time. Our findings indicate that due to financial growth, the ecosystem increasingly loses its natural characteristics. The result makes a theoretical explanation because the US economy has become larger and heavily relies on sources like oil and gas, which damage the natural world. According to Table 5's conclusions, for every 1% increase in GDP, the LCF declines by 1.687% over the long term and by 0.738% during the short term. Increased consumption and development efforts to meet social expectations are linked to rising economic growth and damage to the environment (Raihan and Tuspekova 2022b). The positive relationship between GDP and ecosystem degradation is supported by several studies, including those conducted by Ridwan et al. (2023), Lin and Ullah (2024), Bekun (2024), Kirikkaleli et al. (2023), and Wang et al. (2023). However, Guo et al. (2024) observed that in China, the effect of per capita GDP on the natural world will eventually lessen. In contrast, each unit of GDP2 boosts leads to a 1.644% long-term and 0.668% short-term enhancement of LCF. Given that the coefficient for LGDP is unfavorable and the coefficient for LGDP2 is beneficial, and both are statistically significant, it appears that atmospheric pressure decreases over time, validating the recently offered LCC hypothesis for the United States. However, Dogan et al. (2020) discovered that GDP2 worsens the degree of environmental adaptability in the BRICS.

The LAI coefficients exhibit a positive association with LLCF, predicting a 0.077% long-term and a 0.030% short-term increase in LLCF for every 1% increase in AI innovation. According to Platon (2024), artificial intelligence is an important component that could improve and hasten the rise of the circular economy. Moreover, AI lowers emissions of carbon in China by strengthening information facilities advancing innovations in green technology, and optimizing the structure of industry (Chen et al., 2022). In a similar vein, LCF is positively associated with FA in both long and short run, and this relationship is statistically significant. These findings suggest that access to financial system might be advantageous towards the USA ecosystem. Specifically, a 1% increase in FA upsurges LCF by 0.602% in the long run and by 0.853% in the short run. Similarly, Alam et al. (2024) revealed that financial inclusion minimize CO2 emissions and improves the environment quality across oil-producing countries. But our result is not inconsistent with the research of Le et al.(2020) in Asia, indicating that expansion of FA is harmful for the biodiversity. Furthermore, having easy access to finance uses additional energy, which raises CO2 emissions and harms our planet (Acheampong 2019). However, Hussain et al. (2022) indicate that financial inclusion has a long-term (short-term) positive (negative) impact on environmental pollution in Asian nations.

Additionally, there is a positive correlation between LIQ and LLCF, with each 1% increase in LIQ increasing LCF by 0.257% in the long run and 0.112% in the short run, and this result is significant at conventional level. Our research indicates that strong institutional structures preserve the ecosystem by executing legislation and encouraging green growth. The findings by Zheng et al. (2024) in the E-7 economies, Hussain and Dogan (2021) in the BRICS country, and Ashraf and Javed (2023) in BRI countries that enhanced institutional quality ensure a better atmosphere and considerably reduce pollution. However, Sibanda et al. (2023) in sub-Saharan Africa and Amin et al. (2023) in South Asia have discovered that the rising quality of institutions is contributing to ecological destruction. Conversely, the negative and statistically significant URBA coefficients indicate that both long-term and short-term increases in LURBA negatively affect environmental quality. A 1% increase in URBA raises LCF by 1.715% in the long run and by 1.198% in the short run. Similarly, Voumik et al.(2024) in Bangladesh, Khalid et al.(2022) in G-7 area, Ramzan et al.(2024) in China, Abid et al.(2022) in G-8 countries found that population growth boosts CO2 emissions. But research conducted by Wang et al.(2021) in OECD territories explored that urbanization improves the sustainability of the environment by lowering emissions of carbon dioxide. However, there was not much evidence, according to Diputra and Baek (2018), that URBA had a major influence on the biodiversity of Indonesia.

Table 05: Results of ARDL short-run and Long-run Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run estimation				
LGDP	-1.687	0.0400	-2.080804	0.000
LGDP2	1.644	0.2359	3.971924	0.000
LAI	0.077	0.0305	1.525705	0.023
LFA	0.602	0.3552	1.696772	0.110
LIQ	0.257	0.1159	2.222973	0.042
LURBA	-1.715	0.6682	-4.765392	0.000
C	7.638	8.4340	6.135154	0.000
Short-run estimation				
D(LLCF(-1))	-0.047	0.0601	-0.7883	0.428
D(LGDP)	-0.738	3.3020	-4.7658	0.003
D(LGDP2)	0.668	0.1505	4.4436	0.005
D(LAI)	0.030	0.0178	3.7343	0.033
D(LFA)	0.853	0.1492	5.7165	0.000
D(LIQ)	0.112	0.0211	5.2924	0.000
D(LURBA)	-1.198	2.1359	7.1157	0.000
CointEq(-1)*	-0.7604	0.0718	-10.5823	0.000

4.5 Robustness Check

The DOLS, FMOLS, and CCR methods are additional techniques employed to assess the validity and reliability of the ARDL outcomes. The results of robustness testing in Table 6 confirm the findings obtained through ARDL calculations. The GDP factors in the FMOLS, DOLS, and CCR models are statistically significant at the 1% level and have a negative trend. A 1% rise in GDP diminishes LCF by 1.517%, 1.321%, and 1.508%, correspondingly. In contrast, GDP2 has an upward and substantial relationship with LCF at the 1% significance level in all models. A 1% increase in GDP2 increases LCF by 1.469%, 1.701%, and 1.464%, respectively, implying that greater GDP levels have a favorable impact on LCF. These conclusions are aligning with the outcomes of the ARDL model.

