RESEARCH ARTICLE

Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL

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Abstract
This study investigates the impact of artificial intelligence (AI) innovation on environmental sustainability in the Nordic region. Additionally, it tests the Load Capacity Curve (LCC) hypothesis by incorporating factors such as financial accessibility, environmental tax, and urbanization, using data spanning from 1990 to 2020. The methodology includes the Cross-Sectional Dependence test and the slope homogeneity test, revealing issues of heterogeneity and cross-sectional dependence. Furthermore, first and second-generation panel unit root assessments indicate that the variables are free from unit root problems. Panel Cointegration tests confirm that the variables are cointegrated in the long run. To analyze both short-run and long-run relationships, the study employs the Panel Autoregressive Distributed Lag (ARDL) model. The results from the Panel ARDL model support the LCC hypothesis in the Nordic region, showing a U-shaped relationship between income and load capacity factor. Moreover, AI innovation and environmental tax significantly and positively contribute to environmental sustainability in both the short and long run. In contrast, higher financial accessibility and urbanization degrade environmental sustainability over these timeframes. To validate the robustness of the Panel ARDL estimations, the study also uses Fully Modified OLS, Dynamic OLS, and Fixed Effects OLS approaches, all of which corroborate the ARDL findings. The study employs the D-H causality test to explore causal relationships among the variables. The test results reveal a unidirectional causal relationship between income and AI innovation to the load capacity factor and a bidirectional causal relationship between financial accessibility and the load capacity factor, as well as between urbanization and the load capacity factor. However, no causal relationship is found between environmental tax and the load capacity factor.

Keywords: Artificial Intelligence; Environmental Tax; Financial Accessibility; Load Capacity Factor; Nordic Region

Introduction

Severe environmental degradation is increasingly in line with not just climate change but also other human activities and catastrophes related to the air, water, and soil (Ahmad et al., 2020; Alola et al., 2020; Islam et al.2023). The developed and developing worlds have made it a priority to prevent temperature rise and damage to the planet (Apergis et al., 2023; Polcyn et al.2023; Rana et al.2024). Furthermore, rising global GHG emission levels are mostly caused by variables, including the growth of the urban population, industrialization, financial accessibility, and monetary development (Asongu et al., 2020; Wanof,2023). With its extensive coastline, dense forests, mountains, rivers, valleys, and Arctic tundra in the north and warm regions in the south, Nordic nature is unparalleled. A diversified society, ecosystem, way of life, and health have all been impacted by the threat that climate change poses to the Nordic region (Baral, 2024). Norway is dedicated to a sustainable environment and climate policy, and it serves as a worldwide example for the mitigation of global warming (Anker, 2018). With around 31% of the gas imported by the EU coming from Norway, it is the most significant natural gas supplier among Western European nations. Therefore, the main driver of Norway's GDP growth is the oil and gas sector (Zakeri et al., 2022). In light of the foregoing, the initial objective of the research is to analyze the effects of GDP growth, environmental taxes, financial accessibility, urbanization, and artificial intelligence (AI) innovation on load capacity factor (LCF) connections in the Nordic region. The Nordic countries were chosen because they have become well-known worldwide for their dedication to sustainable growth, environmental quality, and taking the lead on global climate change mitigation (Owusu et al., 2024; Raihan et al.2022a). For example, Norway is now the most sustainable country in the world and plans to become carbon-neutral by 2030. According to projections from the International Hydropower Association, hydropower accounts for 95% of the country's power generation (Malka et al., 2023). The Nordic countries have made great progress, but climate change still presents problems, such as higher rainfall, water damage, and rising sea levels (Depren et al., 2023). Moreover, Norway's CO2 emissions, with 49.3 mt, placed it tenth globally. In 2018, Norway produced 55% of its energy from fossil fuels (Owusu et al., 2024).

The four Nordic nations (Denmark, Sweden, Finland, and Norway) are the first to employ renewable energies extensively, have excellent environmental quality, and have enacted environmental taxes (He et al., 2019). The first nation in the EU to genuinely enact green tax measures is Denmark. The Danish economy has expanded by 78% over the last 30 years, according to official data, while energy consumption has essentially stayed the same (OECD, 2019). The four Nordic nations' combined carbon emissions make up roughly 0.96% of all carbon emissions worldwide (BP, 2019). Moreover, Denmark is at the forefront of the green transition. Since 1996, it has effectively cut its CO2 emissions by more than half. Carlini et al. (2023) report that 47% of the country's 2019 electrical generation came from wind power. Because green methods of economic growth are significantly superior to means of progress that degrade the environment, the five sovereign Nordic countries have a moderately better level of financial stability than China, the United States, and India (Sharif et al., 2023). Finland is thought to be among the leaders in environmental issues (Wurzel et al., 2020). The success of Finland's progressive environmental policies has historically been attributed to the early participation of stakeholders in policy processes (Koskimaa et al., 2021). The policy tool used to reduce the usage of energy, which varies depending on the economy and business, is environmental taxes (Bashir et al., 2021). Several climate change targets, including lower pollution, water disposal, and waste, etc., can be achieved through the execution of the environmental tax to ensure financial and ecosystem effectiveness and clean energy utilization (Bakirtas and Akpolat,2018; Baltagi et al.,2016). The discussion about the financial progress of the E-7, India, and BRICST countries, as documented by Gao et al. (2024), Raihan and Voumik (2023), and Durani et al. (2023), respectively. According to Chen et al. (2019), progress in finance is significant since it can improve the financial system's economic effectiveness in a nation. More energy use is expected to come from faster economic expansion, which may have detrimental consequences on the environment. However, technological innovation can worsen the natural world and boost carbon emissions (Du et al., 2019; Ali et al., 2023).

