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RESEARCH ARTICLE

Analyzing the Nexus between AI Innovation and Ecological Footprint in Nordic Region: Impact of Banking Development and Stock Market Capitalization using Panel ARDL method

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Abstract
This study investigates the impact of Artificial Intelligence (AI) innovation on the ecological footprint in the Nordic region from 1990 to 2020, alongside the effects of banking development, stock market capitalization, economic growth, and urbanization. Utilizing the STIRPAT model, the study incorporates cross-sectional dependence and slope homogeneity tests, revealing issues of heterogeneity and cross-sectional dependence. The analysis employs both first and second-generation panel unit root tests, confirming that the variables are free from unit root problems. Panel cointegration tests demonstrate that the variables are cointegrated in the long run. To explore the short- and long-term relationships, the study utilizes the Panel Autoregressive Distributed Lag (ARDL) model. The Panel ARDL results indicate that economic growth, stock market capitalization, and urbanization positively correlate with the ecological footprint in both the short and long run. Conversely, AI innovation and banking development negatively correlate with the ecological footprint. To validate the Panel ARDL estimations, robustness checks are performed using Fully Modified OLS, Dynamic OLS, and Fixed Effects with OLS, all of which support the initial findings. Furthermore, the study employs the D-H causality test to identify causal relationships. The results show a unidirectional causal relationship between AI innovation, stock market capitalization, urbanization, and the ecological footprint. In contrast, a bidirectional causal relationship exists between economic growth and the ecological footprint, as well as between banking development and the ecological footprint.

Keywords: Artificial Intelligence; Banking Development; Stock Market Capitalization; Ecological Footprint; Nordics Region

Introduction

Because of rising modernization, worldwide population growth, shifting lifestyles, and greater energy consumption, the threat of climate change has worsened in recent years (Voumik et al.,2022; Ahmed et al.2024). Based on data from Global Footprint Network (GFN 2018), over 80% of people on Earth reside in nations experiencing a serious environmental catastrophe. For developed as well as developing nations, combating global warming and environmental damage has been a top concern (Apergis et al., 2023; Raihan et al., 2023a). The Nordic countries (Denmark, Finland, Iceland, Norway, and Sweden) are regarded as worldwide examples of converting to green energy. They are among the most developed in the World, consistently ranking highly on the Human Development Index (HDI) of the United Nations, with Norway leading among them (Urban et al., 2018). They were also effective in splitting their economy from carbon emissions, which is obviously highly desirable but challenging to do. The Nordic nations have forward aggressive climate change and energy policies to eliminate fossil fuels by 2050 (Sovacool, 2017). Moreover, this region is widely considered to be a pioneer in climate environmental sustainability and home to affluent countries that are contributing significantly to climate change beyond their national borders by absorbing a significant portion of the resources and energy used by their citizens (Maczionsek et al., 2023; Ridwan et al.2023). These areas are included in the study to provide an intriguing figure with motivating common characteristics; they have similar socioeconomic circumstances. Furthermore, they are commonly recognized as leaders in the worldwide effort to combat climate change (Jokinen et al., 2020). To address concerns about ecological sustainability in the chosen area, this analysis focused on the relationships across stock market capitalization, banking development, AI, and economic growth. Using panel data analysis techniques, the project seeks to uncover empirical evidence and guide research-based policy recommendations for an improved future that is greener both globally and in the Nordic region.

In the real world, the Nordic area provides a model of how nations, businesses, and individuals have successfully reduced their GHG emissions and fostered clean energy (Raihan et al.2022a). The academic literature continues to endorse it as an example of advances in technology and the implementation of clean energy sources (Borup et al., 2008; Sovacool, 2013). Moreover, Finland, Iceland, Norway, and Sweden (except Denmark) have relatively substantial levels of sustainability disclosure (94%, 91%, 91%, and 98%, respectively) (KPMG, 2022). Numerous global problems, including escalating demands for energy, waste creation, shortages of water, and increasing EFP, are contributing to environmental damage (He et al. 2018; Quan et al. 2021). Researchers are linking several EFP-related elements to reveal potential mitigation strategies that could aid in achieving sustainable development. Ecological footprint (EFP) can effectively handle and analyze natural resources and is a substitute that is heavily used to evaluate ecosystem conditions (Khan et al. 2021; Ridzuan et al.2023). When the population's needs are met outside of the limits of the environment, an ecological deficit results (Dogan et al., 2022; Sahoo and Sethi, 2021). This is known as an ecological footprint exceeding biocapacity. Nordic European countries, including all members of the European Environmental Agency Countries (EEA-32), might evaluate the outcomes of their "Green Deal" initiative and Environmental Action Plans, which represent their primary environmental policy (Apergis et al.,2023; Raihan et al.2024a). In fact, by utilizing 15 indicators, the Nordic community established collaboration in 2019 to make the Nordic European Area the most integrated, competitive, and sustainable region in the World by 2030 (Nordic Statistic Database, 2022). By influencing consumption and manufacturing habits, innovation in technology, utilization of resources, environmental laws, and social welfare of both the business growth and society, the development of stock markets can have a consequence on the EFP (Younis et al., 2021; Sharma et al., 2021; Tsagkanos et al., 2019). Depending on some factors, including the extent, framework, effectiveness fluctuation, and expansion of the financial system; the level of GDP growth; the quality of the institutions; ecological consciousness global context; and advances in the energy field, the rise of stock markets can have both positive and destructive implications on EFP (Paramati et al., 2017; Topcu et al., 2020; Raihan et al.2023b). Furthermore, it has been proven that modern technology fosters sustainable development over time in all countries, and the Nordic region is no exception. By addressing environmental challenges, innovation contributes to the improvement of the natural World (Alola et al.,2024). In 2018, there was a 1.7% increase in emissions of carbon in Sweden, with a peak of almost 33.1 billion metric tons (Khanal, 2021; Raihan et al., 2022b). On the other hand, pollution levels in Norway have

been rising continuously since the 1960s, except for a brief drop that occurred between 1990 and 1995. To stop this growing trend, which was brought on by uncertain macroeconomic conditions, innovative energy technology initiatives, and limitations on greenhouse gas emissions, both nations adopted carbon pricing (Jagers & Hammar, 2009). In our analysis, we investigate the impact of economic growth, urbanization, stock market capitalization, artificial intelligence, and banking development on the Nordic countries' ecological footprint. The following is how the article advances earlier research: (i) some researchers have spoken on the connection between the environment, development, and energy in panel discussions and individual studies. The present research is the first empirical analysis to look at the Nordic countries' advancement in banking, stock market capitalization, AI innovation, and ecological footprint—all encouraging indicators through this work. Nonetheless, the majority of earlier research (Akram et al., 2020; Ali et al., 2019; Salahuddin et al., 2019; Raihan and Voumik, 2022; Voumik et al. 2023a, 2023b) took CO2 emission as a measure of ecological condition. However, the study utilized the EFP as a substitute for environmental sustainability. The EFP calculates an individual's or a community's demand for accessible natural resources (Omojolaibi and Nathaniel 2020). EFP has, therefore, been employed in numerous research to explore the green environment (Pata et al., 2021; Nuta et al.,2024; Idroes et al., 2024) to some extent. (ii) The study also contributed to the body of literature on the use of second-generation panel estimation approaches as more advanced than conventional panel estimation methods. To investigate both the short- and long-term consequences within the chosen variables, we used the Novel ARDL methodology and the STIRPAT framework.
The remaining content is given below: the existing literature is organized in the second part. Data collection and the methodological framework are covered in the next part. The discussion and empirical results are reported in the fourth portion. In the fifth subsection, a conclusion and policy implications are developed.

Literature Review

Multiple studies have measured the condition of the environment utilizing different indicators, like ecological footprint and CO2 emissions. To identify discrepancies in the literature, we conduct a thorough assessment of the current condition of academic work in this part. As a result, we will address previous studies on the effects of EFP on economic development, urbanization, artificial intelligence (AI), banking development, and stock market capitalization, which will support the parameters of our study. The intricate link between GDP and ecological footprint (EFP) can be affected by geographic differences as well as additional pertinent factors. The contemporary economic boom has had an enormous effect on the increase in carbon emissions globally (Longsheng et al., 2022). Sahoo and Sethi (2021) have discovered a similar result in emerging economies using the FMOLS and DOLS approaches, and they propose the need for legislative actions to lessen ecological challenges. Using the panel dynamic Generalized Method of Moments (GMM) in conjunction with Fully Modified Ordinary Least Square (FMOLS), Zhang et al. (2022) conducted research to explore the long-term connection among the chosen factors in five emerging countries between 1990 and 2019. They added that the EFP increased as a result of GDP development. Moreover, Shahbaz et al. (2023) used annual data from 1992 to 2017 for the ten countries with the biggest ecological footprint. They concluded that through a spike in EFP, monetary expansion has a detrimental implication on environmental quality. Similar conclusions were reached by Ahmad et al. (2020), Destek (2020), and Sharif et al. (2020) about the long-term positive link between EFP and economic growth. Conversely, the rise in GDP of the G-7 countries concerning greenhouse gas emissions was done by Balcilar et al. (2018). The results go counter to the EKC hypothesis, which holds that the condition of the ecosystem in Germany and the UK is not negatively impacted by economic growth. Ozturk et al. (2021) discovered that Saudi Arabia's environmental degradation is negatively impacted by economic growth. The findings of Li et al. (2022) showed that, in 120 nations, development in the economy was linked to a decrease in ecological footprint. This conclusion is facilitated by some research, including Ahmed et al. (2021) in the USA, Aslam et al. (2021) in China, and Ali et al. (2021) in Pakistan.

By helping with power administration, combating pollution, biodiversity preservation, and other areas, artificial intelligence plays a critical role in environmental sustainability and helps achieve sustainable development goals (Kumari and Pandey, 2023; Ridwan, 2023). According to Rasheed et al. (2024), artificial intelligence actively contributes to reducing emissions of carbon and sustaining the ecosystem of seven developing Asian nations. Chen et al. (2022) discovered that the consequences of artificial intelligence (AI) on mitigating CO2 emissions are more apparent in big cities, extremely large towns, better-developed facilities, and highly technological cities based on panel data collected for 270 Chinese cities. However, in small and medium-sized towns, as well as in cities with insufficient services and low levels of technology, it is not significant. Research has adopted AI innovation methods, including artificial neural networks (ANNs) and hybrid machine learning models, to examine the environmental effects of multiple operations, including the cultivation of soybeans (Kashka et al., 2022), consumption habits (Janković et al., 2021), and economic global indicators (Roumiani and Mofidi,2022; Roumiani and Mofidi, 2021). These AI models have yielded encouraging predictions of ecological parameters, with ANNs outperforming conventional regression methods in terms of ecological impact indices. In the same way, Arya et al. (2024) revealed that AI-based solutions for GHG emission monitoring, prediction, and reduction may contribute to a cleaner environment. From 2007 to 2020, Liu et al. (2024) illustrated the influences of industrial robots on the ecosystem in ten of the World's top manufacturing AI countries: Singapore, South Korea, Japan, Germany, Sweden, Denmark, USA, China, France, and Italy. The results imply that these robots enhance the ecological health in the selected countries by reducing EFP across different data quantiles.