A 1% rise in LAI increases LCF by 0.041% in the FMOLS model, 0.156% in DOLS, and 0.049% in CCR. These findings are significant and consistent with the ARDL model displayed in Table 5, highlighting that agricultural investment positively influences LCF. Furthermore, an additional 1% in LFA causes an improvement in LCF of 1.012%, 1.387%, and 0.837% in the FMOLS, DOLS, and CCR simulations, accordingly. The results reported here are significant at the 1% level and correlate with both short-term and long-term ARDL evidence. In the FMOLS estimation, a 1% increment in LIQ enhances LCF by 0.126%, 0.141%, and 0.147%, proportionately. Such results are significant at the 5% level for FMOLS and DOLS and at the 1% level for CCR, which supports the ARDL findings. Conversely, a 1% expansion in LURBA falls to the LCF by 0.801% and 1.504% in the FMOLS and DOLS method. On the other hand, one extra percent development in LURBA will upsurge the LLCF by 2.831% in the CCR estimation but the result is significant 5% threshold. These outcomes also align with the ARDL short and long run estimation

Table 06: Results of Robustness check

Variables	FMOLS	DOLS	CCR
LGDP	-1.517***	-1.321***	-1.508***
LGDP^2	1.469***	1.701***	1.464***
LAI	0.041**	0.156**	0.049**
LFA	1.012***	1.387***	0.837***
LIQ	0.126**	0.141**	0.147***
LURBA	-0.801***	-1.504***	2.831***
C	6.975***	5.968***	6.990***

4.6 Pairwise Granger Causality test

The insights provided by Table 7 demonstrate the causal links between several kinds of economic variables. At the 5% significance level, the null hypothesis of no connection is rejected due to the F-statistic of 3.38826 and p-value of 0.0499, which indicate that LLGDP does not Granger-cause LLCF. Furthermore, the null hypothesis that there is no linkage in these circumstances is ruled out due to p-values below the standard significance threshold supporting the existence of one-way causality between LGDP2, LAI, LFA, LURBA, and LLCF. Nevertheless, no association involving LLCF and LIQ was discovered to be causative. The null hypothesis that there is no causality in these interactions could not be rejected because p-values above the conventional significance level suggest no significant causal correlations between LLCF and LGDP, LLCF and LGDP2, LLCF and LAI, LFA and LLCF, and LURBA and LLCF.

Table 07: Results of pairwise Granger Causality test

Null Hypothesis	Obs	F-Statistic	Prob.
LGDP $\neq$ LLCF	30	3.38826	0.0499
LLCF $\neq$ LGDP		0.44313	0.6471
LGDP2 $\neq$ LLCF	30	3.4843	0.0463
LLCF $\neq$ LGDP2		0.44696	0.6446
LAI $\neq$ LLCF	30	2.38966	0.0123
LLCF $\neq$ LAI		1.48366	0.2461
LFA $\neq$ LLCF	30	1.20508	0.3165
LLCF $\neq$ LFA		6.46444	0.0055
LIQ $\neq$ LLCF	30	1.81009	0.1844
LLCF $\neq$ LIQ		1.18981	0.3209
LURBA $\neq$ LLCF	30	2.68762	0.0877
LLCF $\neq$ LURBA		5.37891	0.0114

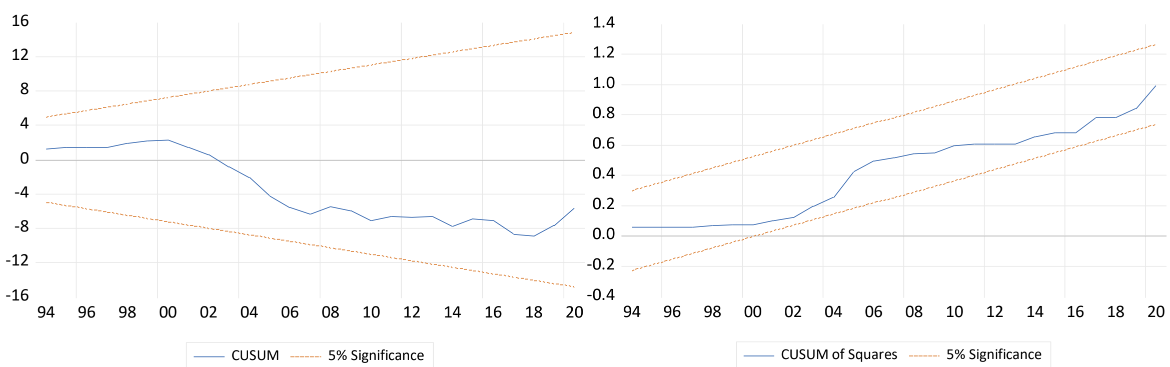
4.7 Diagnostic Test

The results of the diagnostic evaluation are provided in Table 8. The outcomes demonstrate that none of the diagnostic techniques are conducive, hence the null hypothesis cannot be ruled out. The Jarque-Bera test verifies that the residuals seem to be constantly distributed based on the p-value of 0.4231. With a p-value of 0.3612, the Lagrange Multiplier analysis confirms no serial correlation in the residuals. Ultimately, having a p-value of 0.4123, the Breusch-Pagan-Godfrey assessment validates that the residuals have no evidence of heteroscedasticity.

Table 8. The results of diagnostic tests

Diagnostic tests	Coefficient	p-value	Decision
Jarque-Bera test	2.5671	0.4231	Residuals are normally distributed
Lagrange Multiplier test	1.054	0.3612	No serial correlation exits
Breusch-Pagan-Godfrey test	0.8741	0.4123	No heteroscedasticity exists

In addition, the CUSUM and CUSUM-SQ statistics are applied to seek out structural stability in residuals throughout the long and short periods. The outcomes are within the critical limits, with the CUSUM-SQ plot remaining on the crucial line, shown in the following figure. At the 5% level of significance, this indicates that the parameters are consistent and adequately stated.



5. Conclusion

This research investigated the multifaceted connections across economic growth, AI innovation, financial accessibility, institutional quality and urbanization and their effects on the LCF in USA between 1995 and 2021. The investigation studied the load capacity factor to identify the variables affecting environmental sustainability in the chosen area using sophisticated econometric techniques. To ensure the robustness of the investigation, different unit root tests including ADF, P-P and DF-GLS were employed to confirm the non-stationarity of the variables. This created opportunities for assessing the short and long-term influences using the novel Autoregressive Distributed Lag (ARDL) method. The validity and accuracy of the ARDL findings is confirmed by the robustness testing employing FMOLS, DOLS, and CCR, which increases the credibility of the results. Finally, three diagnostic tests were employed to check the heterocesdaticity as well as autocorrelation issues in the chosen data set. The ARDL analysis outcomes indicate multiple significant feedbacks. The outcomes illustrated that economic growth and urbanization exhibited a negative association with LCF in both short and long term. These findings highlight that expansion of the monetary activities and rise of urban population will cause greater pollutions by consuming more fossil fuels and natural resources also. But, GDP squares show a beneficial impact on the environment condition of USA in both periods indicating that greater level of spike in GDP can introduce advanced environment friendly approaches. In a similar vein, AI innovation, financial accessibility and institutional quality were found to have a positive association with LCF, which indicates that utilization of modern AI technologies, advancement in the quality of institution as well as larger inclusion of finances can upsurges the natural health of the selected country. The Pairwise Granger causality test revealed a unidirectional causality from LGDP, LGDP2, and LAI to LLCF, as well as from LLCF to LFA and LURBA. However, there is no evidence that LLCF Granger causes LGDP, LGDP2, or LAI. Similarly, LFA and LURBA do not Granger causes LLCF, and no causal relationship was determined between LIQ and LLCF. These relationships emphasize the relevance of how investments in artificial intelligence, accessibility in finances and good institution impact the dynamics of ecological sustainability in the USA. Therefore, policymakers can create targeted strategies and regulations to reduce ecological degradation while promoting sophisticated technological innovation, stable financial system and standard institutions in the selected area.