The current research considers the trends and main research areas of AI innovation, financial accessibility, environmental tax, urbanization, and economic growth in the LCF of the Nordic territories and offers a structure for upcoming endeavors to investigate. The ecological footprint measures the extent to which human demands for nature exceed nature's ability to provide those requirements (Wackernagel and Kitzes 2008). This specific tool simply illustrates how human need for natural resources has led to ecosystem deterioration (Caglar et al.,2023). Siche et al. (2010) suggested calculating the LCF as the ratio of BIO to EFP to remedy such a deficit. Thus, LCF tackles both sides of the debate: the supply of nature and the demand from humans (Akhayere et al., 2023; Arif et al.2024). An ecosystem can support human demand if its LCF score is one or greater; if it is less than one, human demand cannot be met by the ecosystem (Kartal et al., 2023; Ridwan, 2023; Shiam et al.2024). This study allows us to address the following objectives: What effects do taxation on the environment, financial accessibility, and AI innovation have on LCF in Nordic countries? How do GDP and urbanization affect the environmental sustainability of the chosen area? Our study is significant as it can determine whether the innovative green solutions and vibrant taxation systems that have been suggested can innovatively foster a green environment and lessen the negative effects of monetary availability, economic growth, and rising urban populations in the nations that have been chosen. Analyzing the LCF drivers in the context of the Nordic region will add a great deal of understanding to the body of expertise and provide researchers studying the topic with fresh perspectives. The uneven impacts in the selected areas may be examined by using a unique panel ARDL approach that considers quite recent variables such as the environmental tax, AI innovation, and financial accessibility on LCF. More sophisticated procedures, including both first and second-generation techniques, are utilized in this empirical study to address the obstacles of heterogeneity and the CSD problem. The FMOLS, DOLS, and FE-OLS assessments were also adopted in our study to verify robustness. Several noteworthy empirical findings demonstrated the necessity of appropriate legislation to facilitate the effective use of the latest innovations, provide funding, and enhance policy-level approaches for ecological protection.

The remaining portions of this work are organized this way: The literature is analyzed in the "Literature review" part. The data, conceptual framework, and methods are presented in the section under "Data, Model, and Methodology." The subsection titled "Empirical results and discussion" presents the empirical outcomes and discourse, while the final part titled "Conclusions and policy implications" concludes with strategy proposals.

Literature Review

Numerous investigations have explored the (LCC) theory, the Panel ARDL model as well as the connections between globalization, economic progress, and the expansion of financial institutions. Because load capacity factor (LCF) is still a relatively fresh concept, there is still a lack of research on it in the Nordic region. Furthermore, not much research has been done on recent variables, including environmental taxes, financial accessibility, and innovations in artificial intelligence. Nevertheless, earlier research has influenced the technique and variable choice for these studies. A few of these investigations will be covered in this section.

Within a conventional development process, adverse environmental effects, destruction of ecosystems, and excessive use of assets drive growth in the economy (Khan et al. 2019a; Ridzuan et al.2023). This is an undesirable development mode since it is destructive to the long-term survival of humans. Using the GMM technique, Latiff and Faridi (2023) conducted a study in 48 Asian nations, analyzing data from 1996 to 2020. The results showed that in the selected nations, environmental degradation is a result of economic expansion. From 1990 to 2018, Caglar and Askin (2023) explored the connections between GDP and LCF in the top 10 CIP areas. According to the study, growing GDP degraded the ecosystem and reduced LCF. Similarly, several studies by Akadiri et al. (2022) in India, Addai et al. (2023) within 9 Eastern European economies, and Shah et al. (2021) in South Asian countries also align with this conclusion. Ali et al. (2023) found an unexpected long-term negative association (-0.270) between GDP and the LCF in Pakistan. Dai et al. (2023) evaluated environmental quality and the relationship between green energy (GEN) and ecological quality in ASEAN countries using the LCF. They found that environmental quality decreases with economic growth. Moreover, empirical studies (Sinha and Shahbaz, 2017; Allard et al., 2018) discovered that the connection between ecosystem quality and GDP expansion was inconsistent, inadequate as well as highly reliant on the substitutes selected, the statistical approach employed, and the volume of data. However, Usman et al. (2024) examined a complex link between GDP growth and LCF, with early gains in LCF associated with GDP growth and later depreciation after a certain point in time in China. Moreover, Jin et al. (2023) found that GDP growth in Germany had a U-shaped relationship with LCF.

The academic community has become increasingly aware of AI's rapid growth and has focused research efforts on its socioeconomic implications (Zador et al., 2023; Fosso Wamba, 2022). Certain scholars have noted the possible effects of AI on ecosystems (John et al., 2022). According to Wang et al. (2023), AI significantly reduces ecological footprints. Furthermore, there is a growing tendency for AI to have a marginal impact on lowering the ecological footprint (EFP) as globalization gets deeper. Moreover, AI has shown a greater level of promise in the areas of environmental monitoring and renewable energy (Ahmad et al., 2021; Ye et al., 2020). As per Vinuesa et al. (2020), artificial intelligence (AI) could add considerably to the majority of the 17 goals and 169 targets in the United Nations "2030 Agenda for Sustainable Development." Artificial intelligence actively contributed to the mitigation of CO2 pollution in seven emerging Asian nations between 1990 and 2020 through the use of NARDL and asymmetric panel causality methodology, as reported by Rasheed et al. (2024). Moreover, a major factor in the rise in carbon footprints is the utilization of IT. In a similar vein, Zhao et al. (2023) concurred with this scenario and concluded that, in 30 Chinese provinces, AI could reduce pollution density significantly—by 6.63% for every 10% increase in utilization. According to Chen et al. (2022), AI may reorganize production factors, give traditional industries information drivers to upgrade, encourage rapid growth of new sectors, increase efficiency in energy use through upgrades to business structures, and boost the quality of the natural world.

One effective government policy tool for raising LCF and lowering pollution levels globally is the imposition of environmental levies. Green taxes are a sustainable addition to the government's economic policy and a means of preventing pollutants from spreading into the ecosystem (Hieu, 2022). Governmental entities use stringent alterations, including environmental taxes, to minimize carbon-intensive activities to tackle pressing ecological issues (Ulucak et al., 2020). Using the QQR approach, Depren et al. (2023) executed a study in the Nordic countries between 1994 and 2020. The conclusions suggested that the consequence of ecological taxes on CO2 emissions was multifaceted. Similarly, Javed et al. (2023) demonstrated that one of the main factors lowering ecosystem quality is environmental taxation. Esen and Dundar (2021) highlighted the possible effectiveness of environmental levies in managing environmental plans using data from Turkey using the FMOLS and DOLS methodologies. Bozatli and Akca (2024) showed that the application of the ARDL technique in the Netherlands' environmental tax and conservation investments are both efficient means of guaranteeing environmental sustainability. Moreover, adopting the MMQR approach, Jahangir et al. (2024) examined the influence of environmental taxes on LCF in the top ten SDG countries between 1994 and 2018. The investigation outcomes demonstrate that environmental taxes have an inverse and substantial impact on LCF within the nations. Comparably, between 1994 and 2017, Degirmenci and Aydin (2021) performed research in several African states. The results indicate that green taxes exacerbated conservation efforts in South Africa and boosted ecological damage in Cameroon, Ivory Coast, and Mali. Numerous researchers, including Mehboob et al.(2024) in the top 5 emitting countries, Sharif et al.(2023) in Nordic countries, Dogan et al. (2022) in 25 environmentally friendly countries, and Niu et al. (2028) in China concurred with this conclusion, stating that emission a decline improves the environment.