The growth of banking can spur economic prosperity by allowing households to purchase vehicles, homes, and appliances. However, these activities put pressure on the environment by increasing the demand for and utilization of fossil fuels (Baloch et al., 2019, Al Shium et al.2024a). Yet, the growth of banking might encourage the creation of high-quality environments: vigorous investments in R&D and environmentally friendly projects could be encouraged and financed by a healthy financial system (Zhao et al.,2021; Shahbaz et al.,2016). Financial development includes the growth of the banking industry; generally speaking, current research has focused more on how financial growth contributes to ecological degradation (Samour et al., 2019). Using data from 1990 to 2018, Radulescu et al. (2022) investigate how banking development has affected the ecological impact of 27 OECD nations. The MMQR approach results displayed that an upsurge of 1% in banking expansion is expected to increase the EFP in all quantiles of the OECD countries. The findings thus confirm that the OECD countries' ecological sustainability is compromised by banking development. According to Zafar et al. (2019), the banking development index raises emissions of carbon in N-11 countries while lowering them in G-7 territory. Samour et al.(2022) acknowledge that banking sector development decreases the environmental level and extends the idea that South Africa must leverage the growth of the banking industry to reduce ecosystem damage. From one perspective, the growth of the banking industry could encourage modern innovations in the power sector to aid in the reduction of emissions and ensure environmental sustainability (Khan and Rehan, 2022). However, an investigation carried out in Malaysia between 1980 and 2018 by Altıntaş et al. (2024) found that the improvement of the banking industry has a favorable effect on the green environment. Furthermore, rising loan rates in developed economies, growing rates of deposits in emerging nations, and higher rates in countries that are developing all help decrease greenhouse gases overall (Obiora et al., 2020).

Numerous studies indicate that the size of the stock market can have a positive or inverse effect on EFP, considering several elements. Focusing on rapid financial achievements in the stock market can push companies to prioritize profits over biodiversity concerns, potentially leading to increased environmental damage (Taghizadeh-Hesary et al., 2022; Al Shium et al., 2024b). Incorporating the capitalization of stocks (SMC) into national and regional global warming mitigation efforts is essential, primarily to tackle the adverse impacts of environmental degradation (Azeem et al., 2023). These considerations serve as a basis for examining the connection between environmental damage and stock market capitalization (Ozturk and Acaravci 2013; Sadorsky 2010). When accounting for market shocks, Mhadhbi et al. (2021) demonstrated that the stock market growth measures of emerging market countries have a destructive influence on natural health quality. Li et al. (2022) demonstrated that the stock market had a detrimental effect on ecological sustainability in OECD countries that were undergoing rapid economic growth but that it was positively correlated with better environmental quality in nations that were experiencing slower economic expansion. According to Zafar et al. (2019), stock market activity caused CO2 emissions to grow in G7 countries relative to N-11 countries, while it decreased in N-11 countries and improved the ecological condition. Su (2023) examines the intricate dynamics of stock market capitalization and CO2 emissions. Utilizing the NARDL model demonstrates that China's stock market capitalization is responsible for short-term increases in environmental deterioration. Similarly, Nguyen et al.(2021) demonstrated that SMS is not good for the ecological condition of G-6 countries as it leads to a rise in carbon emissions. However, Zeqiraj et al. (2020) revealed that the stock market assisted EU nations in building economies with low emissions. Habiba et al. (2021) also agreed that environmental pollution decreased in industrialized economies and the G20 countries as stock markets developed but climbed in emerging economies. Moreover, Asiedu (2024) found that in rising countries, stock market capitalization reduces EFP. Since urbanization is thought to be one of the primary drivers of ecological decline, it has garnered much attention in empirical as well as theoretical studies (Adebayo and Kirikkaleli, 2021; Rana et al., 2024). Multiple scholars have empirically examined the adverse and beneficial correlation between urbanization and ecological conditions. Using FMOLS and DOLS long-run estimators, Ulucak et al. (2020) assessed the BRICS countries from 1992 to 2016. The evidence indicates urbanization reduces EFP, suggesting that it improves the ecology. Similarly, urbanization improves the ecosystem quality in Sri Lanka (Gasimli et al. 2019). Chien et al. (2023) analyzed the consequences of urbanization on the generation of GHGs in the G-7 nations using the innovative MMQR method. They found that an increasing population reduces pollution in high-emission economies. Conversely, Nathaniel et al. (2021) observed a negative correlation between URBA and ecological effects at the top 10 tourist locations. According to Ahmed et al. (2020a), from 1971 to 2014, urbanization boosted the EFP in the G7 areas. Similar findings were made by Nathaniel et al. (2020) within the MENA region, Zhang et al. (2021) in Malaysia, Ridwan et al. (2024) in six South Asian countries, Raihan et al. (2024b) in the G-7 region, Liu et al. (2024) in China, Voumik and Ridwan (2023) in Argentina, and others which showed that urbanization degrades the environment. Moreover, Addai et al. (2022) in Eastern Europe revealed that urbanization is not a uniform cause of ecological footprint. In Pakistan, negative trends in urbanization caused a decline in environmental degradation, while positive urbanization movements prompted an increase in it (Arif et al.,2023).

Regarding the link between the improvement in the banking sector, artificial intelligence (AI), stock market capitalization, and the ecological footprint, there is a deficiency in the literature currently in publication, especially when it comes to the Nordic region. Previous research has largely concentrated on greenhouse gas emissions, or CO2 emissions, and has overlooked the important factor of ecological footprint (EFP). In particular, by encouraging funding for environmentally friendly projects and green technologies, banking growth, and stock market capitalization may improve the condition of the environment. Moreover, efforts in the application of Green AI might support green habits, reduce climate risk, promote clean energy, and create ecological practices, all of which would lessen the negative effects on the environment. Together, these elements constitute artificial intelligence, the growth of banks, and stock market capitalization, which is a whole new area of study from a Nordic standpoint. To address those drawbacks, the research assists academicians and stakeholders in developing strategies that are specific to the ecological and macroeconomic fields of the Nordic region by utilizing statistical techniques such as ARDL, FMOLS, DOLS, and FE-OLS processes.

Methodology

Data and Variables

This study used data from the Global Footprint Network (GFN), Global Financial Development (GFD), and World Development Indicators (WDI) from 1995 to 2021 to check out the consequences of GDP, banking development, stock market capitalization, artificial intelligence (AI), and urbanization on the EFP of the Nordic area. These countries were picked for consideration due to the value and accessibility of their statistical information for our ongoing research requirements. The ecological footprint is the dependent variable in our work. The GFN delivered the EFP statistics, and the WDI gave the GDP per capita in US dollars. Statistics on urbanization were also taken from WDI. Our research relies on data from the GFD to determine important elements such as banking development and stock market capitalization. Our World in Data is where the AI variable data came from. Table 1 straightforwardly illustrates the factors.

In this study logarithmic variables is used to handle non-linear connections and stabilize variance. Logarithmic transformations facilitate the linearization of connections between variables, simplifying the application of linear regression techniques and enabling the interpretation of coefficients as percentage changes. In addition, they tackle heteroscedasticity problems by reducing the range of data, which can enhance the accuracy of the model and the statistical significance. Furthermore, log transformations can mitigate the influence of extreme values or outliers, resulting in more resilient and dependable outcomes in empirical investigations.

Table 1. Description and Source of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
EFP	Ecological Footprint	LEFP	Gha per person	GFN
LGDP	Gross Domestic Product	LGDP	GDP per capita (Current US$)	WDI
LAI	AI Innovation	LAI	Annual patent applications related to AI	Our World in data
LBD	Banking Development	LBD	Deposit money banks assets to GDP (%)	Global Financial Development
LSMC	Stock Market Capitalization	LSMC	Stock market capitalization to GDP (%)	Global Financial Development
LURBA	Urbanization	LURBA	Urban Population (% of total population)	WDI

Theoretical Framework

According to Voumik and Ridwan (2023), the IPAT model can be utilized to evaluate how business activity impacts the environment as well as energy consumption. The environmental pressure resulting from prosperity, population trends, and innovations in technology is measured by the framework using a random effects regression (Ehrlich and Holdren, 1971). Through the selection of dependent and independent variables, we illustrate the use of the widely accepted IPAT/STIRPAT model. The term STIRPAT stands for population, wealth, and technology-related stochastic effects through regression. Many nations have acknowledged this approach as a legitimate choice, including Malaysia, Italy, the Nordic, China, and the OECD (Shahbaz et al.,2016; Pattak et al.,2023; Owusu et al.,2024; Amin & Dogan, 2021; Hashmi & Alam, 2019). This investigation is conducted considering some factors such as population dynamics, financial situations, and technological innovations:

$$I = \int PAT \qquad (1)$$

In this study, we employed EFP as an indication of ecosystem damage (I). Following the STIRPAT framework offered by Dietz and Rosa (1997), we utilized urbanization as a measure of population (P), economic growth, banking development, stock market capitalization as an indicator of affluence (A), and AI as a measure of technology (T). Equation (2) displays the updated form after the intercept term (C) and standard error term (ε) were included.

$$I_i = C.P_i^{\beta}.A_i^{\gamma}.T_i^{\delta}.\varepsilon_i \qquad (2)$$

The empirical model used in this article is the outcome of a thorough review of the relevant research, and this review has informed the subsequent representations.

$$Environmental\ Impact = f(Population, Affluence, Technology) \qquad (3)$$

In addition to independent factors, we included environmental impact and used EFP as a proxy indicator. To obtain Equation (4), apply the following procedure:

$$EFP_{it} = \alpha_0 + \alpha_1 GDP_{it} + \alpha_2 AI_{it} + \alpha_3 BD_{it} + \alpha_4 SMC_{it} + \alpha_5 URBA_{it} \qquad (4)$$

Here, GDP means gross domestic product, AI stands for Artificial intelligence, BD indicates banking development, SMC for stock market capitalization, and URBA for urbanization. In equation (4), we adapted α_1 to α_5 for coefficients of the independent variables and α_0 denoted intercept term. The log forms of the variables are used in equation (5) to ensure normal distribution.

$$LEFP_{it} = \alpha_0 + \alpha_1 LGDP_{it} + \alpha_2 LAI_{it} + \alpha_3 LBD_{it} + \alpha_4 LSMC_{it} + \alpha_5 LURBA_{it} \quad (5)$$

Econometric Framework

The characteristics of the panel data in the Nordic nations might face stationary CSD, SH, or mixed-order stationary challenges. While all of these economies are growing, the rates of growth vary significantly. Here, the slope homogeneity test is employed for this reason. In this endeavor, the first and second-generation unit root assessments, along with the cointegration examination, are required to confirm the CSD and SH concerns. After the study had considered all of these criteria, the ARDL approach was adopted. The estimations of FMOLS, DOLS, and FE-OLS were featured in our analysis to determine the accuracy. The conclusions of the research, their interpretation, and potential implications for the study are all concisely and precisely described in this section, which may be subdivided by areas.