Reference

Abdulmagid Basheer Agila, T., Khalifa, W.M.S., Saint Akadiri, S. *et al.* Determinants of load capacity factor in South Korea: does structural change matter?. *Environ Sci Pollut Res* **29**, 69932–69948 (2022). https://doi.org/10.1007/s11356-022-20676-2

Abid, A., Mehmood, U., Tariq, S. *et al.* The effect of technological innovation, FDI, and financial development on CO2 emission: evidence from the G8 countries. *Environ Sci Pollut Res* 29, 11654–11662 (2022). https://doi.org/10.1007/s11356-021-15993-x

Abir, S. I., Shoha, S., Al Shiam, S. A., Dolon, M. S. A., Bala, S., Hossain, H., ... & Bibi, R. Enhancing Load Capacity Factor: The Influence of Financial Accessibility, AI Innovation, and Institutional Quality in the United States.

Acar, S., Altıntaş, N. & Haziyev, V. The effect of financial development and economic growth on ecological footprint in Azerbaijan: an ARDL bound test approach with structural breaks. *Environ Ecol Stat* 30, 41–59 (2023). https://doi.org/10.1007/s10651-022-00551-6

Acheampong AO (2019) Modelling for insight: does financial development improve environmental quality? Energy Econ 83:156–179

Achuo, E. D., Miamo, C. W., & Kouhomou, C. Z. (2024). Resource rents and environmental pollution in developing countries: Does the quality of institutions matter?. *Review of Development Economics*, *28*(1), 360-387. https://doi.org/10.1111/rode.13060

Adnan, M., Xiao, B., Ali, M. U., Bibi, S., Yu, H., Xiao, P., ... & An, X. (2024). Human inventions and its environmental challenges, especially artificial intelligence: New challenges require new thinking. *Environmental Challenges*, 100976. https://doi.org/10.1016/j.envc.2024.100976

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Pakistan's trade relations with BRICS countries: trends, export-import intensity, and comparative advantage. *Frontiers of Finance*, *2*(2).

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. *Journal of Economy and Technology*.

Ahmed, Z., Asghar, M. M., Malik, M. N., & Nawaz, K. (2020). Moving towards a sustainable environment: the dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. *Resources Policy*, *67*, 101677. https://doi.org/10.1016/j.resourpol.2020.101677

Akhter, A., Al Shiam, S. A., Ridwan, M., Abir, S. I., Shoha, S., Nayeem, M. B., ... & Bibi, R. (2024). Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States. *Journal of Environmental Science and Economics*, *3*(3), 99-127.

Al Shiam, S. A., Ridwan, M., Hasan, M. M., Akhter, A., Arefeen, S. S., Hossain, M. S., ... & Shoha, S. Analyzing the Nexus between AI Innovation and Ecological Footprint in Nordic Region: Impact of Banking Development and Stock Market Capitalization using Panel ARDL method.

Alam, I., Shichang, L., Muneer, S., Alshammary, K. M., & Zia ur Rehman, M. (2024). Does financial inclusion and information communication technology affect environmental degradation in oil-producing countries?. *Plos one*, *19*(3), e0298545. https://doi.org/10.1371/journal.pone.0298545

Ali HS, Zeqiraj V, Lin WL, Law SH, Yusop Z, Bare UAA, Chin L (2019) Does quality institutions promote environmental quality? Environ Sci Pollut Res 26:10446–10456

Ali, H. S., Zeqiraj, V., Lin, W. L., Law, S. H., Yusop, Z., Bare, U. A. A., & Chin, L. (2019). Does quality institutions promote environmental quality?. *Environmental Science and Pollution Research*, *26*, 10446-10456. https://doi.org/10.1007/s11356-019-04670-9

Ali, K., Jianguo, D., & Kirikkaleli, D. (2022). Modeling the natural resources and financial inclusion on ecological footprint: The role of economic governance institutions. Evidence from ECOWAS economies. *Resources Policy*, *79*, 103115. https://doi.org/10.1016/j.resourpol.2022.103115

Alola, A. A., Bekun, F. V., Obekpa, H. O., & Adebayo, T. S. (2024). Explaining the environmental efficiency capability of energy mix innovation among the Nordic countries. *Energy Reports*, *11*, 233-239. https://doi.org/10.1016/j.egyr.2023.11.051

Amin, N., Shabbir, M. S., Song, H., Farrukh, M. U., Iqbal, S., & Abbass, K. (2023). A step towards environmental mitigation: Do green technological innovation and institutional quality make a difference?. *Technological Forecasting and Social Change*, *190*, 122413. https://doi.org/10.1016/j.techfore.2023.122413

Anwar, A., & Malik, S. (2021). Cogitating the role of technological innovation and institutional quality on environmental degradation in G-7 countries. *International Journal of Green Economics*, *15*(3), 213-232. https://doi.org/10.1504/IJGE.2021.120871

Ashraf, J., & Javed, A. (2023). Food security and environmental degradation: Do institutional quality and human capital make a difference?. *Journal of Environmental Management*, *331*, 117330. https://doi.org/10.1016/j.jenvman.2023.117330

Ashraf, J., & Javed, A. (2023). Food security and environmental degradation: Do institutional quality and human capital make a difference?. *Journal of Environmental Management*, *331*, 117330. https://doi.org/10.1016/j.jenvman.2023.117330

Atasoy, F. G., Atasoy, M., Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., ... & Al Jubayed, A. (2022). An Econometric Investigation of How the Usage of Non-Renewable Energy Resources Affects the Load Capacity Factor in the United States. *Journal of Environmental and Energy Economics*, *1*(2), 32-44.

Atasoy, F. G., Atasoy, M., Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., ... & Al Jubayed, A. (2022). Factors Affecting the Ecological Footprint in The United States: The Influences of Natural Resources, Economic Conditions, Renewable Energy Sources, and Advancements in Technology. *Journal of Environmental and Energy Economics*, *1*(1), 35-52.