The concept of financial accessibility (FA) is gaining recognition as complex, and several indicators are helpful when assessing it (Tian and Li, 2024). Financial accessibility is the way of enabling financial goods and the availability of services that are equal to all viable individuals and organizations (Menkeh 2021; Zaidi et al. 2021). It includes financial accounts, loans for homes, credit cards, trade facilities, ATMs, savings, and remittances (United Nations 2006). The empirical literature (Fakher, 2019; Zaidi et al., 2019) attests to the fact that the growth of a profitable sector can mitigate environmental damage. Islam (2022) examined how five South Asian economies' environments were affected by financial expansion between 1980 and 2018. The improvement of finance is destructively linked with the deterioration of ecosystems due to the linear relationship between finance and CO2 emissions, which does not diminish as financial inclusion increases. Research has shown that FA increases carbon emissions over time in Sub-Saharan African countries. This highlights the necessity for legislative frameworks that connect financial inclusion programs with restrictions on the environment (Ogede and Tiamiyu, 2023). Raihan et al.(2024a) conducted a study in the G-7 area by using the ARDL framework and found that FA harms the ecosystem. However, Hussain et al. (2024) found that the integration has a short-term negative impact on carbon emissions and a long-term positive effect using a balanced panel data set of 26 Asian countries. On the other hand, in China, Feng et al. (2022) and Shahbaz et al. (2022) discovered that financial accessibility improves the condition of the natural world. Similarly, Chaudhry et al. (2022) investigated the fluctuating effects of financial integration on carbon emissions in the OECD economies between 2004 and 2017 using the DCCE approach. Greater financial inclusion has been shown to have both short- and long-term effects on lowering CO2 emissions.

Due to the substantial shift in population from rural to urban areas, URB's rapid growth, which has been reliant on industrial growth, increased demand for commodities and needed higher output levels (Caglar et al.,2023). Urbanization affects the LCF in a country that grows swiftly in several ways. Balsalobre-Lorente et al. (2021) determined that URBA enhanced ecological well-being, with a 1% increase in URBA decreasing emission levels by 0.389 percent in the BRICS region. Pata et al. (2023) observed that URBA reduced LCF in the USA after running an ARDL model. Similarly, using DKSE, Alola et al. (2023) analyzed various environmental indicators for the panel of Sweden, Denmark, Finland, Norway, and Finland. Their findings demonstrate that rising emissions of greenhouse gases from urbanization worsen environmental quality. On the other hand, Gang et al. (2023) evaluated how the MENA area's urbanization affected the environment between 2004 and 2019. Urbanization has contributed significantly to ecological sustainability both in the short and long terms, according to research done using the CS-ARDL approach. The ARDL methodology was applied in the publication by Ali et al. (2017) to find a significant detrimental consequence of urbanization on Singapore's pollution of carbon. They revealed that the degradation of the environment is not caused by it. Moreover, Wang et al. (2021) analyzed that urbanization lowers carbon emissions using the ARDL methodology; however, the impact is negligible in OECD countries. In order to lower carbon emissions, they advise promoting the urbanization process and utilizing its scale effect. In the same way, Khan et al. (2023) showed through the NARDL method that urbanization benefits India's environment in the long run. Surprisingly, Xu et al. (2022) explored the connection between urbanization and LCF in Brazil between 1970 and 2017, concluding that URBA does not influence LCF.

The majority of the literature now in publication focuses on research related to the environment's demand side, and the beneficial and detrimental impacts of explanatory indicators on ecological footprint have been documented. Furthermore, a procedure that prioritizes the LCF and considers the supply aspect of the environment is presently in place. A research opportunity has arisen because there are currently no studies looking at the possible implications of green taxes, financial accessibility, and AI innovation on the LCF for Nordic economies. In addition, innovation and environmental taxes can improve sustainable development by optimizing the utilization of resources, cutting emissions, leveraging contemporary technologies, and motivating greener lifestyles. A thorough examination of the competitive advances achieved in economies is required by taking into account the most recent timeframes and new metrics. Thus, by employing cutting-edge techniques like ARDL methodologies to assess the validity of the LCC hypothesis in Nordic nations, this study contributes to the growing body of literature.

Methodology

Data and Variables

The World Bank Development Indicators (WDI), Global Footprint Network (GFN), Global Financial Development (GFD), and Our World in Statistics are the sources of the statistics, which cover the years 1990 to 2022. The factors used in the study are listed in Table 1. The GFN provides the LCF data, which is measured as Gha per person. Urbanization, GDP squared, and GDP per capita information from WDI. The number of annual patent applications related to AI is gathered from Our World in Data and is used to estimate AI innovation. The ratio of deposit money banks' assets to GDP (%) is used as an indication for environmental tax (ENT), and data on ENT and financial accessibility comes from GFD. The table below presents the logarithmic expression of each factor.

Table 1. Description and Sources of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
LGDP	Gross Domestic Product	LGDP	GDP per capita (Current US$)	WDI
$LGDP^2$	Gross Domestic Product	$LGDP^2$	GDP per capita (Current US$)	WDI
LAI	AI Innovation	LAI	Annual patent applications related to AI	Our World in data
LENT	Environmental Tax	LENT	Deposit money banks assets to GDP (%)	Global Financial Development
LFA	Financial Accessibility	LFA	Stock market capitalization to GDP (%)	Global Financial Development
LURBA	Urbanization	LURBA	Urban Population (% of total population)	WDI

Theoretical Framework

The load capacity curve (LCC) provides valuable insights into the complex links between environmental sustainability, financial stability, and the development of people, and it is a vital instrument in ecological education (Ridwan et al.2023). This curve is important because it demonstrates if the environment's capability of recovering its resources (biocapacity) and how it utilizes human resources (ecological footprint) are balanced or not. The LCC is thought to have a U-shaped relationship, with GDP and GDP square functioning as the primary contributors. A U-shaped curve relationship has been suggested in the context of LCF (Pata and Tanriover, 2023; Pata and Ertugrul, 2023; Urbee et al.2024), indicating that there are different patterns in the impact of GDP and GDP square on environmental quality. According to Wu et al. (2024), there is initially an inverse association between GDP growth and resource exploitation and energy use. Several researchers (Apergis et al., 2023; Aydin & Degirmenci, 2023; Shahzad et al., 2024; Pata & Samour, 2022) examined the LCC hypothesis in the literature.