Cross-Sectional Dependence Test

In panel data, an increase in CSD is expected as monetary integration grows and additional barriers are eliminated (Ridwan et al.,2024). If researchers ignore the issue and handle the cross-sections as isolated, CSD may produce disorganized, misleading, and contradicting results (Hoyos et al., 2006). It is essential to explore the information for CSD because panel data are utilized in this study; this test can be seen by the following equation.

$$CSD = \sqrt{\frac{2T}{N(N-1)N}\left(\sum_{i=1}^{N-1}\sum_{K=i+1}^{N}\widehat{Corr_{i,t}}\right)} \text{.......................... (6)}$$

Slope Homogeneity Test

Slopes in panel data are often consistent because cross-sections usually share the same properties. For this reason, it is essential to handle slope homogeneity in panel data analysis (Ayad and Djedaiet, 2022). According to Pesaran and Yamagata (2008), the homogeneity of the slopes is confirmed using the SH test. This evaluation makes use of each individual's weighted slope dispersion. The slope heterogeneity is shown by Equation (7) as follows:

$$\breve{\Delta} = \sqrt{N}\left(\frac{N^{-1}S\%-k}{\sqrt{2k}}\right) \text{ and } \breve{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}S\%-k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right) \text{...................... (7)}$$

Panel Unit root test

To guarantee the correct cointegration order for panel data, Rauf (2018) advised utilizing both parametric and nonparametric approaches. The first generation of the panel unit root test fails to consider heterogeneity, CSD consequences, or over-rejection of null hypotheses into account (Choi, 2001). To solve this issue, the investigation leverages the first-generation unit root examination, known as the Levin, Lin, and Chu (LLC) test, which was developed by Levin et al. (2002), and the IPS test introduced by Im et al. (2003). Conversely, Pesaran (2007) established the CIPS and CADF, which are second-generation unit root methods that take CSD and slope variability into account. The following formula may be used to represent the IPS test:

$$\Delta y_{it} = \alpha_i + \beta_i t + \gamma y_{it-1} + \delta_i \Delta y_{it-1} + \varepsilon_{it} \text{................................ (8)}$$

The following formulas were used for the LLC test statistics:

$$\Delta \mathrm{y_{it}} = \beta_i \mathrm{y_{it-1}} + \sum_{\mathrm{j=1}}^{\vartheta \mathrm{i}} \mathrm{d_{ij}} \Delta \mathrm{y_{it-1}} + \mathrm{G'_{it}} \eta + \mu_{\mathrm{it}} \qquad \text{.......................................(9)}$$

Here, G'_{it} means the column vector of the independent variable, and in regression, η indicates the vector of parameters. The CIPS unit root analysis ensures unit roots in individual time series are checked and addresses CSD in panel data to prevent inaccurate inference if not adequately addressed (Polcyn et al.,2023). The CIPS test is conducted using Equation (10):

$$CIPS = \frac{1}{N}\sum_{t=1}^{N} t_1(N,T) \text{.................................. (10)}$$

Here, N denotes a cross-sectional dimension, and T indicates a time series dimension. The CADF test has a strong relationship with the CIPS test. Equation (11) provides the following method for computing the CADF:

$$\Delta Yi_t = \varphi_i + \rho i Y i_{t-1} + \varphi i \bar{Y}_{t-1} + \sum_{j=1}^{m} \varphi_{ij} \bar{Y}_{t-1} + \sum_{j=1}^{m} \gamma_{ij} \Delta Y_{i,t-1} + \varepsilon_{it} \text{ ... ... (11)}$$

Here, $\bar{Y}_{t-1}$ and $\Delta Y_{i,t-1}$ represent the mean values of the cross-sectional analysis for both the first difference and lag.

Panel Cointegration test

Our examination used a second-generation panel cointegration assessment to assess for long-term cointegration among the variables after data stationarity. This method provides more accurate and consistent cointegration estimates than first-generation panel cointegration techniques (Ridwan et al., 2024, Arif et al.2024). A stable, long-term correlation across two or more non-stationary factors is referred to as cointegration. In other words, cointegrated factors typically follow the same course throughout time despite periodic variations (Westerlund and Edgerton, 2008). This method was invented by Westerlund (2007), and the four equations below describe this test form.

$$G_a = \frac{1}{n}\sum_{i=1}^{N}\frac{\acute{a}_i}{SE(\acute{a}_i)} \text{……………………..} \quad (12)$$

$$G_t = \frac{1}{n}\sum_{i=1}^{N}\frac{T\acute{a}_i}{a_i\acute{(}1)} \text{………………………} \quad (13)$$

$$P_t = \frac{\acute{a}}{SE(\acute{a})} \text{…………………………….} \quad (14)$$

$$P_a = T\acute{a} \text{………………………………} \quad (15)$$

Moreover, panel means statistics (Pt and Pa), there are additional group means statistics (Gt and Ga), each with its own set of symbols. The same test results are expected if the model variables are assumed to be "null" or disconnected; otherwise, if the assumption is placed that "there exist cointegrating links."

Panel ARDL method

We used the panel ARDL technique, recommended by Pesaran et al. (2001), as the variables are a combination of the I(0) and I(1) procedures. Regardless of the specified variables' order of integration, the ARDL methodology can simultaneously and rigorously estimate the short- and long-term associations (Alsamara et al., 2024). Pesaran and Shin (1995) claimed that since the ARDL model has no residual correlation and removes both serial correlation and endogeneity, it provides less reason for concern over the endogeneity issue. Furthermore, it produces consistent findings even when endogeneity problems arise because the dynamic speciation of the model can be sufficiently enhanced to make serial mistakes uncorrelated and regressors purely exogenous (Loayza & Rancière, 2006). The following are some reasons why the ARDL approach is beneficial: In a mixed order of integration, such as I(0) and I(1), or strictly I(1) but not I(2), it can be used. (ii) It addresses the endogeneity and serial correlation challenges. (iii) Robust for a limited number of samples (Nathaniel et al., 2024).

The long-term relationship models for PMG are expressed as follows:

$$\Delta Y_{1,it} = \partial_{1i} + \alpha_{1i}Y_{1,it-1} + \sum_{l=2}^{k}\alpha_{1i}X_{1,it-1} + \sum_{j=1}^{p-1}\delta_{1ij}\Delta Y_{1,it-j} + \sum_{j=0}^{q-1}\sum_{l=2}^{k}\delta_{lij}\Delta X_{1,it-j} + \varepsilon_{1i,t} \quad (16)$$

Here, Y_1 refers to the dependent variable, and X_1 is an independent variable where l=1,2,3,4. ε_{it} and Δ are residual & first difference operators, respectively.

Two steps are considered when applying the ARDL technique. The initial step is to employ the F test to assess whether there is a long-term link among the pertinent variables in the presence of an error correction. Estimating the coefficients of the long-run relations is the second stage of the ARDL, which comes after confirming that the F tests from the first step fall within acceptable limits (Hazmi et al.,2024). As a result, the long-term links between development in the economy, urbanization, banking development, stock market capitalization, AI, and ecological footprint of Nordic territory can be expressed using the ARDL models:

$$\Delta LEFP_{it} = \partial_{1i} + \alpha_{1i}LEFP_{i,t-1} + \alpha_{2i}LGDP_{i,t-1} + \alpha_{3i}LAI_{i,t-1} + \alpha_{4i}LBD_{i,t-1} + \alpha_{5i}LSMC_{i,t-1} + \alpha_{6i}LURBA_{i,t-1} + \sum_{j=1}^{p}\delta_{1i}\Delta LEFP_{i,t-j} + \sum_{i=0}^{q}\delta_{2i}\Delta LGDP_{i,t-j} + \sum_{i=0}^{q}\delta_{3i}\Delta LAI_{i,t-j} + \sum_{i=0}^{q}\delta_{4i}\Delta LBD_{i,t-j} + \sum_{i=0}^{q}\delta_{5i}\Delta LSMC_{i,t-j} + \sum_{i=0}^{q}\delta_{6i}\Delta LURBA_{i,t-j} + \varepsilon_{1i,t} \quad \ldots\ldots\ldots\ldots(17)$$

Furthermore, the following is the short-run association that takes ECM into account:

$$\Delta \mathrm{LEFP}_{\mathrm{it}} = \sum_{\mathrm{j=1}}^{\mathrm{p-1}}\beta_{1\mathrm{ij}}\Delta \mathrm{LEFP}_{\mathrm{i,t-j}} + \sum_{\mathrm{i=0}}^{\mathrm{q-1}}\beta_{2\mathrm{ij}}\Delta \mathrm{LGDP}_{\mathrm{i,t-j}} + \sum_{\mathrm{i=0}}^{\mathrm{q-1}}\beta_{3\mathrm{i}}\mathrm{j}\Delta \mathrm{LAI}_{\mathrm{i,t-j}} + \sum_{\mathrm{i=0}}^{\mathrm{q-1}}\beta_{4\mathrm{i}}\mathrm{j}\Delta \mathrm{LBD}_{\mathrm{i,t-j}} + \sum_{\mathrm{i=0}}^{\mathrm{q-1}}\beta_{5\mathrm{ij}}\Delta \mathrm{LSMC}_{\mathrm{i,t-j}} + \sum_{\mathrm{i=0}}^{\mathrm{q-1}}\beta_{6\mathrm{ij}}\Delta \mathrm{LURBA}_{\mathrm{i,t-j}} + \mu_{1\mathrm{i}}\mathrm{ECT}_{1,\mathrm{it-1}} + \varepsilon_{1\mathrm{i,t}} \quad \ldots\ldots\ldots\ldots(18)$$

Robustness Check

We have used the robustness check estimators CCR, FMOLS, and DOLS. For a more accurate and comprehensive view of the effects over time, the researchers carried out FMOLS and DOLS calculations. For time-series modeling, FMOLS was initially proposed by Phillips and Perron as a method of regression for effective parameter estimation in cointegrated systems (Phillips and Perron, 1988). It is especially renowned for its dependability in small sample sizes and its capacity to deal with endogeneity and serial correlation, as noted by Hamit-Haggar (Hamit-Haggar, 2012). However, Kao and Chiang have proved that the DOLS estimation approach, which was developed by Stock and Watson, performs better than FMOLS in terms of estimating outcomes. This is because Kao and Chiang took into account correlations among regressors (Stock and Watson, 1993; Kao, 1999). Additionally, the FE-OLS approach is applied, which is a great tool for verifying that FMOLS and DOLS are legitimate. FE-OLS is robust with autocorrelation and CSD, and it is enhanced by DKSE (Driscoll and Kraay 1998). Also, this approach is robust to common forms of autocorrelation and CSD up to a predetermined lag (Adebayo et al., 2022).