Awan, A., Kocoglu, M., Tunc, A. *et al.* Nuclear energy, human capital, and urbanization tackling environmental concerns in India: evidence from QARDL and quantile co-integration. *Environ Dev Sustain* (2024). https://doi.org/10.1007/s10668-024-04789-x

Aydin, M., Sogut, Y. & Erdem, A. The role of environmental technologies, institutional quality, and globalization on environmental sustainability in European Union countries: new evidence from advanced panel data estimations. *Environ Sci Pollut Res* **31**, 10460–10472 (2024). https://doi.org/10.1007/s11356-024-31860-x

Azam W, Khan I, Ali SA (2023) Alternative energy and natural resources in determining environmental sustainability: a look at the role of government final consumption expenditures in France. Environ Sci Pollut Res 30(1):1949–1965. https://doi.org/10.1007/s11356-022-22334-z

Azam, M., & Khan, A. Q. (2016). Testing the Environmental Kuznets Curve hypothesis: A comparative empirical study for low, lower middle, upper middle and high income countries. *Renewable and Sustainable Energy Reviews*, *63*, 556-567. https://doi.org/10.1016/j.rser.2016.05.052

Azam, M., & Khan, A. Q. (2016). Urbanization and environmental degradation: Evidence from four SAARC countries—Bangladesh, India, Pakistan, and Sri Lanka. *Environmental progress & sustainable energy*, *35*(3), 823-832. https://doi.org/10.1002/ep.12282

Bala, S., Al Shiam, S. A., Arefeen, S. S., Abir, S. I., & Hossain, H. Measuring How AI Innovations and Financial Accessibility Influence Environmental Sustainability in the G-7: The Role of Globalization with Panel ARDL and Quantile Regression Analysis.

Balcilar, M., Ozdemir, Z. A., Ozdemir, H., & Shahbaz, M. (2018). Carbon dioxide emissions, energy consumption and economic growth: The historical decomposition evidence from G-7 countries. *Work Pap*.

Barut A, Kaya E, Bekun FV, Cengiz S (2023) Environmental sustainability amidst financial inclusion in five fragile economies: Evidence from lens of environmental Kuznets curve. Energy 126802.https://doi.org/10.1016/j.energy.2023.126802

Begum, R. A., Raihan, A., & Said, M. N. M. (2020). Dynamic impacts of economic growth and forested area on carbon dioxide emissions in Malaysia. *Sustainability*, *12*(22), 9375. https://doi.org/10.3390/su12229375

Bekun, F. V. (2024). Race to carbon neutrality in South Africa: what role does environmental technological innovation play?. *Applied Energy*, *354*, 122212. https://doi.org/10.1016/j.apenergy.2023.122212

Borges AFS, Laurindo FJB, Spínola MM, Gonçalves RF, Mattos CA (2021) The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. Int J Inf Manag 57:102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Borgi, H., Mabrouk, F., Bousrih, J., & Mekni, M. M. (2023). Environmental change and inclusive finance: Does governance quality matter for African countries? *Sustainability*, *15*(4), 1–15. https://doi.org/10.3390/su15043533

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the econometric society*, 1287-1294. https://doi.org/10.2307/1911963

Byaro, M., Rwezaula, A. & Mafwolo, G. Does institutional quality play a role in mitigating the impact of economic growth, population growth and renewable energy use on environmental sustainability in Asia?. *Environ Dev Sustain* (2024). https://doi.org/10.1007/s10668-024-04780-6

Chen, P., Gao, J., Ji, Z., Liang, H., & Peng, Y. (2022). Do artificial intelligence applications affect carbon emission performance?—evidence from panel data analysis of Chinese cities. *Energies*, *15*(15), 5730. https://doi.org/10.3390/en15155730

Chen, P., Gao, J., Ji, Z., Liang, H., & Peng, Y. (2022). Do artificial intelligence applications affect carbon emission performance?—evidence from panel data analysis of Chinese cities. *Energies*, *15*(15), 5730. https://doi.org/10.3390/pr11092705

Chhabra, M., Giri, A. K., & Kumar, A. (2023). Do trade openness and institutional quality contribute to carbon emission reduction? Evidence from BRICS countries. *Environmental Science and Pollution Research*, *30*(17), 50986–51002. https://doi.org/10.1007/s11356-023-25789-w

Chien, F., Hsu, C. C., Zhang, Y., & Sadiq, M. (2023). Sustainable assessment and analysis of energy consumption impact on carbon emission in G7 economies: mediating role of foreign direct investment. *Sustainable Energy Technologies and Assessments*, *57*, 103111. https://doi.org/10.1016/j.seta.2023.103111

Cortés, U., Sànchez-Marrè, M., Ceccaroni, L. *et al.* Artificial Intelligence and Environmental Decision Support Systems. *Applied Intelligence* **13**, 77–91 (2000). https://doi.org/10.1023/A:1008331413864

Dai, J., Ahmed, Z., Alvarado, R., & Ahmad, M. (2024). Assessing the nexus between human capital, green energy, and load capacity factor: policymaking for achieving sustainable development goals. *Gondwana Research*, *129*, 452-464. https://doi.org/10.1016/j.gr.2023.04.009

Dam, M. M., Durmaz, A., Bekun, F. V., & Tiwari, A. K. (2024). The role of green growth and institutional quality on environmental sustainability: A comparison of CO2 emissions, ecological footprint and inverted load capacity factor for OECD countries. *Journal of Environmental Management*, *365*, 121551. https://doi.org/10.1016/j.jenvman.2024.121551

Danish, Hassan, S.T. Investigating the interaction effect of urbanization and natural resources on environmental sustainability in Pakistan. *Int. J. Environ. Sci. Technol.* **20**, 8477–8484 (2023). https://doi.org/10.1007/s13762-022-04497-x

Degirmenci, T., & Aydin, M. (2024). Testing the load capacity curve hypothesis with green innovation, green tax, green energy, and technological diffusion: A novel approach to Kyoto protocol. *Sustainable Development*. https://doi.org/10.1002/sd.2946

Destek, M.A., Shahbaz, M., Okumus, I. *et al.* The relationship between economic growth and carbon emissions in G-7 countries: evidence from time-varying parameters with a long history. *Environ Sci Pollut Res* **27**, 29100–29117 (2020). https://doi.org/10.1007/s11356-020-09189-y

Dhar P (2020) The carbon impact of artificial intelligence. Nat Mach Intell 2(8):423–425. https://doi.org/10.1038/s42256-020-0219-9

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 1057-1072. https://doi.org/10.2307/1912517

Diputra, E. M., & Baek, J. (2018). Is growth good or bad for the environment in Indonesia?. *International Journal of Energy Economics and Policy*, *8*(1), 1-4.