For LCC theory, we can consider the following equation:

$$\text{load Capacity Factor} = \mathrm{f}(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{Y_t}) \qquad (1)$$

Here, wealth is expressed by GDP and GDP squared in equation (1), while other factors influencing the load capacity factor are shown by $\mathrm{Y_t}$. To generate a greater idea of the factors affecting the LCF, equation (2) integrates other noteworthy variables, including artificial intelligence innovation, economic expansion, financial accessibility, environmental taxation, and urbanization.

$$\mathrm{LCF} = \mathrm{f}(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{AI}, \mathrm{ENT}, \mathrm{FA}, \mathrm{URBA}) \qquad (2)$$

LCF stands for the load capacity factor in equation (2); AI innovation is represented by AI; FA refers to the environmental tax; FA represents financial accessibility; and URBA means urbanization. The econometric explanation of equation (3) is given above.

$$\mathrm{LCF_{it}} = \partial_0 + \partial_1\mathrm{GDP_{it}} + \partial_2\mathrm{GDP_{it}^2} + \partial_3\mathrm{AI_{it}} + \partial_4\mathrm{ENT_{it}} + \partial_5\mathrm{FA_{it}} + \partial_6\mathrm{URBA_{it}} \quad (3)$$

The variables' logarithmic values are shown in equation (4). This conversion improves interpretation and makes statistical results conceivable by breaking down complex interactions into simpler linear forms.

$$\mathrm{LLCF_{it}} = \partial_0 + \partial_1\mathrm{LGDP_{it}} + \partial_2\mathrm{LGDP_{it}^2} + \partial_3\mathrm{LAI_{it}} + \partial_4\mathrm{LENT_{it}} + \partial_5\mathrm{LFA_{it}} + \partial_6\mathrm{LURBA_{it}} \quad (4)$$

Empirical Method

In the Nordic region, our investigation used the ARDL framework for data assessment to figure out the link across LCF and variables such as GDP, AI, ENT, FA, and URBA. Moreover, we utilized the FMOLS, DOLS, and FE-OLS techniques to guarantee robustness. To ensure stationarity, the CSD, slope homogeneity examination, and unit root assessments (IPS, CIPS, and CADF) were conducted at the start of the inquiry. The estimates for the short- and long-term ARDL were then finished. The causal link among the chosen factors was then demonstrated using the D-H causality analysis. After a difficult evaluation process, we were able to determine which econometric framework was the most precise and efficient.

Cross-Sectional Dependence Test

We first confirm that panel data indicate cross-sectional dependency (CSD) before starting our econometric analysis. For projections to be trustworthy and observations to be reliable, the CSD phenomenon must be addressed (Grossman and Krueger, 1995). Due to greater financial integration and the removal of other obstacles, CSD in panel data econometrics is going to increase (Tufail et al., 2021; Voumik et al.2023a; Voumik et al.2023b). If we overlook the issue and think that cross-sections are independent, we might get reliable and consistent results (Westerlund & Edgerton, 2007). CSD is investigated in this study using large panel data econometrics with weak exogenous CSD (Pesaran, 2015). Equation (5) provides a quick explanation of the typical equation used in CSD testing below.

$$CSD = \sqrt{\frac{2T}{N(N-1)N}} \left(\sum_{i=1}^{N-1} \sum_{K=i+1}^{N} \widehat{Corr_{i,t}}\right) \ldots\ldots\ldots\ldots\ldots\ldots \text{(5)}$$

Slope Homogeneity test

Slope heterogeneity must be considered when evaluating panel data (Voumik et al.2023c). The experiments on slope homogeneity by Pesaran and Yamagata (2008) are then carried out. The test results are determined by accounting for each participant's weighted slope. The following is how Equation (6) depicts the slope heterogeneity:

$$\breve{\Delta} = \sqrt{N}\left(\frac{N^{-1}S\% - k}{\sqrt{2k}}\right) \text{ and } \breve{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}S\% - k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right) \ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

Panel Unit root test

Traditional unit root analyses may yield inaccurate results due to CSD issues and slope variability (Dogan & Seker, 2016). Initially, the researchers employed the first-generation IPS test introduced by Im et al. (2003). The first generation of panel unit root testing does not take heterogeneity, CSD effects, or over-rejection of null hypotheses into account (Choi, 2001). For this reason, second-generation tests like CIPS and CADF, introduced by Pesaran (2007), were utilized in our study. The IPS unit root test is given below:

$$\Delta Y_{i,t} = \beta_i + \rho_{i,t} + \vartheta y_{i,t-1} + \sum_{j=1}^{k} \theta_k \Delta y_{i,t-j} + \mu_{i,t} \qquad (7)$$

In contemporary literature, the ability of CIPS to regulate heterogeneity and CSD has gained popularity (Akther et al.,2024). The CIPS test is conducted using Equation (8):

$$CIPS = \frac{1}{N}\sum_{t=1}^{N} t_1(N,T) \ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

The CADF test has a strong relationship with the CIPS test. The alternative in the CADF assessment is some cross-section units in the panel do not have a unit root, while the null hypothesis is each cross-section unit in the panel includes a unit root (Hossain et al.,2024). Equation (9) provides the following method for computing the CADF:

$$\Delta Yi_t = \varphi_i + \delta i Y i_{t-1} + \varphi i \bar{Y}_{t-1} + \sum_{j=1}^{m} \varphi_{ij} \bar{Y}_{t-1} + \sum_{j=1}^{m} \rho_{ij}\, \Delta Y_{i,t-1} + \varepsilon_{it} \ldots\ldots\ldots \text{(9)}$$