D-H Causality test

Lastly, this study applies Dumitrescu and Hurlin's (2012) causality examination to confirm the short-term correlation across the variables, which is required for policymaking. For non-homogeneous panel data models with consistent coefficients, the D-H panel causality analysis is a straightforward variant of the Granger non-causality test (Ahmed et al., 2022). The DH causality test is a more appropriate and reliable method than the Granger non-causality test (Hashmi et al., 2021) and can be used in both short and long panels ($N > T$). Additionally, this method may address multiple significant issues with pooled data, like CSD and individual heterogeneity. It has been used in earlier research (Destiartono and Hartono, 2022; Ajanaku and Collins, 2021). The following can be used to write a general model:

$$P_{i,t} = \vartheta_i + \sum_{i=1}^{k}\lambda_i^n P_{i,t-i} + \sum_{i=1}^{k}\alpha_i^n\beta_{i,t-i} + \varepsilon_t \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (19)$$

In the D-H equation, the constant, regression parameter, and auto regressions are represented by ϑ_i, λ_i^n, and α_i^n.

Results and Discussion

Table 2 presents the descriptive information of GDP, AI, BD, SMC, URB, and EFP in logarithmic format for the study period (1980–2018). The data's standard deviation, median, minimum, mean, and maximum values were all displayed properly in the table. The calculated standard deviations of the majority of the variables are quite small, indicating that the data points are somewhat temporally variable and centered around the mean. The majority of the variables exhibit a negative skew, except LEFP and LURBA. Furthermore, the Jarque-Bera test and low kurtosis and skewness statistics support the normal distribution of the variables.

Table 2. Descriptive Statistics of Variables

Statistic	LEFP	LGDP	LAI	LBD	LSMC	LURBA
Mean	2.172568	10.86771	3.102615	4.804582	3.799236	4.452720
Median	1.897619	10.87999	3.135494	4.832309	3.922183	4.447006
Maximum	3.776661	11.54785	3.89182	5.72111	4.82769	4.542699
Minimum	1.587192	10.10012	1.791759	3.834337	2.332338	4.335695
Std. Dev.	0.641229	0.312364	0.502838	0.345983	0.535468	0.053723
Skewness	1.37579	-0.179975	-0.529248	-0.120022	-0.843834	0.045105
Kurtosis	3.348248	3.055801	2.47716	2.933702	2.949145	2.550493
Jarque-Bera	35.25716	0.608104	6.388144	0.284241	13.0662	0.963392
Probability	0	0.737823	0.041005	0.867517	0.001454	0.617735
Sum	238.9825	1195.448	341.2877	528.504	417.9160	489.7992
Sum Sq. Dev.	44.81805	10.63526	27.56027	13.04774	31.25316	0.314587
Observations	110	110	110	110	110	110

Table 3 illustrates the CSD test findings for the selected elements. Test statistics and p-values are available for all explanation variables. If the p-value is less than one of the three significant levels (1%, 5%, or 10%), the null hypothesis that there is no CSD is rejected. The p-values (0.000) for the tests performed on cross-sectional variables in Table 3 provide evidence of a CSD for each variable studied at the 1% level. It implies, then, that there may be a CSD issue with our data collection.

Table 3. Results of the CSD test

Variables	CD-Statistics	P-Value
LEFP	8.75***	0.000
LGDP	13.03***	0.000
LAI	6.11***	0.000
LBD	6.64***	0.000
LSMC	7.28***	0.000
LURBA	14.18***	0.000

Panel data analysis commonly uses the Slope Homogeneity assessment to ascertain whether the independent variable coefficients are constant across several cross-sectional units (in this case, country). With p-values of 0.000, the $\check{\Delta}$ statistic of 4.654*** and the $\breve{\Delta}_{adj}$ test statistic of 5.637*** both from Table 4 suggest that there is a considerable degree of variance in the slopes across the parameters. The fact that the links among the model's elements change during the cross-sectional units suggests the existence of unique effects or coefficients for the explanatory variables.

Table 4. Results of Slope Homogeneity test

Slope homogeneity tests	Δ statistic	P-value
$\breve{\Delta}$ test	4.654***	0.000
$\breve{\Delta}_{adj}$ test	5.637***	0.000

Table 5 reveals the outcomes from three distinct unit root analyses. The IPS test shows that all other variables (LGDP, LAI, LBD, and LSMC) are level stationary at the 1% significance level, except for LEFP and LURBA. However, at their first difference, I(1), each factor becomes stationary. Second-generation tests, such as CIPS and CADF, provide more accurate findings than first-generation testing when dealing with panel data, which might exhibit cross-sectional interdependence. Such tests include cross-sectional means of lagged levels and initial differences. The results of the IPS tests accord with those of the CIPS and CADF examinations, as Table 5 demonstrates. According to the results, every component is primarily integrated at either level (I(0)) or first difference (I(1)). As a result, there is no unit root issue, and the elements have cointegrated over a long period.

Table 5. Results of Panel Unit root test

Variables	IPS		CIPS		CADF		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LEFP	-1.939	-7.031***	-1.268	-5.874***	-2.131	-4.088***	I(1)
LGDP	-3.296***	-6.452***	-4.961***	-6.496***	-3.115***	-4.981***	I(0)
LAI	-3.270***	-8.991***	-3.630***	-5.352***	-3.853***	-5.778***	I(0)
LBD	-3.131***	-6.656***	-4.736***	-5.831***	-3.140***	-4.503***	I(0)
LSMC	-3.851***	-5.312***	-3.289***	-5.066***	-3.231***	-4.556***	I(0)
LURBA	-1.555	-3.495***	-1.444	-3.611***	-1.691	-4.632***	I(1)

After establishing that every parameter stays constant, the next step is to assess whether the variables are cointegrated within time. The results of Westerlund's (2007) cointegration assessment conducted for this investigation are displayed in Table 6. Given that the Gt, Ga, Pt, and Pa statistics all have statistically significant p-values (less than 0.05), therefore we can reject the null hypothesis. The results of this test indicate that long-run cointegration prevails between the factors under consideration.

Table 6. Results of Westerlund Panel Cointegration test

Statistics	Value	Z-Value	P-value
Gt	-2.956	-2.956	0.010
Ga	-5.829	1.717	0.021
Pt	-4.829	-1.560	0.034
Pa	-4.400	1.021	0.012

The Panel ARDL model's results, given in Table 07, demonstrate the intricate dynamics influencing the Nordic region's ecological footprint. In terms of LGDP, the short-term coefficient is 0.166 but statistically insignificant, with a p-value greater than the typical threshold, while the long-run coefficient is 0.095 and statistically significant at conventional levels. This suggests that economic expansion alone may notably contribute to environmental degradation in this setting, as GDP has an encouraging influence on the EFP. Nathaniel et al. (2020a) identified that in MENA nations, GDP growth raises the EFP and degrades the environment. Moreover, Ahmed et al.(2020a) in G-7 countries, Mikayilov et al. (2018) in oil-rich economies, Khan et al.(2021) in Malaysia, and Ahmed et al.(2020b) in China also align with these findings. However, in the long run, environmental quality in Europe is improved by 0.81% for every 1% growth in real GDP (Alola et al., 2019). Georgescu and Kinnunen (2024) in Finland reveal that GDP negatively influences ecological footprint. Surprisingly, economic expansion has no adverse effects on the ecosystems in CIVETS (Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa) (Nathaniel et al.,2020b).

In the short and long terms, there is a negative link between LAI and LEFP; the short-term results are not significant, but the long-term coefficients are. This conclusion demonstrates that while AI technology has a short-term destructive implication on the environment, it has a long-term favorable advantage. LEFP drops by 0.057% in the near run and 0.097% in the long term for every 1% increase in LAI. This could be because while urgent green initiatives need assets, AI can improve energy efficiency across a range of industries, such as manufacturing, travel, and residence power. Dhar (2020) talked about AI's dual role in the fight against climate change, emphasizing that technology is a major carbon emitter as well as a tool for tackling the issue. Furthermore, Liang et al. (2022) made use of AI's ability to reduce emissions of carbon in China's industrial sector. The findings showed that China still has a long way to go in improving its performance in this area. Similarly, there is an obvious connection between banking sector activities and the environment, as evidenced by the inverse relationship observed between LBD and LEFP across both short and long periods. These results imply that banking development could boost ecological conditions in the long run but not in the short term, with p-values over the usual level in the short run and below 0.05 in the long run. Based on Sadorsky (2011), the established banking industry also increases consumer credit, which motivates people to purchase more appliances and cars, increasing energy demand and harming the natural environment. However, domestic bank lending to the private sector helps businesses create more cash assets and manufacturing inputs to create energy-efficient machinery and tools (Kareem et al.,2023). In contrast to our findings, Radulescu et al. (2022) contend that the OECD countries' ecological sustainability is negatively impacted by banking expansion.

In both the short and long term, the table demonstrates an encouraging relationship between LSMS and LEFP. The long-term statistical significance of the effect is supported by a slight short-term effect, indicating that stock market capitalization stimulates higher monetary and business transactions but may not have a positive short-term impact on the ecosystem. Asiedu (2024) disputes our results, stating that stock market capitalization ensures environmental sustainability in emerging nations and reduces the ecological footprint in those nations. However, Paramati et al. (2017) discovered that long-term environmental sustainability is guaranteed by stock market expansion in industrialized nations. Based on both short- and long-term assessments, urbanization (LURBA) and LEFP have an encouraging interaction. Over time, there is a small but statistically significant 0.0870% increase in LEFP with a p-value of less than 0.05 for every 1% increase in LURBA. A notable short-term spike in LEFP of 0.706% is associated with a 1% rise in LURBA. This could be because of the continual consequences of urban expansion, which lower ecological diversity and disrupt the natural World, such as the destruction of trees and the removal of natural ecosystems for redevelopment. According to Abid et al. (2022), there is a need for improved laws in the G-8 countries due to the substantial impact that urbanization has on environmental deterioration. Moreover, Nathaniel (2021) in South Africa, Salahuddin et al.(2019) in Sub-Saharan Africa (SSA) economies, and Alola et al.(2024) in the Nordic region also agree that urbanization increases the EFP and degrades the ecosystem. Conversely, Zhu et al. (2018) found that in the BRICS region, urbanization lowers carbon emissions and hence enhances environmental quality.