Dogan, A., & Pata, U. K. (2022). The role of ICT, R&D spending and renewable energy consumption on environmental quality: Testing the LCC hypothesis for G7 countries. *Journal of Cleaner Production*, *380*, 135038. https://doi.org/10.1016/j.jclepro.2022.135038

Dogan, E., Mohammed, K.S., Khan, Z. *et al.* Analyzing the nexus between environmental sustainability and clean energy for the USA. *Environ Sci Pollut Res* **31**, 27789–27803 (2024). https://doi.org/10.1007/s11356-024-32765-5

Dogan, E., Ulucak, R., Kocak, E., & Isik, C. (2020). The use of ecological footprint in estimating the environmental Kuznets curve hypothesis for BRICST by considering cross-section dependence and heterogeneity. *Science of the total environment*, *723*, 138063. https://doi.org/10.1016/j.scitotenv.2020.138063

Dong, M., Wang, G., & Han, X. (2024). Impacts of Artificial Intelligence on Carbon Emissions in China, in terms of Artificial Intelligence Type and Regional Differences. *Sustainable Cities and Society*, 105682. https://doi.org/10.1016/j.scs.2024.105682

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1992). Efficient tests for an autoregressive unit root.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276. https://doi.org/10.2307/1913236

Fareed Z, Rehman MA, Adebayo TS, Wang Y, Ahmad M, Shahzad F (2022) Financial inclusion and the environmental deterioration in Eurozone: the moderating role of innovation activity. Technol Soc 69:101961. https://doi.org/10.1016/j.techsoc.2022.101961

Farooq, F., Aurang Zaib, Faheem, M. *et al.* Public debt and environment degradation in OIC countries: the moderating role of institutional quality. *Environ Sci Pollut Res* 30, 55354–55371 (2023). https://doi.org/10.1007/s11356-023-26061-x

Feng J, Sun Q, Sohail S (2022) Financial inclusion and its influence on renewable energy consumption-environmental performance: the role of ICTs in China. Environ Sci Pollut Res 29(35):52724–52731. https://doi.org/10.1007/s11356-022-19480-9

Fuller, W. A. (2009). *Introduction to statistical time series*. John Wiley & Sons.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438. https://doi.org/10.2307/1912791

Guo, X., Shi, R., & Ren, D. (2024). Reduce carbon emissions efficiently: The influencing factors and decoupling relationships of carbon emission from high-energy consumption and high-emission industries in China. *Energy & Environment*, *35*(3), 1416-1433. https://doi.org/10.1177/0958305X221140567

Hao, Y., Li, X., & Murshed, M. (2023). Role of environmental regulation and renewable energy technology innovation in carbon neutrality: A sustainable investigation from China. *Energy Strategy Reviews*, *48*, 101114. https://doi.org/10.1016/j.esr.2023.101114

Hasanov, F. J., Khan, Z., Hussain, M., & Tufail, M. (2021). Theoretical framework for the carbon emissions effects of technological progress and renewable energy consumption. *Sustain Dev* sd.2175. https://doi.org/10.1002/sd.2175

Hossain, M. S., Ridwan, M., Akhter, A., Nayeem, M. B., Choudhury, M. T. H., Asrafuzzaman, M., & Shoha, S. Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL.

Hussain, M., & Dogan, E. (2021). The role of institutional quality and environment-related technologies in environmental degradation for BRICS. *Journal of Cleaner Production*, *304*, 127059. https://doi.org/10.1016/j.jclepro.2021.127059

Hussain, M., Ye, C., Ye, C. *et al.* Impact of financial inclusion and infrastructure on ecological footprint in OECD economies. *Environ Sci Pollut Res* **29**, 21891–21898 (2022). https://doi.org/10.1007/s11356-021-17429-y

Hussain, S., Ahmad, T., Ullah, S., Rehman, A. U., & Shahzad, S. J. H. (2024). Financial inclusion and carbon emissions in Asia: Implications for environmental sustainability. *Economic and Political Studies*, *12*(1), 88-104. https://doi.org/10.1080/20954816.2023.2273003

Islam, S., Raihan, A., Paul, A., Ridwan, M., Rahman, M. S., Rahman, J., ... & Al Jubayed, A. (2024). Dynamic Impacts of Sustainable Energies, Technological Innovation, Economic Growth, and

Financial Globalization on Load Capacity Factor in the Top Nuclear Energy-Consuming Countries. *Journal of Environmental and Energy Economics*, 1-14.

Islam, S., Raihan, A., Ridwan, M., Rahman, M. S., Paul, A., Karmakar, S., ... & Al Jubayed, A. (2023). The influences of financial development, economic growth, energy price, and foreign direct investment on renewable energy consumption in the BRICS. *Journal of Environmental and Energy Economics*, *2*(2), 17-28.

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review/Revue Internationale de Statistique*, 163-172. https://doi.org/10.2307/1403192.

Kar AK, Choudhary SK, Singh VK (2022) How can artificial intelligence impact sustainability: a systematic literature review. J Clean Prod 376:134120. https://doi.org/10.1016/j.jclepro.2022.134120

Kar AK, Choudhary SK, Singh VK (2022) How can artificial intelligence impact sustainability: a systematic literature review. J Clean Prod 376:134120. https://doi.org/10.1016/j.jclepro.2022.134120

Karp, N., & Nash-Stacey, B. (2015). Technology, opportunity & access: Understanding financial inclusion in the US. *BBVA Research paper*, *15*, 25.

Kartal, M. T., Pata, U. K., Destek, M. A., & Caglar, A. E. (2023). Environmental effect of clean energy research and development investments: Evidence from Japan by using load capacity factor. *Journal of Cleaner Production*, *416*, 137972. https://doi.org/10.1016/j.jclepro.2023.137972

Khalid, L., Hanif, I., & Rasul, F. (2022). How are urbanization, energy consumption and globalization influencing the environmental quality of the G-7?. *Green Finance*, *4*(2), 231-252.