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

Investigating the existence of long-term relationships across the factors under study is crucial once the sequence of integration has been determined (Larsson et al., 2001). The Pedroni (1999, 2004) heterogeneous panel cointegration assessment is appropriate for CSD with distinctive particular results. It was utilized in the research; unlike Kao (1999), this method allows the AR coefficients to differ throughout panels. Seven statistics are offered by this test to evaluate the cointegration properties; three of the statistics are based on the between-dimension, and four are based on the within-dimension. It is carried out in this manner:

$$sh_{it} = \lambda_0 + \alpha_i t + \delta_{1i} bkd_{it} + \gamma_{2i} ib_{it} + \beta_{3i} ihr_{it} + \varepsilon_{it} \ldots\ldots\ldots \text{(10)}$$

Where, i=1... N for each firm in the panel and t=1,..., T denotes the time period. The estimated residuals, or ε_{it}, reveal how far the long-run association deviates from expectations.

Panel ARDL Technique

The study employed the ARDL model, initially introduced by Pesaran et al. (2001), as an innovative way to assess the short- and long-term connections among the model's parameters. This approach allows for cross-sectional heterogeneity, which is necessary to capture the distinct technological and economic environments of the Nordic nations. It takes two phases to put the ARDL approach into practice. The first step is to adopt the F test to determine whether there is a long-term link between the pertinent variables in the presence of an error correction. After confirming that the F tests from the first process fall within acceptable bounds, the ARDL's second step involves estimating the long-run relations' coefficients (Hazmi et al.,2024).

$$\begin{aligned} lnLCF_t = {} & \varphi_0 + \varphi_1 \mathrm{lnLCF}_{\mathrm{t-1}} + \varphi_2 lnGDP_{t-1} + \varphi_3 lnGDP\hat{}2_{t-1} + \varphi_4 lnAI_{t-1} + \varphi_6 lnENT_{t-1} + \varphi_7 lnFA_{t-1} \\ & + \varphi_8 lnURBA_{t-1} + \sum_{i=1}^{w} \aleph_1 \, \Delta lnLCF_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_2 \, \Delta\mathrm{lnGDP}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_3 \Delta\mathrm{lnGDP\hat{}2}_{\mathrm{t-i}} \\ & + \sum_{i=1}^{w} \aleph_4 \, \Delta \, lnAI_{t-i} + \sum_{i=1}^{w} \aleph_5 \Delta\mathrm{lnENT}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_6 \Delta\mathrm{lnFA}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_7 \Delta\mathrm{lnURBA}_{\mathrm{t-i}} \\ & + \varepsilon_t \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11) \end{aligned}$$

The ARDL model has the ability to evaluate both short-run and long-run factors at the same time, which is one of its primary benefits. Furthermore, I (0) or I (1), or whatever frictionally integrated time series variable these variables tend to be, might be applied with this framework. To guarantee an appropriate regression or ARDL procedure consequence, appropriate variables must be used (Raihan et al.,2024b). The null hypothesis, which claims that there is no cointegration, is compared with the evidence in favor of cointegration (the alternative hypothesis). Equations 12 and 13 represent the null hypothesis (H0) and the alternative hypothesis (H1).

$$H_0 = \aleph_1 = \aleph_2 = \aleph_3 = \aleph_4 = \aleph_5 = \aleph_6 \qquad (12)$$

$$H_1 = \aleph_1 \neq \aleph_2 \neq \aleph_3 \neq \aleph_4 \neq \aleph_5 \neq \aleph_6 \qquad (13)$$

After long-term connections are established, the error correction model (ECM), developed by Engle and Granger (1987), is utilized to evaluate the Error Correction Term (ECT) and short-term correlations.

$$\begin{aligned} lnLCF_t = {} & \aleph_0 + \sum_{i=1}^{w} \aleph_1 \Delta\mathrm{lnLCF}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_2 \Delta\mathrm{lnGDP}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_3 \Delta\mathrm{lnGDP\hat{}2}_{\mathrm{t-i}} \\ & + \sum_{i=1}^{w} \aleph_4 \Delta \, lnAI_{t-i} + \sum_{i=1}^{w} \aleph_6 \Delta\mathrm{lnENT}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_6 \Delta\mathrm{lnFA}_{\mathrm{t-i}} + \sum_{i=1}^{w} \aleph_6 \Delta\mathrm{lnURBA}_{\mathrm{t-i}} \\ & + \forall ECT_{t-i} + \varepsilon_t \qquad (14) \end{aligned}$$

Where ∀ is the rate of adaptation?

Robustness Check (FMOLS, DOLS, FE-OLS)

First, the Fully Modified Ordinary Least Square (FM-OLS) was introduced by Phillips and Hansen (1990), and then the Dynamic Ordinary Least Square, established by Stock and Watson (1993), was employed. FM-OLS modifies the OLS to reduce serial correlation effects and endogeneity in the regressors resulting from a co-integrating connection. The FMOLS method uses a non-parametric strategy to manage the autocorrelation and endogeneity problems (Adebayo et al., 2022). In contrast, the DOLS test takes into account both the timing of differences and their eventual leads and delays through explanatory factors to remove serial correlation in the covariance matrix of errors used to calculate standard deviations (Raihan et al., 2023a). The authors further use the FE-OLS estimator expanded with Driscoll and Kraay's (1998) standard errors, which have been proven more robust.

D-H Causality Test

Lastly, this research employs the Dumitrescu and Hurlin (2012) causality assessment to confirm the short-term link between variables, which is essential regarding policymaking. This test may be used to predict cross-sectional independence and dependency scenarios. Granger causality tests on the conventional panel show that the homogenous null hypothesis is the reason for any causal relationship found in a subgroup of the variable due to a deficiency of cross-sectional data (Ahmed et al., 2022). There are certain benefits to the Dumitrescu and Hurlin (2012) test procedure. Firstly, this causality test's standardized, average Wald statistics have a conventional normal asymptotic distribution and are easy to compute. Furthermore, no specific panel estimations are needed for the statistics. This method can be versatile and helpful for obtaining reliable outcomes during CD as it can calculate both N > T and T > N samples (Ahmed and Le, 2021).