Table 7. Results of Panel ARDL method

Long-run Estimation				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LGDP	0.095	0.047113	1.918186	0.0032
LAI	-0.097	0.04754	-2.055968	0.0435
LBD	-0.247	0.14441	-1.710938	0.0115
LSMC	0.233	0.04906	4.754246	0.0000
LURBA	0.870	0.79054	2.896378	0.0000
Short-run Estimation				
Variable	Coefficient	Std. Error	t-Stat	p-Value
COINTEQ01	-0.533	0.173518	-3.072053	0.0030
D(LGDP)	0.166	0.029231	5.700034	0.0000
D(LAI)	-0.057	0.041075	-1.396781	0.1669
D(LBD)	-0.129	0.090518	-1.427376	0.1579
D(LSMC)	0.067	0.046865	1.440284	0.1542
D(LURBA)	0.706	4.496835	1.713697	0.0911
C	10.068	3.226847	3.120119	0.0026

Multiple kinds of estimating methods, such as FMOLS, DOLS, and FE-OLS, were utilized to investigate the accuracy of the ARDL results in more detail in Table 8. For each of the three tests, the projected LGD values are 0.012, 0.285, and 0.082, accordingly. These outcomes indicate that the Nordic countries' ecological health has been harmed by economic expansion. The results are consistent with the ARDL model's short and long-term conclusions despite the fact that all estimators show significant coefficient values at the 1% level of thresholds. Conversely, based on the findings of all three tests, the LEFP variable exhibits a negative connection with both LAI and LBD. In the FMOLS test, the LAI coefficient values are significant at the 5% level; in the DOLS and FE-OLS tests, they are significant at the 1% level. In particular, EFP reduces by 0.023%, 0.089%, and 0.026%, respectively, for every 1% boost in AI innovation. This implies that the ecosystems in the Nordic nations might benefit from the application and adoption of AI technologies. These findings are consistent with statements drawn from the Panel ARDL calculation. In a similar vein, the three estimation procedures reveal a negative correlation between the LBD variable and LEFP. In particular, LEFP will fall by 0.088%, 0.287%, and 0.039%, respectively, for every 1% increase in banking development. The variable is statistically significant at the 1% level in each instance. This is parallel to the discoveries of the ARDL model and demonstrates the positive impact of banking development on the ecosystems of the Nordic nations. In contrast, the LEFP variable showed negative correlations with both LSMC and LURBA, indicating that increasing levels of urbanization and stock market capitalization are detrimental to the biodiversity in the chosen regions. At the 1% level, the LSMC variable is significant for each of the three estimation instances. Furthermore, an additional 1% in URBA will result in an elevated LEFP of 0.353% for FMOLS, 0.516% for DOLS, and 0.036% for FE-OLS. The variable is significant at the 5% level in the FMOLS estimation but at the 1% level in the other two scenarios. The ARDL model's conclusions are supported by the LSMC and LURBA data. These results thereby verify the ARDL model, which is the primary estimating approach used in this paper.

Table 8. Result of Robustness check

Variables	FMOLS	DOLS	FE-OLS
LGDP	0.012***(0.0702)	0.285***(0.0892)	0.082***(0.0597)
LAI	-0.023**(0.049)	-0.089***(0.0512)	-0.026***(0.0426)
LBD	-0.088***(0.0621)	-0.287***(0.2170)	-0.039***(0.0508)
LSMC	0.036***(0.073)	0.254***(0.2745)	0.005***(0.0572)
LURBA	0.353**(0.2340)	0.516***(0.0691)	0.036***(0.8967)

A panel causality assessment was performed using the Dumitrescu and Hurlin (2012) technique, which made it possible to determine if the associations were linear or nonlinear, as illustrated in Table 9. If the p-value is significant at the 1%, 5%, or 10% levels, the null hypothesis—which states that the variable under investigation does not consistently cause another variable—can be rejected. According to the study, at the 1% level, the p-value of 0.0223 denotes a statistically significant impact of LGDP on LEFP. Hence, it is possible to reject the null hypothesis and establish a unidirectional causal relationship between LGDP and LEFP. On the other hand, as the p-value exceeds the crucial levels, no meaningful association is seen between LEFP and LGDP. A greater examination reveals that LEFP and LAI have a comparable one-way relationship. The results imply that changes in LEFP have no effect on LAI, as the null hypothesis cannot be rejected in this instance. However, statistically significant p-values in all research point to a bidirectional link between LEFP and LAI. Furthermore, neither LEFP nor LURBA appear to be causally related to one another, according to the p-values. The p-value is below 0.05 and significant at the 1% level, indicating a substantial unidirectional causal link between LBD and LEFP. This result enables us to conclude that banking development has a detrimental effect on the ecosystem and to reject the null hypothesis. To summarize, out of all the regressors, the factors that affect LEFP are LGDP, LAI, LBD, LSMC, and LURBA.

Table 9. Results of the D-H causality test

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
LGDP $\neq$ LEFP	5.06159	2.2851	0.0223
LEFP $\neq$ LGDP	4.66212	1.95363	0.0507
LAI $\neq$ LEFP	4.12222	1.50564	0.0322
LEFP $\neq$ LAI	7.0682	3.95013	0.2551
LBD $\neq$ LEFP	5.02193	2.25219	0.0243
LEFP $\neq$ LBD	4.71521	1.99769	0.0458
LSMC $\neq$ LEFP	6.41532	3.40838	0.0007
LEFP $\neq$ LSMC	3.63803	1.10387	0.2696
LURBA $\neq$ LEFP	7.69494	4.47018	0.0023
LEFP $\neq$ LURBA	3.52225	1.0078	0.3135

Conclusion and Policy Implications

In this paper, we investigated the factors influencing the EFP in Nordic countries from 1995 to 2021 using the ARDL framework and the STIRPAT model. Our study sought to determine the main drivers of environmental deterioration while making recommendations for future legislation about green practices. The ARDL technique makes a detailed examination of the intricate relationships between the dependent and explanatory variables possible. The study finds an unexpectedly strong positive correlation between ecological footprint, stock market value, and GDP per capita, which contradicts our assumptions. This suggests that financial activity and economic progress harm biodiversity.

The study also emphasizes the detrimental effects of urbanization on the ecological footprint, demonstrating a positive association between LEFP and LURBA and highlighting the necessity of sustainable urban planning in Nordic countries. Furthermore, the analysis indicates advantageous patterns that suggest a correlation between the advancement of banking, the integration of AI technology, and upgrades in environmental quality. These findings point to the possibility of incorporating environmental factors with the goals of sustainable development and eco-friendly behaviors into socio-economic strategies. Our analytical framework was rigorously tested using FMOLS, DOLS, and FE-OLS techniques. The Dumitrescu and Hurlin (D-H) causality tests were employed to examine the causal linkages among the variables. The findings indicated unidirectional causality between LGDP and LEFP, LAI and LEFP, LSMS and LEFP, and LEFP and LURBA. For stakeholders and legislators dedicated to advancing green policies and sustainable growth in these nations, this study offers insightful information about the evolving patterns of the ecological footprint in the Nordic region.

Based on the research that shows how economic growth, stock market capitalization, and urbanization contribute to the ecological footprint in the Nordic region, it is crucial to implement specific policy suggestions to reduce the environmental impact. Initiate sustainable economic growth by using green technologies and renewable energy sources to diminish carbon emissions and resource exhaustion. In addition, promotes ecologically conscious investment practices in the stock market by offering incentives to companies that embrace sustainable business strategies and disclose their environmental footprint. Moreover, stringent urban planning regulations should be enforced to manage the expansion of cities, improve the quality of green areas, and encourage the construction of environmentally sustainable infrastructure. Furthermore, it is crucial to enhance both public and private funding for research and development in order to promote sustainable technologies and ideas. Additionally, implement and uphold rigorous environmental regulations and standards for industries in order to minimize pollution and waste. In addition, public awareness and education initiatives should be implemented to promote sustainable consumption patterns and minimize the ecological impact. Engage in cooperative efforts with international organizations and neighboring countries to exchange successful methods and establish collective projects aimed at preserving the environment. Lastly, consistently oversee and assess the efficiency of these strategies and make essential modifications to guarantee ongoing advancement towards sustainability objectives.

In order to leverage the inverse relationship between AI advancement and environmental impact in the Nordic region, authorities should prioritize investing in eco-friendly AI technologies that encourage sustainability, such as those that improve energy efficiency and waste management. It is essential to create strong legislative frameworks that encourage the advancement and adoption of environmentally friendly AI technologies. One way to accomplish this is by providing tax incentives, grants, and subsidies to corporations and research institutes that prioritize the use of AI to minimize environmental harm. In addition, the success of these activities can be maximized by promoting public-private partnerships, which involve merging resources and expertise. By implementing these strategies, the Nordic area may enhance its AI capabilities while also promoting its dedication to ecological sustainability.

Policymakers have to concentrate on incorporating sustainable finance practices into the banking industry since the study indicates a negative correlation between the expansion of banking and the ecological footprint in the Nordic area. Promoting green banking efforts is one way to do this, such as giving loans intended for renewable energy projects or environmental projects better interest rates. To guarantee that their funding promotes low-impact and sustainable businesses, financial institutions should also be urged to implement strict environmental, social, and governance (ESG) standards in their investment portfolios. Regulators may improve this by giving banks explicit instructions and financial incentives to prioritize green investments and integrate sustainability into their lending procedures. Moreover, enforcing stricter reporting requirements and enhancing transparency about the environmental effect of projects financed by banks will encourage the adoption of more responsible banking practices and help hold institutions accountable. The Nordic area can maintain economic growth while drastically lowering its ecological imprint by coordinating banking expansion with ecological sustainability.

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Consent for publication: All participants provided consent for the publication of data and findings derived from their participation in the study. The consent forms are available upon request from the corresponding author.

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Authors' contributions: Mohammad Ridwan contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by Sarder Abdulla Al Shiam, Afsana Akhter, Md Mahdi Hasan, S M Shamsul Arefeen, Md Sibbir Hossain, Shake Ibna Abir, Shaharina Shoha. All authors read and approved the final manuscript.