Khan, M. I., Kamran Khan, M., Dagar, V., Oryani, B., Akbar, S. S., Salem, S., & Dildar, S. M. (2021). Testing environmental Kuznets curve in the USA: What role institutional quality, globalization, energy consumption, financial development, and remittances can play? New evidence from dynamic ARDL simulations approach. *Frontiers in Environmental Science*, *9*, 789715. https://doi.org/10.3389/fenvs.2021.789715

Khan, M. K., Teng, J. Z., & Khan, M. I. (2019). Asymmetric impact of oil prices on stock returns in Shanghai stock exchange: Evidence from asymmetric ARDL model. *Plos one*, *14*(6), e0218289. https://doi.org/10.1371/journal.pone.0218289

Khan, M., Raza, S., & Vo, X. V. (2024). Government spending and economic growth relationship: can a better institutional quality fix the outcomes?. *The Singapore Economic Review*, *69*(01), 227-249. https://doi.org/10.1142/S0217590820500216

Kirikkaleli, D., Abbasi, K.R. & Oyebanji, M.O. The asymmetric and long-run effect of environmental innovation and CO_2 intensity of GDP on consumption-based CO_2 emissions in Denmark. *Environ Sci Pollut Res* 30, 50110–50124 (2023). https://doi.org/10.1007/s11356-023-25811-1

Kirikkaleli, D., Güngör, H., Adebayo, T.S. (2022). Consumption-based carbon emissions, renewable energy consumption, financial development and economic growth in Chile. Bus. Strategy Environ. 31 (3), 1123–1137.

Kocoglu, M., Awan, A., Tunc, A., & Aslan, A. (2021). The Nonlinear links between urbanization And CO_2 in 15 emerging countries: Evidence From unconditional quantile and threshold regression. *Environmental Science and Pollution Research*. https://doi.org/10.21203/rs.3.rs-676290/v1

Le TH, Le HC, Taghizadeh-Hesary F (2020) Does financial inclusion impact CO2 emissions? Evidence from Asia. Finance Res Lett. https://doi.org/10.1016/j.frl.2020.101451

Le, T. H., Le, H. C., & Taghizadeh-Hesary, F. (2020). Does financial inclusion impact CO2 emissions? Evidence from Asia. *Finance Research Letters*, *34*, 101451. https://doi.org/10.1016/j.frl.2020.101451

Lin, B., & Ullah, S. (2024). Evaluating forest depletion and structural change effects on environmental sustainability in Pakistan: Through the lens of the load capacity factor. *Journal of Environmental Management*, *353*, 120174. https://doi.org/10.1016/j.jenvman.2024.120174

Majeed, M.T., Tauqir, A., Mazhar, M. *et al.* Asymmetric effects of energy consumption and economic growth on ecological footprint: new evidence from Pakistan. *Environ Sci Pollut Res* **28**, 32945–32961 (2021). https://doi.org/10.1007/s11356-021-13130-2

Marvin HJP, Bouzembrak Y, van der Fels-Klerx HJ, Kempenaar C, Veerkamp R, Chauhan A et al (2022) Digitalisation and artificial intelligence for sustainable food systems. Trends Food Sci Technol 120:344–348. https://doi.org/10.1016/j.tifs.2022.01.020

Ni Z, Yang J, Razzaq A (2022) How do natural resources, digitalization, and institutional governance contribute to ecological sustainability through load capacity factors in highly resource-consuming economies? Resour Policy 79:103068

Ni, Z., Yang, J., & Razzaq, A. (2022). How do natural resources, digitalization, and institutional governance contribute to ecological sustainability through load capacity factors in highly resource-consuming economies? *Resources Policy*, *79*, 103068. https://doi.org/10.1016/J.RESOURPOL.2022.103068

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, *53*, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Nurgazina, Z., Guo, Q., Ali, U., Kartal, M. T., Ullah, A., & Khan, Z. A. (2022). Retesting the influences on CO2 emissions in China: evidence from dynamic ARDL approach. *Frontiers in Environmental Science*, *10*, 868740. https://doi.org/10.3389/fenvs.2022.868740

Nuţă, F. M., Sharafat, A., Abban, O. J., Khan, I., Irfan, M., Nuţă, A. C., ... & Asghar, M. (2024). The relationship among urbanization, economic growth, renewable energy consumption, and environmental degradation: A comparative view of European and Asian emerging economies. *Gondwana Research*, *128*, 325-339. https://doi.org/10.1016/j.gr.2023.10.023

Nwokediegwu, Z. Q. S., & Ugwuanyi, E. D. (2024). Implementing ai-driven waste management systems in underserved communities in the USA. *Engineering Science & Technology Journal*, *5*(3), 794-802. https://doi.org/10.51594/estj.v5i3.903

Onwe, J. C., Ridzuan, A. R., Uche, E., Ray, S., Ridwan, M., & Razi, U. (2024). Greening Japan: Harnessing energy efficiency and waste reduction for environmental progress. *Sustainable Futures*, *8*, 100302.

Ozkan, O., Haruna, R. A., Alola, A. A., Ghardallou, W., & Usman, O. (2023). Investigating the nexus between economic complexity and energy-related environmental risks in the USA: empirical evidence from a novel multivariate quantile-on-quantile regression. *Structural Change and Economic Dynamics*, *65*, 382-392. https://doi.org/10.1016/j.strueco.2023.03.010

Park, J.Y., 1992. Canonical cointegrating regressions. É conom.: J. Econom. Soc. 60 (1), 119–143. https://doi.org/10.2307/2951679.

Pata, U. K., & Isik, C. (2021). Determinants of the load capacity factor in China: a novel dynamic ARDL approach for ecological footprint accounting. *Resources Policy*, *74*, 102313. https://doi.org/10.1016/j.resourpol.2021.102313

Pata, U. K., & Isik, C. (2021). Determinants of the load capacity factor in China: a novel dynamic ARDL approach for ecological footprint accounting. *Resources Policy*, *74*, 102313. https://doi.org/10.1016/j.resourpol.2021.102313

Pata, U. K., & Kartal, M. T. (2023). Impact of nuclear and renewable energy sources on environment quality: Testing the EKC and LCC hypotheses for South Korea. *Nuclear Engineering and Technology*, *55*(2), 587-594. https://doi.org/10.1016/j.net.2022.10.027

Pata, U. K., Kartal, M. T., Adebayo, T. S., & Ullah, S. (2023). Enhancing environmental quality in the United States by linking biomass energy consumption and load capacity factor. *Geoscience Frontiers*, *14*(3), 101531. https://doi.org/10.1016/j.gsf.2022.101531

Pata, U.K. Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues. *Eur J Health Econ* **22**, 1427–1439 (2021). https://doi.org/10.1007/s10198-021-01321-0

Pata, U.K., Balsalobre-Lorente, D. Exploring the impact of tourism and energy consumption on the load capacity factor in Turkey: a novel dynamic ARDL approach. *Environ Sci Pollut Res* **29**, 13491–13503 (2022). https://doi.org/10.1007/s11356-021-16675-4

Pata, U.K., Samour, A. Assessing the role of the insurance market and renewable energy in the load capacity factor of OECD countries. *Environ Sci Pollut Res* **30**, 48604–48616 (2023). https://doi.org/10.1007/s11356-023-25747-6

Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., ... & Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. *Energies*, *16*(15), 5845.

Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., ... & Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. *Energies*, *16*(15), 5845. https://doi.org/10.3390/en16155845

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326. https://doi.org/10.1002/jae.616

Phillips, P. C., & Hansen, B. E. (1990). Statistical inference in instrumental variables regression with I (1) processes. *The review of economic studies*, *57*(1), 99-125. https://doi.org/10.2307/2297545

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *biometrika*, *75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Pickett STA, Cadenasso ML, Grove JM, Nilon CH, Pouyat RV, Zipperer WC, Costanza R. 2001. Urban ecological systems: linking terrestrial ecological, physical, and socioeconomic components of metropolitan areas. Annu Rev Ecol Evol S 32:127–57

Platon, V., Pavelescu, F. M., Antonescu, D., Constantinescu, A., Frone, S., Surugiu, M., ... & Popa, F. (2024). New evidence about artificial intelligence and eco-investment as boosters of the circular economy. *Environmental Technology & Innovation*, 103685. https://doi.org/10.1016/j.eti.2024.103685

Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. *International Journal of Environmental Research and Public Health*, *20*(5), 4000.

Rahman, J., Raihan, A., Tanchangya, T., & Ridwan, M. (2024). Optimizing the digital marketing landscape: A comprehensive exploration of artificial intelligence (AI) technologies, applications, advantages, and challenges. *Frontiers of Finance*, *2*(2).

Rahman, M. S., Ridwan, M., Raihan, A., Tanchangya, T., Rahman, J., Foisal, M. Z. U., ... & Islam, S. (2022). Nexus Between Agriculture, Economy, Energy Use, and Ecological Footprint Toward Sustainable Development in Bangladesh. *Journal of Environmental and Energy Economics*, *1*(2), 18-31.

Rai PK, Singh JS (2020) Invasive alien plant species: their impact on environment, ecosystem services and human health. Ecol Indic 111:106020. https://doi.org/10.1016/j.ecolind.2019.106020

Raihan, A., Atasoy, F. G., Atasoy, M., Ridwan, M., & Paul, A. (2022). The role of green energy, globalization, urbanization, and economic growth toward environmental sustainability in the United States. *Journal of Environmental and Energy Economics*, *1*(2), 8-17.

Raihan, A., Atasoy, F. G., Coskun, M. B., Tanchangya, T., Rahman, J., Ridwan, M., ... & Yer, H. (2024). Fintech adoption and sustainable deployment of natural resources: Evidence from mineral management in Brazil. *Resources Policy*, *99*, 105411.

Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024). Advancing environmental sustainability in the G-7: The impact of the digital economy, technological innovation, and financial accessibility using panel ARDL approach. *Journal of Economy and Technology*.

Raihan, A., Hasan, M. A., Voumik, L. C., Pattak, D. C., Akter, S., & Ridwan, M. (2024). Sustainability in Vietnam: Examining Economic Growth, Energy, Innovation, Agriculture, and Forests' Impact on CO2 Emissions. *World Development Sustainability*, 100164.

Raihan, A., Rahman, J., Tanchangtya, T., Ridwan, M., & Islam, S. (2024). An overview of the recent development and prospects of renewable energy in Italy. *Renewable and Sustainable Energy*, *2*(2), 0008.

Raihan, A., Rahman, J., Tanchangya, T., Ridwan, M., & Bari, A. B. M. (2024). Influences of economy, energy, finance, and natural resources on carbon emissions in Bangladesh. *Carbon Research*, *3*(1), 1-16.

Raihan, A., Rahman, J., Tanchangya, T., Ridwan, M., Rahman, M. S., & Islam, S. (2024). A review of the current situation and challenges facing Egyptian renewable energy technology. *Journal of Technology Innovations and Energy*, *3*(3), 29-52.

Raihan, A., Ridwan, M., & Rahman, M. S. (2024). An exploration of the latest developments, obstacles, and potential future pathways for climate-smart agriculture. *Climate Smart Agriculture*, 100020.

Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., & Ahmad, S. (2023). Environmental Effects of China's Nuclear Energy within the Framework of Environmental Kuznets Curve and Pollution Haven Hypothesis. *Journal of Environmental and Energy Economics*, *2*(1), 1-12.

Raihan, A., Tanchangya, T., Rahman, J., & Ridwan, M. (2024). The Influence of Agriculture, Renewable Energy, International Trade, and Economic Growth on India's Environmental Sustainability. *Journal of Environmental and Energy Economics*, 37-53.

Raihan, A., Tanchangya, T., Rahman, J., Ridwan, M., & Ahmad, S. (2022). The influence of Information and Communication Technologies, Renewable Energies and Urbanization toward Environmental Sustainability in China. *Journal of Environmental and Energy Economics*, *1*(1), 11-23.

Raihan, A., Voumik, L. C., Ridwan, M., Akter, S., Ridzuan, A. R., Wahjoedi, ... & Ismail, N. A. (2024). Indonesia's Path to Sustainability: Exploring the Intersections of Ecological Footprint, Technology, Global Trade, Financial Development and Renewable Energy. In *Opportunities and Risks in AI for Business Development: Volume 1* (pp. 1-13). Cham: Springer Nature Switzerland.

Raihan, A., Voumik, L. C., Ridwan, M., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023). From growth to green: navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. *Energy Reports*, *10*, 4318-4331.

Ridwan, M. (2023). Unveiling the powerhouse: Exploring the dynamic relationship between globalization, urbanization, and economic growth in Bangladesh through an innovative ARDL approach.

Ridwan, M. R., & Hossain, M. I. H. I. (2024). Does trade liberalization policy accelerate foreign direct investment in Bangladesh?: An empirical investigation.

Ridwan, M., Akther, A., Al Absy, M. S. M., Tahsin, M. S., Ridzuan, A. R., Yagis, O., & Mukhtar, K. J. (2024). The Role of Tourism, Technological Innovation, and Globalization in Driving Energy Demand in Major Tourist Regions. *International Journal of Energy Economics and Policy*, *14*(6), 675-689.

Ridwan, M., Akther, A., Tamim, M. A., Ridzuan, A. R., Esquivias, M. A., & Wibowo, W. (2024). Environmental health in BIMSTEC: the roles of forestry, urbanization, and financial access using LCC theory, DKSE, and quantile regression. *Discover Sustainability*, *5*(1), 429.