Results and Discussion

Summary Statistics

Descriptive statistics and the findings of several analyses that were performed to determine whether the data were normal are given in Table 2. The table shows that LCF has the lowest mean value of 0.01950 while GDP squared has the highest mean value of 118.2038. In addition, all of the variables' estimated standard deviations are extremely low, indicating that the data points are mostly centered around the mean and exhibit limited cyclical variation. The data is skewed to the left as the skewness statistics for most of the factors are negative. Both the probability values and the Jarque–Bera analysis revealed that each of the components had a normal distribution. The investigation's findings additionally showed that no variable had a notable departure from the associated mean values.

Table 2. Summary statistics of variables

Statistic	LLCF	LGDP	LGDP2	LAI	LENT	LFA	LURBA
Mean	0.019509	10.86771	118.2038	3.102615	5.287321	3.909362	4.45272
Median	0.234705	10.87999	118.3742	3.135494	8.523018	3.862088	4.447006
Maximum	0.860973	11.54785	133.3528	3.89182	9.311575	4.712179	4.542699
Minimum	-0.945215	10.10012	102.0124	1.791759	-1.134136	3.301475	4.335695
Std. Dev.	0.582664	0.312364	6.773281	0.502838	4.407573	0.363945	0.053723

Skewness	-0.244537	-0.179975	-0.092862	-0.529248	-0.376236	0.464751	0.045105
Kurtosis	1.416313	3.055801	3.038905	2.47716	1.171219	2.141118	2.550493
Jarque-Bera	12.59159	0.608104	0.165031	6.388144	17.92383	7.340905	0.963392
Probability	0.001844	0.737823	0.920797	0.041005	0.000128	0.025465	0.617735
Sum	2.146037	1195.448	13002.42	341.2877	581.6054	430.028	489.7992
Sum Sq. Dev.	37.00517	10.63526	5000.63	27.56027	2117.51	14.43768	0.314587
Observations	110	110	110	110	110	110	110

Results of Cross-Sectional Dependence Test

A CSD test is the primary step for analyzing econometric panel data. The Pesaran CD test outcomes are shown in Table 3. All of the CSD statistics values are highly significant at the 1% significance threshold, and for each variable, the value is less than 0.05. The results demonstrate that the null hypothesis, according to which no CSD prevails between countries, is rejected for each variable. This suggests that an unforeseen incident that takes place in one of the sample nations may also have an impact on the countries that follow.

Table 3. Results of CSD test

Variables	CD-Statistics	P-Value
LLCF	3.48***	0.003
LGDP	11.03***	0.000
$LGDP^2$	12.97***	0.000
LAI	6.11***	0.000
LENT	5.21***	0.000
LFA	6.83***	0.000
LURBA	14.18***	0.000

Results of the Slope Homogeneity Test

The slope heterogeneity (SH) examination results are summarized in Table 4. Based on the determined p-values of 0.002 and 0.000, the null hypothesis, which asserts that the slope coefficients are homogeneous and is rejected at the 1% significance level. These p-values illustrate that distinct variables have different coefficients, which is sufficient evidence to reject the homogeneity hypothesis.

Table 4. Results of Slope Homogeneity test

Slope Homogeneity test	Δ statistic	P-value
$\breve{\Delta}$ test	3.171***	0.002
$\breve{\Delta}_{adj}$ test	3.975***	0.000

Results of panel unit root test

The IPS test findings demonstrate that only LAI is stationary in its level form at a 1% significance level, while the remaining variables are significant and stationary at the first difference, ensuring consistency in the panel data analysis process. At a 5% significance level, the outcomes of the CIPS test likewise reveal that LAI is the only variable that is stationary at the level form (I(0)). The remaining variables (LLCF, LGDP, LGDPSQ, LENT, LFA, and LURBA) are stable at the first difference (I(1)) at a significance threshold of 1%. Comparably, the CADF unit root analysis verifies that, at the 1% significance level, only LAI is stationary at the level form (I(0)), whereas the others are stationary at the first difference (I(1)). Furthermore, every factor stays significant at the level of 1% upon differencing, except LGDP, which maintains significance at the 5% level. These conclusions indicate significant cointegration and indicate that the variables do not have a unit root problem.

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)	
LLCF	-2.038	-6.811***	-2.085	-5.331***	-1.813	-4.475***	I(1)
LGDP	-2.096	-3.452***	-2.035	-3.469***	-0.155	-4.355**	I(1)
$LGDP^2$	-2.062	-3.482***	-2.001	-3.456***	-1.132	-5.651***	I(1)
LAI	-3.270***	-8.881***	-3.304**	-5.352***	-3.412***	-4.211***	I(0)
LENT	-2.023	-4.220***	-2.152	-3.827***	-1.552	-4.662***	I(1)
LFA	-0.218	-3.562***	-1.652	-3.411***	-0.551	-3.311***	I(1)
LURBA	-0.558	-4.234***	-2.076	-4.166***	-1.652	-4.290***	I(1)

Results of panel cointegration test

The Pedroni panel cointegration test findings, covering within- and between-dimension evaluations, are provided in Table 05. The p-values for the Panel v-statistic and Panel rho-statistic (0.2436 and 0.5612, respectively) are greater than the traditional significance threshold, indicating that there is no evidence of cointegration. However, the null hypothesis of no cointegration is rejected because the Panel PP and Panel ADF-Statistic p-values (0.000) are smaller than the conventional significance criterion. The figures suggest the presence of cointegration. With a very high p-value of 0.9271, the Group rho-statistic in the between-dimension analysis suggests there is insufficient evidence for cointegration in any of the panels. On the other hand, with p-values of 0.000, the Group ADF and the Group PP-Statistic both show evidence of cointegration across the panels. According to Pedroni's cointegration methods, each factor is cointegrated over a long period.