References

A Omojolaibi, J., & P Nathaniel, S. (2022). Assessing the potency of environmental regulation in maintaining environmental sustainability in MENA countries: An advanced panel data estimation. Journal of Public Affairs, 22(3), e2526. https://doi.org/10.1002/pa.2526

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

Addai, K., Serener, B. & Kirikkaleli, D. Empirical analysis of the relationship among urbanization, economic growth and ecological footprint: evidence from Eastern Europe. Environ Sci Pollut Res 29, 27749–27760 (2022). https://doi.org/10.1007/s11356-021-17311-x

Adebayo, T.S., Akadiri, S.S., Haouas, I. et al. Criticality of geothermal and coal energy consumption toward carbon neutrality: evidence from newly industrialized countries. Environ Sci Pollut Res 29, 74841–74850 (2022). https://doi.org/10.1007/s11356-022-21117-w

Adebayo, T.S., Kirikkaleli, D. Impact of renewable energy consumption, globalization, and technological innovation on environmental degradation in Japan: application of wavelet tools. Environ Dev Sustain 23, 16057–16082 (2021). https://doi.org/10.1007/s10668-021-01322-2

Ahmad M, Jiang P, Majeed A, Umar M, Khan Z, Muhammad S (2020) The dynamic impact of natural resources, technological innovations and economic growth on ecological footprint: an advanced panel data estimation. Resour Policy 69(September):101817. https://doi.org/10.1016/j.resourpol.2020.101817

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.04.008

Ahmed Z, Cary M, Le HP (2021) Accounting asymmetries in the long-run nexus between globalization and environmental sustainability in the United States: an aggregated and disaggregated investigation. Environ Impact Assess Rev 86:106511 https://doi.org/10.1016/j.eiar.2020.106511

Ahmed Z, Zafar MW, Ali S (2020a) Linking urbanization, human capital, and the ecological footprint in G7 countries: an empirical analysis. Sustain Cities Soc 55:102064 https://doi.org/10.1016/j.scs.2020.102064

Ahmed, N., Sheikh, A. A., Hamid, Z., Senkus, P., Borda, R. C., Wysokińska-Senkus, A., & Glabiszewski, W. (2022). Exploring the causal relationship among green taxes, energy intensity, and energy consumption in Nordic countries: Dumitrescu and Hurlin causality approach. Energies, 15(14), 5199. https://doi.org/10.3390/en15145199

Ahmed, Z., Asghar, M. M., Malik, M. N., & Nawaz, K. (2020b). 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

Ajanaku, B. A., & Collins, A. R. (2021). Economic growth and deforestation in African countries: Is the environmental Kuznets curve hypothesis applicable?. Forest Policy and Economics, 129, 102488.

Akram R, Chen F, Khalid F, Ye Z, Majeed MT (2020) Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: evidence from developing countries. J Clean Prod 247:119122. https://doi.org/10.1016/j.jclepro.2019.119122

Al Shiam, S. A., Hasan, M. M., Nayeem, M. B., Choudhury, M. T. H., Bhowmik, P. K., Shochona, S. A., ... & Islam, M. R. (2024a). Deep Learning for Enterprise Decision-Making: A Comprehensive Study in Stock Market Analytics. Journal of Business and Management Studies, 6(2), 153-160.

Al Shiam, S. A., Hasan, M. M., Pantho, M. J., Shochona, S. A., Nayeem, M. B., Choudhury, M. T. H., & Nguyen, T. N. (2024b). Credit Risk Prediction Using Explainable AI. Journal of Business and Management Studies, 6(2), 61-66.

Ali R, Bakhsh K, Yasin MA (2019) Impact of urbanization on CO2 emissions in emerging economy: evidence from Pakistan. Sustain Cities Soc 48:101553. https://doi.org/10.1016/j.scs.2019.101553

Ali S, Ying L, Anjum R, Nazir A, Shalmani A, Shah T, Shah F (2021) Analysis on the nexus of CO2 emissions, energy use, net domestic credit, and GDP in Pakistan: an ARDL bound testing analysis. Environ Sci Pollut Res 28:4594–4614 https://doi.org/10.1007/s11356-020-10763-7

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

Alola, A.A., Bekun, F.V., Sarkodie, S.A.: Dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on ecological footprint in Europe. Sci. Total Environ. 685, 702–709 (2019) https://doi.org/10.1016/j.scitotenv.2019.05.139

Alsamara, M., Mimouni, K., Barkat, K., & Kayaly, D. (2024). Can exchange rate policies and trade partners' income enhance the trade balance in Algeria? Evidence from the nonlinear ARDL model. International Journal of Emerging Markets, 19(5), 1135-1156. https://doi.org/10.1108/IJOEM-02-2022-0341

Altıntaş, N., Açıkgöz, F., Okur, M., Öztürk, M., & Aydın, A. (2024). Renewable Energy and Banking Sector Development Impact on Load Capacity Factor in Malaysia. Journal of Cleaner Production, 434, 140143. https://doi.org/10.1016/j.jclepro.2023.140143

Amin, A., & Dogan, E. (2021). The role of economic policy uncertainty in the energy-environment nexus for China: evidence from the novel dynamic simulations method. Journal of Environmental Management, 292, 112865. https://doi.org/10.1016/J.JENVMAN.2021.112865

Apergis, N., Pinar, M. & Unlu, E. How do foreign direct investment flows affect carbon emissions in BRICS countries? Revisiting the pollution haven hypothesis using bilateral FDI flows from OECD to BRICS countries. Environ Sci Pollut Res 30, 14680–14692 (2023). https://doi.org/10.1007/s11356-022-23185-4

Arif, M., Gill, A.R. & Ali, M. Analyzing the non-linear association between urbanization and ecological footprint: an empirical analysis. Environ Sci Pollut Res 30, 109063–109076 (2023). https://doi.org/10.1007/s11356-023-30012-x

Arif, M., Hasan, M., Al Shiam, S. A., Ahmed, M. P., Tusher, M. I., Hossan, M. Z., ... & Imam, T. (2024). Predicting Customer Sentiment in Social Media Interactions: Analyzing Amazon Help Twitter Conversations Using Machine Learning. International Journal of Advanced Science Computing and Engineering, 6(2), 52-56.

Arya, A., Bachheti, A., Bachheti, R.K., Singh, M., Chandel, A.K. (2024). Role of Artificial Intelligence in Minimizing Carbon Footprint: A Systematic Review of Recent Insights. In: Chandel, A.K. (eds) Biorefinery and Industry 4.0: Empowering Sustainability. Green Energy and Technology. Springer, Cham. https://doi.org/10.1007/978-3-031-51601-6_14

Asiedu, B.A. (2024), "The combine impact of stock market, international investment and clean energy consumption on ecological footprint in emerging countries", International Journal of Energy Sector Management, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/IJESM-12-2023-0027

Aslam B, Hu J, Shahab S, Ahmad A, Saleem M, Shah SSA, Javed MS, Aslam MK, Hussain S, Hassan M (2021) The nexus of industrialization, GDP per capita and CO2 emission in China. Environ Technol Innov 23:101674 https://doi.org/10.1016/j.eti.2021.101674

Ayad, H., Djedaiet, A. Does the unemployment rate matter for environmental issues in the G7 nations? New testing for the environmental Phillips curve using the load capacity factor. Environ Dev Sustain (2024). https://doi.org/10.1007/s10668-024-04956-0

Azam M, Khan AQ (2016) Urbanization and environmental degradation: evidence from four SAARC countries—Bangladesh, India, Pakistan, and Sri Lanka. Environ Prog Sustain Energy 35(3):823–832 https://doi.org/10.1002/ep.12282

Azeem, A., Naseem, M.A., Hassan, N.U. et al. A novel lens of stock market capitalization and environmental degradation. Environ Sci Pollut Res 30, 11431–11442 (2023). https://doi.org/10.1007/s11356-022-22885-1

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.

Baloch, M.A., Zhang, J., Iqbal, K. et al. The effect of financial development on ecological footprint in BRI countries: evidence from panel data estimation. Environ Sci Pollut Res 26, 6199–6208 (2019). https://doi.org/10.1007/s11356-018-3992-9

Borup, M. (2008). Nordic energy innovation systems-patterns of need integration and co-operation. In NORIA-Energy Policy Seminar. Sovacool, B. K. (2013). Energy policymaking in Denmark: Implications for global energy security and sustainability. Energy Policy, 61, 829-839.

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

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

Choi, I.n. (2001). Unit root tests for panel data. Journal of International Money and Finance, 20(2), 249–272. https://doi.org/10.1016/S0261-5606(00)00048-6

Danish, Ulucak R, Khan SU (2020) Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. Sustain Cities Soc 101996 https://doi.org/10.1016/j.scs.2019.101996

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. The stata journal, 6(4), 482-496. https://doi.org/10.1177/1536867X0600600403.

Destek, M. A. (2020). Investigation on the role of economic, social, and political globalization on environment: evidence from CEECs. Environmental Science and Pollution Research, 27(27), 33601-33614. https://doi.org/10.1007/s11356-019-04698-x

Destiartono, M. E., & Hartono, D. (2022). Does Rapid Urbanization Drive Deforestation? Evidence From Southeast Asia. Economics Development Analysis Journal, 11(4), 442-453.

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

Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences, 94(1), 175-179. https://doi.org/10.1073/pnas.94.1.175

Dogan, E., Majeed, M. T., & Luni, T. (2022). Revisiting the nexus of ecological footprint, unemployment, and renewable and non-renewable energy for South Asian economies: Evidence from novel research methods. Renewable Energy, 194, 1060-1070. https://doi.org/10.1016/j.renene.2022.05.165

Driscoll JC, Kraay AC (1998) Consistent covariance matrix estimation with spatially dependent panel data. Rev Econ Stat 80(4):549–560

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. Economic modelling, 29(4), 1450-1460. https://doi.org/10.1016/j.econmod.2012.02.014

Ehrlich, P. R., & Holdren, J. P. (1971). Impact of Population Growth: Complacency concerning this component of man's predicament is unjustified and counterproductive. Science, 171(3977), 1212-1217. https://doi.org/10.1126/science.171.3977.1212

Gasimli O, ul Haq I, Gamage SKN et al (2019) Energy, trade, urbanization and environmental degradation nexus in Sri Lanka: bounds testing approach. Energies 12:1–16. https://doi.org/10.3390/en12091655

Georgescu, I., & Kinnunen, J. (2024). Effects of FDI, GDP and energy use on ecological footprint in Finland: An ARDL approach. World Development Sustainability, 4, 100157. https://doi.org/10.1016/j.wds.2024.100157

GFN (2018) Global Footprint Network. WWW Document https://data.footprintnetwork.org/?_ga=2.134472181.508123949.1609248689-1393775646.1607921298#/

Habiba, U., Xinbang, C. The impact of financial development on CO2 emissions: new evidence from developed and emerging countries. Environ Sci Pollut Res 29, 31453–31466 (2022). https://doi.org/10.1007/s11356-022-18533-3

Hamit-Haggar, M. (2012). Greenhouse gas emissions, energy consumption and economic growth: A panel cointegration analysis from Canadian industrial sector perspective. Energy Economics, 34(1), 358-364. https://doi.org/10.1016/j.eneco.2011.06.005

Hashmi, R., & Alam, K. (2019). Dynamic relationship among environmental regulation, innovation, CO2 emissions, population, and economic growth in OECD countries: A panel investigation. Journal of Cleaner Production, 231, 1100–1109. https://doi.org/10.1016/j.jclepro.2019.05.325

Hashmi, S. H., Fan, H., Habib, Y., & Riaz, A. (2021). Non-linear relationship between urbanization paths and CO2 emissions: A case of South, South-East and East Asian economies. Urban Climate, 37, 100814. https://doi.org/10.1016/j.uclim.2021.100814

Hassan ST, Xia E, Khan NH, Shah SMA (2019) Economic growth, natural resources, and ecological footprints: evidence from Pakistan. Environ Sci Pollut Res 26(3):2929–2938 https://doi.org/10.1007/s11356-018-3803-3

Hazmi, A., Kort, H. M., Khallouli, W., & Raissi, N. (2024). A Dynamic Interrelationships among Clean Energy, Environmental Pollution, and Economic Growth in GCC Economies: A Panel ARDL Approach. International Journal of Energy Research, 2024(1), 5571175. https://doi.org/10.1155/2024/5571175

He L, Shen J, Zhang Y (2018) Ecological vulnerability assessment for ecological conservation and environmental management. J Environ Manag 206:1115–1125. https://doi.org/10.1016/j.jenvman.2017.11.059

Idroes, G.M., Hardi, I., Rahman, M.H. et al. The dynamic impact of non-renewable and renewable energy on carbon dioxide emissions and ecological footprint in Indonesia. Carbon Res. 3, 35 (2024). https://doi.org/10.1007/s44246-024-00117-0

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of econometrics, 115(1), 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

Jagers, S. C., & Hammar, H. (2009). Environmental taxation for good and for bad: The efficiency and legitimacy of Sweden’s carbon tax. Environmental Politics, 18(2), 218–237. https://doi.org/10.1080/09644010802682601

Janković, R., Mihajlović, I., Štrbac, N. et al. Machine learning models for ecological footprint prediction based on energy parameters. Neural Comput & Applic 33, 7073–7087 (2021). https://doi.org/10.1007/s00521-020-05476-4

Jokinen, J., Nilsson, K., Karlsdóttir, A., Heleniak, T., Kull, M., Stjernberg, M., ... & Gassen, N. S. (2020). State of the Nordic Region 2020. Nordic Council of Ministers.