Ridwan, M., Aspy, N. N., Bala, S., Hossain, M. E., Akther, A., Eleais, M., & Esquivias, M. A. (2024). Determinants of environmental sustainability in the United States: analyzing the role of financial development and stock market capitalization using LCC framework. *Discover Sustainability*, *5*(1), 319.

Ridwan, M., Bala, S., Al Shiam, S. A., Akhter, A., Asrafuzzaman, M., Shochona, S. A., ... & Shoha, S. Leveraging AI for a Greener Future: Exploring the Economic and Financial Impacts on Sustainable Environment in the United States.

Ridwan, M., Bala, S., Al Shiam, S. A., Akhter, A., Hasan, M. M., Asrafuzzaman, M., ... & Bibi, R. Leveraging AI for Promoting Sustainable Environments in G-7: The Impact of Financial Development and Digital Economy via MMQR Approach.

Ridwan, M., Raihan, A., Ahmad, S., Karmakar, S., & Paul, P. (2023). Environmental sustainability in France: The role of alternative and nuclear energy, natural resources, and government spending. *Journal of Environmental and Energy Economics*, *2*(2), 1-16.

Ridwan, M., Urbee, A. J., Voumik, L. C., Das, M. K., Rashid, M., & Esquivias, M. A. (2024). Investigating the environmental Kuznets curve hypothesis with urbanization, industrialization, and service sector for six South Asian Countries: Fresh evidence from Driscoll Kraay standard error. *Research in Globalization*, *8*, 100223.

Ridzuan, A. R., Rahman, N. H. A., Singh, K. S. J., Borhan, H., Ridwan, M., Voumik, L. C., & Ali, M. (2023, May). Assessing the Impact of Technology Advancement and Foreign Direct Investment on Energy Utilization in Malaysia: An Empirical Exploration with Boundary Estimation. In *International Conference on Business and Technology* (pp. 1-12). Cham: Springer Nature Switzerland.

Shang, Y., Razzaq, A., Chupradit, S., An, N. B., & Abdul-Samad, Z. (2022). The role of renewable energy consumption and health expenditures in improving load capacity factor in ASEAN countries: exploring new paradigm using advance panel models. *Renewable Energy*, *191*, 715-722. https://doi.org/10.1016/j.renene.2022.04.013

Sibanda, K., Garidzirai, R., Mushonga, F., & Gonese, D. (2023). Natural resource rents, institutional quality, and environmental degradation in resource-rich Sub-Saharan African countries. *Sustainability*, *15*(2), 1141. https://doi.org/10.3390/su15021141

Siche, R., Pereira, L., Agostinho, F., & Ortega, E. (2010). Convergence of ecological footprint and emergy analysis as a sustainability indicator of countries: Peru as case study. *Communications in Nonlinear Science and Numerical Simulation*, *15*(10), 3182-3192. https://doi.org/10.1016/j.cnsns.2009.10.027

Singh, A. K., Raza, S. A., Nakonieczny, J., & Shahzad, U. (2023). Role of financial inclusion, green innovation, and energy efficiency for environmental performance? Evidence from developed and emerging economies in the lens of sustainable development. *Structural Change and Economic Dynamics*, *64*, 213-224. https://doi.org/10.1016/j.strueco.2022.12.008

Stock, J.H., Watson, M.W., 1993. A simple estimator of cointegrating vectors in higher order integrated systems. É conom.: J. Econom. Soc. 61 (4), 783–820. https://doi. org/10.2307/2951763

Sui, Y., Hu, J., Zhang, N., & Ma, F. (2024). Exploring the dynamic equilibrium relationship between urbanization and ecological environment--A case study of Shandong Province, China. *Ecological Indicators*, *158*, 111456. https://doi.org/10.1016/j.ecolind.2023.111456 \

Sun, A., Bao, K., Aslam, M., Gu, X., Khan, Z., & Uktamov, K. F. (2024). Testing load capacity and environmental Kuznets curve hypothesis for China: Evidence from novel dynamic autoregressive distributed lags model. *Gondwana Research*, *129*, 476-489. https://doi.org/10.1016/j.gr.2023.07.018

Tamazian A, Chousa JP, Vadlamannati KC (2009) Does higher economic and financial development lead to environmental degradation: evidence from BRIC countries. Energy Policy 37(1):246–253

Tanchangya, T., Raihan, A., Rahman, J., Ridwan, M., & Islam, N. (2024). A bibliometric analysis of the relationship between corporate social responsibility (CSR) and firm performance in Bangladesh. *Frontiers of Finance*, *2*(2).

Tanveer, A., Song, H., Faheem, M. *et al*. Caring for the environment. How do deforestation, agricultural land, and urbanization degrade the environment? Fresh insight through the ARDL approach. *Environ Dev Sustain* (2024). https://doi.org/10.1007/s10668-023-04368-6

Ulucak ZŞ, İlkay SÇ, Burcu Özcan AG (2020) Financial globalization and environmental degradation nexus: evidence from emerging economies. Resour Policy. https://doi.org/10.1016/j.resourpol.2020.101698

Unies, N. (2004). *World urbanization prospects: the 2003 revision*. UN.

Urbee, A. J., Ridwan, M., & Raihan, A. (2024). Exploring Educational Attainment among Individuals with Physical Disabilities: A Case Study in Bangladesh. *Journal of Integrated Social Sciences and Humanities*.

Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S et al (2020) The role of artificial intelligence in achieving the Sustainable Development Goals. Nat Commun 11(1):233. https://doi.org/10.1038/s41467-019-14108-y

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. *Heliyon*, *9*(1).

Voumik, L. C., Akter, S., Ridwan, M., Ridzuan, A. R., Pujiati, A., Handayani, B. D., ... & Razak, M. I. M. (2023). Exploring the factors behind renewable energy consumption in Indonesia: Analyzing the impact of corruption and innovation using ARDL model. *International Journal of Energy Economics and Policy*, *13*(5), 115-125.

Voumik, L. C., Rahman, M. H., Rahman, M. M., Ridwan, M., Akter, S., & Raihan, A. (2023). Toward a sustainable future: Examining the interconnectedness among Foreign Direct Investment (FDI), urbanization, trade openness, economic growth, and energy usage in Australia. *Regional Sustainability*, *4*(4), 405-415.

Voumik, L. C., Ridwan, M., Rahman, M. H., & Raihan, A. (2023). An investigation into the primary causes of carbon dioxide releases in Kenya: Does renewable energy matter to reduce carbon emission?. *Renewable Energy Focus*, *47*, 100491.