Table 6. Results of Panel Cointegration test

Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	Prob.	Weighted Statistics	Prob.
Panel v-Statistic	0.34364	0.4123	-1.56832	0.9632
Panel rho-Statistic	0.56126	0.7127	0.87654	0.8106
Panel PP-Statistic	-3.81602	0.0000	-7.91435	0.0000
Panel ADF-Statistic	-2.07614	0.0000	-4.79875	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)		
	Statistic	Prob.
Group rho-Statistic	4.71273	0.9271
Group PP-Statistic	-9.53764	0.0000
Group ADF-Statistic	-4.25297	0.0000

Panel ARDL results

The Panel ARDL model's outcomes, presented in Table 07, demonstrate the intricate dynamics influencing the Nordic region's LCF. In terms of LGDP, the short-term coefficient is -0.320 and statistically insignificant, with a p-value greater than the typical threshold, while the long-run coefficient is -0.337 and statistically significant at conventional levels. This suggests that economic expansion alone may notably contribute to environmental degradation in this setting, as GDP has a detrimental impact on the LCF. This outcome agrees with Eleais et al. (2024) finding that when GDP rises by 1%, carbon emissions in MENA nations rise by 79.8%. Several researchers such as Raihan et al.(2023c) in Malaysia, Ahmad et al.(2024) in China, Addai et al.(2023) in Eastern Europe, Raihan et al.(2022b) in China agree with this and concluded that GDP growth degrades the biodiversity. However, due to the development of GDP, emissions somewhat decrease in China and India (Raihan et al.,2024c; Raihan et al.,2023b). Additionally, an investigation across Vietnam by Minh et al. (2023) shows that economic growth is correlated with CO2 emissions up to a specific threshold; after that, CO2 pollutions decline. On the other hand, GDP2 has an encouraging link with LCF in both periods. In the short run, the coefficient has a positive value of 0.681, and in the long run, the value is 0.107. This is significant as the p-value is less than the conventional level for both periods. This finding highlights that though shorter period expansion in the economy is not good for the Nordic ecosystem, long-term stable GDP is beneficial for biodiversity. However, Ridwan et al. (2024) disagree, stating that GDP2 raises CO2 emissions in the South Asian region.

Similarly, in the short and long terms, there is a beneficial connection between LAI and LLCF; the short-term and long-term results are significant as the p values are 0.0388 and 0.0061, respectively. These conclusions demonstrate that while AI technology has a favorable advantage on the Nordic ecosystem. LLCF boosts by 0.263% in the near run and 0.128% in the long term for every 1% increase in LAI. This could be because the implementation of green initiatives may need AI, which can improve energy efficiency across a range of industries, such as manufacturing, travel, and residence power. By using artificial intelligence (AI), humans can better manage climate change and achieve sustainability while using natural assets (Habila et al.,2023, Raihan et al.2024d). Moreover, technological advancements help BRI economies offset the damaging impacts of excessive resource use on the ecology (Majeed et al., 2022). Similarly, there is an obvious connection between environmental tax and the environment, as evidenced by the beneficial relationship observed between LENT and LLCF across both short and long periods. This implies that environmental tax could boost ecological conditions in both terms, and the results are significant, with p-values that are less than the usual level in both terms. Specifically, a 1% expansion of LENT in the short term will spike LLCF by 0.429% and in the long term by 0.526%. Kartal (2024) found that there is variation in the implication of ENT on LCF in G-7 countries. Furthermore, ENT advantages for the United Kingdom, whilst France and Germany just partially benefit. Galvez (2024) finds that green taxes in Mexico must be included in the UN 2030 agenda and that governments should implement and assess them to promote environmental protection in the future.

The table demonstrates a discouraging correlation between LFA and LLCF. The long-term and short-term results illustrated statistical significance outcomes as the p-value is less than the conventional thresholds. Specifically, the effect indicates that accessibility of finance stimulates higher monetary and business transactions but may not have a positive short-term impact on the ecosystem. Moreover, the financial growth was supported by Shahbaz et al. (2017) and Baloch et al. (2019) to enhance the ecosystem condition in technologically advanced Asian nations like Malaysia and Indonesia, respectively. According to Hussain et al. (2023), financial accessibility has a long (short) term beneficial (negative) influence on carbon emissions in the Asian economies. Similarly, Shang et al.(2024) in top emitting countries and Qing et al.(2024) in G-2- economies agree that FA degrades environmental quality. On the other hand, Liu et al.(2024) in China and Vietnam and Sharif et al.(2024) in ASEAN territories revealed that FA is beneficial for environmental quality. Based on both short and long-term assessments, urbanization (LURBA) and LLCF have an adverse interaction. Over time, there will be a -0.567% reduction in LLCF with a p-value of less than 0.05 for every 1% expansion of LURBA. A notable short-term decrease in LLCF of -0.876% 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. Voumik and Ridwan (2023) discovered that population expansion in Argentina negatively impacts the ecosystem over a long period, supporting this conclusion. Similarly, Malik et al.(2024) in Pakistan, Ekeocha (2021) in Africa, and Zhang et al.(2021) in China provided a similar conclusion. On the other hand, Khan et al.(2024), in 48 BRI economies, concluded that urbanization reduces emission levels.

Table 7. Results of Panel ARDL test

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
Long-run Estimation				
LGDP	-0.337	2.64166	-4.88469	0.0199
LGDP2	0.107	0.12212	3.87941	0.0327
LAI	0.128	0.08704	3.47276	0.0061
LENT	0.526	0.16386	3.19773	0.0022
LFA	-0.988	0.13977	-3.07333	0.0000
LURBA	-0.567	0.87849	-1.87662	0.0000
Short-run Estimation				
COINTEQ01	-0.47152	0.1738	-2.712433	0.0087
D(LLCF(-1))	-0.375935	0.0906	-4.144349	0.0001
D(LGDP)	-0.320	0.97443	-4.09634	0.0774
D(LGDP2)	0.681	0.65254	3.04459	0.0005
D(LAI)	0.263	0.22113	4.18998	0.0388
D(LENT)	0.429	0.43703	-3.98353	0.0294
D(LFA)	-0.112	0.23788	4.47306	0.0379
D(LURBA)	-0.876	1.12977	-4.04147	0.0671
C	5.499	1.73640	3.16741	0.0024

Results of robustness check

Table 8 describes the utilization of three distinct estimating techniques—FMOLS, DOLS, and FE-OLS to investigate the accuracy of the ARDL estimations. The projected LGDP values for each of these methods are -0.256, -0.085, and -0.219, in that order. These results suggest that the Nordic countries' environmental quality has suffered as a result of economic expansion. All estimators have significant coefficients at the 1% level, except DOLS, which is significant at the 5%. These outcomes are consistent with the short- and long-term conclusions of the ARDL framework. In contrast, LLCF and LGDP2 have an upward correlation, suggesting that long-term economic growth has no negative effects on the Nordic ecosystem. In particular, only in the DOLS estimation is the coefficient significant at the 10% level; in all other cases, it is significant at the 1% level. Our findings of the ARDL estimation are in line with this assessment. In all three examinations, the LLCF variable demonstrates a positive correlation with both LENT and LAI. In the FMOLS and DOLS examinations, the LAI coefficient values are significant at the 5% threshold; in the FE-OLS test, they are significant at the 1% point. The Nordic ecosystems may gain from the adoption and use of AI technology, as evidenced by the fact that for every 1% growth in AI innovation, LCF expands by 0.076%, 0.210%, and 0.603%, correspondingly. This conclusion agrees with the Panel ARDL computations.