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. Journal of econometrics, 90(1), 1-44. https://doi.org/10.1016/S0304-4076(98)00023-2

Kareem, P. H., Ali, M., Tursoy, T., & Khalifa, W. (2023). Testing the effect of oil prices, ecological footprint, banking sector development and economic growth on energy consumptions: Evidence from bootstrap ARDL approach. Energies, 16(8), 3365. https://doi.org/10.3390/en16083365

Kashka, F. M., Sarvestani, Z. T., Pirdashti, H., Motevali, A., & Nadi, M. (2022). Predicting of Agro-environmental Footprint with Artificial Intelligence (Soybean cultivation in various scenarios). https://doi.org/10.21203/rs.3.rs-1098555/v1

Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. Science of the Total Environment, 754, 142222. https://doi.org/10.1016/j.scitotenv.2020.142222

Khan, M. A., & Rehan, R. (2022). Revealing the impacts of banking sector development on renewable energy consumption, green growth, and environmental quality in China: does financial inclusion matter?. Frontiers in Energy Research, 10, 940209. https://doi.org/10.3389/fenrg.2022.940209

Khan, M.K., Abbas, F., Godil, D.I. et al. Moving towards sustainability: how do natural resources, financial development, and economic growth interact with the ecological footprint in Malaysia? A dynamic ARDL approach. Environ Sci Pollut Res 28, 55579–55591 (2021). https://doi.org/10.1007/s11356-021-14686-9

Khanal, A. (2021). Does energy consumption impact the environment?: Evidence from Australia using the JJ Bayer-Hanck cointegration technique and the autoregressive distributed lag test. International Journal of Energy Economics and Policy, 11(4), 185-194. https://doi.org/10.32479/ijeep.11163.

KPMG, 2022. Survey of Sustainability Reporting 2022. Available at https://kpmg.com/no/nb/home/nyheter-og-innsikt/2022/10/survey-of-sustainability-reporting-2022.html.

Kumari, N., & Pandey, S. (2023). Application of artificial intelligence in environmental sustainability and climate change. In Visualization techniques for climate change with machine learning and artificial intelligence (pp. 293-316). Elsevier. https://doi.org/10.1016/B978-0-323-99714-0.00018-2

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. Journal of econometrics, 108(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, R., Wang, X., & Wang, Q. (2022). Does renewable energy reduce ecological footprint at the expense of economic growth? An empirical analysis of 120 countries. Journal of Cleaner Production, 346, 131207. https://doi.org/10.1016/j.jclepro.2022.131207

Liang S, Yang J, Ding T (2022) Performance evaluation of AI driven low carbon manufacturing industry in China: an interactive network DEA approach. Comput Ind Eng 170:108248. https://doi.org/10.1016/j.cie.2022.108248

Liu, K., Mahmoud, H. A., Liu, L., Halteh, K., Arnone, G., Shukurullaevich, N. K., & Alzoubi, H. M. (2024). Exploring the Nexus between Fintech, natural resources, urbanization, and environment sustainability in China: A QARDL study. Resources Policy, 89, 104557. https://doi.org/10.1016/j.resourpol.2023.104557

Liu, L., Rasool, Z., Ali, S., Wang, C., & Nazar, R. (2024). Robots for sustainability: Evaluating ecological footprints in leading AI-driven industrial nations. Technology in Society, 76, 102460. https://doi.org/10.1016/j.techsoc.2024.102460

Loayza, N. V., & Rancière, R. (2006). Financial development, financial fragility, and growth. Journal of Money, Credit, and Banking, 38(4), 1051–1076.

Longsheng, C., Shah, S. A. A., Solangi, Y. A., Ahmad, M., & Ali, S. (2022). An integrated SWOT-multi-criteria analysis of implementing sustainable waste-to-energy in Pakistan. Renewable Energy, 195, 1438-1453. https://doi.org/10.1016/j.renene.2022.06.112

Maczionsek, M. I. J., Dillman, K. J., & Heinonen, J. (2023). Linking perception and reality: Climate-sustainability perception and carbon footprints in the Nordic countries. Journal of Cleaner Production, 430, 139750. https://doi.org/10.1016/j.jclepro.2023.139750

Mhadhbi, M., Gallali, M. I., Goutte, S., & Guesmi, K. (2021). On the asymmetric relationship between stock market development, energy efficiency and environmental quality: A nonlinear analysis. International Review of Financial Analysis, 77, 101840.

Mikayilov JI, Galeotti M, Hasanov FJ (2018) The impact of economic growth on CO2 emissions in Azerbaijan. J Clean Prod 197:1558–1572. https://doi.org/10.1016/j.jclepro.2018.06.269

Nathaniel S, Nwodo O, Sharma G, Shah M (2020b) Renewable energy, urbanization, and ecological footprint linkage in CIVETS. Environ Sci Pollut Res 27(16):19616–19629 https://doi.org/10.1007/s11356-020-08466-0

Nathaniel SP, Barua S, Ahmed Z (2021) What drives ecological footprint in top ten tourist destinations? Evidence from advanced panel techniques. Environ Sci Pollut Res:1–10. https://doi.org/10.1007/s11356-021-13389-5

Nathaniel, S. P. (2021). Natural resources, urbanisation, economic growth and the ecological footprint in South Africa: the moderating role of human capital. Quaestiones Geographicae, 40(2), 63-76. https://doi.org/10.2478/quageo-2021-0012

Nathaniel, S. P., Ahmed, Z., Shamansurova, Z., & Fakher, H. A. (2024). Linking clean energy consumption, globalization, and financial development to the ecological footprint in a developing country: Insights from the novel dynamic ARDL simulation techniques. Heliyon, 10(5). https://doi.org/10.1016/j.heliyon.2024.e27095

Nathaniel, S., Anyanwu, O. & Shah, M. Renewable energy, urbanization, and ecological footprint in the Middle East and North Africa region. Environ Sci Pollut Res 27, 14601–14613 (2020a). https://doi.org/10.1007/s11356-020-08017-7

Nguyen, D. K., Huynh, T. L. D., & Nasir, M. A. (2021). Carbon emissions determinants and forecasting: Evidence from G6 countries. Journal of Environmental Management, 285, 111988. https://doi.org/10.1016/j.jenvman.2021.111988

Nordic Statistic database, (2022). accessible at www.nordicstatistics.org. Accessed on 03 May 2022.

Nuta, F., Shahbaz, M., Khan, I. et al. Dynamic impact of demographic features, FDI, and technological innovations on ecological footprint: evidence from European emerging economies. Environ Sci Pollut Res 31, 18683–18700 (2024). https://doi.org/10.1007/s11356-024-32345-7

Obiora, S. C., Bamisile, O., Opoku-Mensah, E., & Kofi Frimpong, A. N. (2020). Impact of banking and financial systems on environmental sustainability: An overarching study of developing, emerging, and developed economies. Sustainability, 12(19), 8074. https://doi.org/10.3390/su12198074

Owusu, S. M., Chuanbo, F., & Qiao, H. (2024). Examining economic policy uncertainty's impact on environmental sustainability: Insights from nordic nations. Journal of Cleaner Production, 449, 141688. https://doi.org/10.1016/j.jclepro.2024.141688

Ozturk I, Aslan A, Altinoz B (2021) Investigating the nexus between CO2 emissions, economic growth, energy consumption and pilgrimage tourism in Saudi Arabia. Econ Res-Ekonomska Istraživanja 35(1):3083–3098. https://doi.org/10.1080/1331677X.2021.1985577

Ozturk, I., & Acaravci, A. (2013). The long-run and causal analysis of energy, growth, openness and financial development on carbon emissions in Turkey. Energy economics, 36, 262-267. https://doi.org/10.1016/j.eneco.2012.08.025

Paramati, S. R., Mo, D., & Gupta, R. (2017). The effects of stock market growth and renewable energy use on CO2 emissions: evidence from G20 countries. Energy economics, 66, 360-371. https://doi.org/10.1016/j.eneco.2017.06.025

Pata, U. K., Aydin, M., & Haouas, I. (2021). Are natural resources abundance and human development a solution for environmental pressure? Evidence from top ten countries with the largest ecological footprint. Resources policy, 70, 101923. https://doi.org/10.1016/j.resourpol.2020.101923

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. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of applied econometrics, 22(2), 265-312. https://doi.org/10.1002/jae.951

Pesaran, M. H., & Shin, Y. (1995). An autoregressive distributed lag modelling approach to cointegration analysis (Vol. 9514, pp. 371-413). Cambridge, UK: Department of Applied Economics, University of Cambridge.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. Journal of Econometrics, 142(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

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., & 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

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. https://doi.org/10.3390/ijerph20054000

Quan Q, Gao S, Shang Y, Wang B (2021) Assessment of the sustainability of Gymnocypris eckloni habitat under river damming in the source region of the Yellow River. Sci Total Environ 778:146312. https://doi.org/10.1016/j.scitotenv.2021.146312

Radulescu, M., Balsalobre-Lorente, D., Joof, F., Samour, A., & Türsoy, T. (2022). Exploring the impacts of banking development, and renewable energy on ecological footprint in OECD: new evidence from method of moments quantile regression. Energies, 15(24), 9290. https://doi.org/10.3390/en15249290

Raihan, A., & Voumik, L. C. (2022). Carbon emission reduction potential of renewable energy, remittance, and technological innovation: empirical evidence from China. Journal of Technology Innovations and Energy, 1(4), 25-36. https://doi.org/10.56556/jtie.v1i4.398

Raihan, A., Atasoy, F. G., Atasoy, M., Ridwan, M., & Paul, A. (2022a). 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. https://doi.org/10.56946/jeee.v1i2.377

Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024a). 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. https://doi.org/10.1016/j.ject.2024.06.001

Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., & Ahmad, S. (2023a). 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. (2024b). 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. (2022b). 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., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023b). From growth to green: navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. Energy Reports, 10, 4318-4331. https://doi.org/10.1016/j.egyr.2023.10.084

Rana, M. N. U., Al Shiam, S. A., Shochona, S. A., Islam, M. R., Asrafuzzaman, M., Bhowmik, P. K., ... & Asaduzzaman, M. (2024). Revolutionizing Banking Decision-Making: A Deep Learning Approach to Predicting Customer Behavior. Journal of Business and Management Studies, 6(3), 21-27.

Rasheed, M. Q., Yuhuan, Z., Haseeb, A., Ahmed, Z., & Saud, S. (2024). Asymmetric relationship between competitive industrial performance, renewable energy, industrialization, and carbon footprint: Does artificial intelligence matter for environmental sustainability?. Applied Energy, 367, 123346. https://doi.org/10.1016/j.apenergy.2024.123346

Rauf, A., et al. (2018). Testing EKC hypothesis with energy and sustainable development challenges: A fresh evidence from belt and road initiative economies. Environmental Science and Pollution Research, 25, 32066–32080. https://doi.org/10.1007/s11356- 018-3052-5

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., 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. https://doi.org/10.56946/jeee.v2i2.343

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. https://doi.org/10.1016/j.resglo.2024.100223

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. https://doi.org/10.1007/978-3-031-55911-2_1

Roumiani, ., Mofidi, A. Predicting ecological footprint based on global macro indicators in G-20 countries using machine learning approaches. Environ Sci Pollut Res 29, 11736–11755 (2022). https://doi.org/10.1007/s11356-021-16515-5

Roumiani, A., & Mofidi, A. (2021). Ecological Footprint Prediction based on Global Macro Indicators in G-20 Countries using Machine Learning Approaches. https://doi.org/10.21203/rs.3.rs-489246/v1

Sadorsky P (2010) The impact of financial development on energy consumption in emerging economies. Energy Policy 38(5):2528–2535

Sadorsky, P. (2011). Financial development and energy consumption in Central and Eastern European frontier economies. Energy policy, 39(2), 999-1006. https://doi.org/10.1016/j.enpol.2010.11.034

Sahoo, M., Sethi, N. The intermittent effects of renewable energy on ecological footprint: evidence from developing countries. Environ Sci Pollut Res 28, 56401–56417 (2021). https://doi.org/10.1007/s11356-021-14600-3

Salahuddin M, Ali MI, Vink N, Gow J (2019) The effects of urbanization and globalization on CO 2 emissions: evidence from the Sub-Saharan Africa (SSA) countries. Environ Sci Pollut Res 26(3):2699–2709

Salahuddin, M., Ali, M.I., Vink, N. et al. The effects of urbanization and globalization on CO2 emissions: evidence from the Sub-Saharan Africa (SSA) countries. Environ Sci Pollut Res 26, 2699–2709 (2019). https://doi.org/10.1007/s11356-018-3790-4

Samour, A., Isiksal, A. Z., & Resatoglu, N. G. (2019). TESTING THE IMPACT OF BANKING SECTOR DEVELOPMENT ON TURKEY'S CO 2 EMISSIONS. Applied Ecology & Environmental Research, 17(3). http://dx.doi.org/10.15666/aeer/1703_64976513

Samour, A., Moyo, D., & Tursoy, T. (2022). Renewable energy, banking sector development, and carbon dioxide emissions nexus: A path toward sustainable development in South Africa. Renewable Energy, 193, 1032-1040. https://doi.org/10.1016/j.renene.2022.05.013

Shahbaz, M., Dogan, M., Akkus, H.T. et al. The effect of financial development and economic growth on ecological footprint: evidence from top 10 emitter countries. Environ Sci Pollut Res 30, 73518–73533 (2023). https://doi.org/10.1007/s11356-023-27573-2

Shahbaz, M., Jam, F. A., Bibi, S., & Loganathan, N. (2016). Multivariate Granger causality between CO2 emissions, energy intensity and economic growth in Portugal: evidence from cointegration and causality analysis. Technological and Economic Development of Economy, 22(1), 47-74.

Shahbaz, M., Loganathan, N., Muzaffar, A. T., Ahmed, K., & Jabran, M. A. (2016). How urbanization affects CO2 emissions in Malaysia? The application of STIRPAT model. Renewable and Sustainable Energy Reviews, 57, 83-93. https://doi.org/10.1016/j.rser.2015.12.096

Sharif A, Baris-Tuzemen O, Uzuner G, Ozturk I, Sinha A (2020) Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: evidence from quantile ARDL approach. Sustain Cities Soc 57(February):102138. https://doi.org/10.1016/j.scs.2020.102138

Sharma, G. D., Tiwari, A. K., Erkut, B., & Mundi, H. S. (2021). Exploring the nexus between non-renewable and renewable energy consumptions and economic development: Evidence from panel estimations. Renewable and Sustainable Energy Reviews, 146, 111152. https://doi.org/10.1016/j.rser.2021.111152

Sovacool, B. K. (2013). Energy policymaking in Denmark: Implications for global energy security and sustainability. Energy Policy, 61, 829-839. https://doi.org/10.1016/j.enpol.2013.06.106

Sovacool, B. K. (2017). Contestation, contingency, and justice in the Nordic low-carbon energy transition. Energy Policy, 102, 569-582. https://doi.org/10.1016/j.enpol.2016.12.045

Stock, J. H., & Watson, M. W. (1993). A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica: journal of the Econometric Society, 783-820. https://doi.org/10.2307/2951763

Su, N. (2023). Green energy imports, FDI, Stock market capitalization, globalization and environmental degradation in China: Paving the Path to Sustainability in COP26 Agenda. https://doi.org/10.21203/rs.3.rs-3244670/v1

Taghizadeh-Hesary, F., Zakari, A., Alvarado, R., & Tawiah, V. (2022). The green bond market and its use for energy efficiency finance in Africa. China Finance Review International, 12(2), 241-260. https://doi.org/10.1108/CFRI-12-2021-0225

Topcu, M., Tugcu, C. T., & Ocal, O. (2020). How Does Environmental Degradation React to Stock Market Development in Developing Countries?. Econometrics of Green Energy Handbook: Economic and Technological Development, 291-301.

Tsagkanos, A., Siriopoulos, C., & Vartholomatou, K. (2019). Foreign direct investment and stock market development: Evidence from a “new” emerging market. Journal of Economic Studies, 46(1), 55-70. https://doi.org/10.1108/JES-06-2017-0154

Ulucak, R., & Khan, S. U. D. (2020). Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. Sustainable Cities and Society, 54, 101996. https://doi.org/10.1016/j.scs.2019.101996

Urban, F., & Nordensvärd, J. (2018). Low carbon energy transitions in the Nordic countries: Evidence from the environmental Kuznets curve. Energies, 11(9), 2209. https://doi.org/10.3390/en11092209

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. Heliyon, 9(1). https://doi.org/10.1016/j.heliyon.2023.e12872

Voumik, L. C., Hossain, M. S., Islam, M. A., & Rahaman, A. (2022). The Impact of Electricity Production Sources on CO2 Emission in BRICS Countries: A GMM and Quantile Regression Analysis. Strategic Planning for Energy and the Environment, 41(4), 1-24. https://doi.org/10.13052/spee1048-5236.4143

Voumik, L. C., Islam, M. A., Ray, S., Mohamed Yusop, N. Y., & Ridzuan, A. R. (2023a). CO2 emissions from renewable and non-renewable electricity generation sources in the G7 countries: static and dynamic panel assessment. Energies, 16(3), 1044. https://doi.org/10.3390/en16031044

Voumik, L. C., Ridwan, M., Rahman, M. H., & Raihan, A. (2023b). 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. https://doi.org/10.1016/j.ref.2023.100491

Wang, Q., Sun, T. & Li, R. Does artificial intelligence (AI) reduce ecological footprint? The role of globalization. Environ Sci Pollut Res 30, 123948–123965 (2023). https://doi.org/10.1007/s11356-023-31076-5

Westerlund, J. (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics, 69(6), 709–748. https://doi.org/10.1111/j.1468- 0084.2007.00477.x

Westerlund, J., & Edgerton, D. L. (2008). A simple test for cointegration in dependent panels with structural breaks. Oxford Bulletin of Economics and statistics, 70(5), 665-704. https://doi.org/10.1111/j.1468-0084.2008.00513.x

Younis, I., Naz, A., Shah, S.A.A. et al. Impact of stock market, renewable energy consumption and urbanization on environmental degradation: new evidence from BRICS countries. Environ Sci Pollut Res 28, 31549–31565 (2021). https://doi.org/10.1007/s11356-021-12731-1

Zafar, M. W., Zaidi, S. A. H., Sinha, A., Gedikli, A., & Hou, F. (2019). The role of stock market and banking sector development, and renewable energy consumption in carbon emissions: Insights from G-7 and N-11 countries. Resources Policy, 62, 427-436. https://doi.org/10.1016/j.resourpol.2019.05.003

Zafar, M. W., Zaidi, S. A. H., Sinha, A., Gedikli, A., & Hou, F. (2019). The role of stock market and banking sector development, and renewable energy consumption in carbon emissions: Insights from G-7 and N-11 countries. Resources Policy, 62, 427-436. https://doi.org/10.1016/j.resourpol.2019.05.003

Zeqiraj, V., Sohag, K., & Soytas, U. (2020). Stock market development and low-carbon economy: The role of innovation and renewable energy. Energy Economics, 91, 104908. https://doi.org/10.1016/j.eneco.2020.104908

Zhang L, Li Z, Kirikkaleli D, Adebayo TS, Adeshola I, Akinsola GD (2021) Modeling CO2 emissions in Malaysia: an application of Maki cointegration and wavelet coherence tests. Environ Sci Pollut Res 28(20):26030–26044

Zhang, Q., Shah, S. A. R., & Yang, L. (2022). Modeling the effect of disaggregated renewable energies on ecological footprint in E5 economies: Do economic growth and R&D matter?. Applied Energy, 310, 118522. https://doi.org/10.1016/j.apenergy.2022.118522

Zhao, J., Shahbaz, M., Dong, X., & Dong, K. (2021). How does financial risk affect global CO2 emissions? The role of technological innovation. Technological Forecasting and Social Change, 168, 120751. https://doi.org/10.1016/j.techfore.2021.120751

Zhu H, Xia H, Guo Y, Peng C (2018) The heterogeneous effects of urbanization and income inequality on CO 2 emissions in BRICS economies: evidence from panel quantile regression. Environ Sci Pollut Res 25:17176–17193 1-18