In a similar vein, the LENT and LLCF coefficients exhibit positive correlations in all three estimation techniques. To be precise, for each 1% rise in green taxes, LCF climbs by 0.052%, 0.234%, and 0.054%, respectively. In calculations using FMOLS, DOLS, and FE-OLS, this variable is statistically significant at the 1%, 10%, and 5% levels, accordingly. This outcome illustrates the beneficial effects of environmental levies on the ecosystems of the Nordic nations and is in line with the ARDL model. Conversely, the LLCF variable had adverse interactions with both LFA and LURBA, suggesting that greater degrees of urbanization and financial accessibility are harmful to biodiversity in the areas under consideration. Using all three estimating techniques, the LFA variable is significant at the 1% level. In addition, a 1% increase in urbanization (URBA) leads the LLCF for FMOLS, DOLS, and FE-OLS to drop by 1.562%, 0.543%, and 0.543%, respectively. In the FMOLS and FE-OLS estimations, the variable is significant at the 5% level; however, in the DOLS estimation, it is significant at the 1% threshold. The ARDL model was the main estimating method employed in this work, and these results validate its conclusions.

Table 8. Results of Robustness Check

Variables	FMOLS	DOLS	FE-OLS
LGDP	-0.256***(0.0362)	-0.085**(0.0012)	-0.219***(0.6807)
$LGDP^2$	0.061***(0.0109)	0.125*(0.0281)	0.011***(0.0782)
LAI	0.076**(0.0502)	0.210**(0.1520)	0.603***(0.0369)
LENT	0.052***(0.3025)	0.234*(0.8201)	0.054**(0.0120)
LFA	-0.181***(0.0892)	-0.213***(0.0295)	-0.177***(0.0675)
LURBA	-1.562**(0.5987)	-0.543***(0.0451)	-0.543**(0.6043)

D-H Causality test

Table 9 provides an overview of the findings of the D-H causality assessment for the Nordic economy's LCF. At a 1% significance level, the p-value of 0.0032 denotes a statistically significant influence of LGDP on LLCF. As a result, it is feasible to reject the null hypothesis and conclude that there is a one-way causal connection between LGDP and LLCF. In contrast, there is no significant link between LLCF and LGDP because the p-value is larger than the predicted threshold, suggesting that development in the economy has a unidirectional consequence on natural health in the Nordic region. A closer look indicates that the connections between LAI and LLCF and LGDP2 and LLCF are also unidirectional. Furthermore, as the null hypothesis cannot be ruled out under these circumstances, the findings show that changes in LLCF have no impact on LGDP2 or LAI. On the other hand, statistically insignificant higher p-values in each investigation suggest that there is no causal link between LCF and LENT. Moreover, there is no correlation across LLCF and LENT or between LENT and LLCF, as the proposed p-values are higher than the conventional significance thresholds. Nonetheless, there prevails a strong causal correlation that is bidirectional within LFA and LLCF as well as between LURBA and LLCF. These coefficients are significant at the 1% significance level, with the p-values being 0.0367, 0.0035, 0.0001, and 0.0047, accordingly. In conclusion, among all the regressor specifications, LGDP, LAI, LFA, and LURBA are the factors that significantly influence changes in the LCF.

Table 9. Results of D-H Causality test

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
LGDP $\neq$ LLCF	7.03257	3.92056	0.0032
LLCF $\neq$ LGDP	4.2925	1.64693	0.2981
LGDP2 $\neq$ LLCF	7.15055	4.01846	0.0521
LLCF $\neq$ LGDP2	4.3399	1.68626	0.1417
LAI $\neq$ LLCF	2.69682	0.32289	0.0468
LLCF $\neq$ LAI	3.11499	0.66987	0.5029
LENT $\neq$ LLCF	3.00297	0.57692	0.5641
LLCF $\neq$ LENT	1.92676	-0.31609	0.1519
LFA $\neq$ LLCF	4.82512	2.08889	0.0367
LLCF $\neq$ LFA	4.87029	2.12637	0.0035
LURBA $\neq$ LLCF	6.97203	3.87033	0.0001
LLCF $\neq$ LURBA	4.70097	1.98587	0.0047

Conclusion and Policy Implications

Throughout the Nordic countries between 2000 and 2022, this research looked at the complex relationships underlying economic growth, artificial intelligence (AI) innovation, environmental taxes, financial accessibility, urbanization, and LCF. The study explored the LCF hypothesis using sophisticated econometric techniques to identify variables affecting regional load capacity. The analysis used both first-generation and second-generation panel unit root examinations, verifying the lack of unit root problems in the dataset to address any methodological concerns. Moreover, several panel cointegration experiments revealed long-term cointegration among the parameters under investigation, highlighting their interdependence. Additionally, the chosen variables were characterized by both short- and long-term interactions adopting the ARDL framework.

The FMOLS, DOLS, and FE-OLS techniques were applied extensively to discover the correlations between dependent and independent factors and guarantee robust conclusions. The investigation revealed that while financial accessibility, urbanization, and short-term GDP development have a detrimental implication on the LCF in the selected region, long-term economic growth, AI innovation, and environmental taxation have an advantageous effect. Furthermore, the D-H causality examination reveals that no causal association between LLCF and LGD2, LAI, and LENT, nor between LLCF and LENT, was found in the study. Moreover, a bidirectional causal association was also explored between LFA and LLCF and LURBA and LLCF. The intricate elements influencing load capacity in the Nordic area were examined, emphasizing the role of the urban population and sustainable ecosystem. Our investigation seeks to establish green urban growth as well as sustainable financial growth and imposition of environmental taxation to ensure environmental sustainability in the Nordic territory. Lastly, this study offers a basis for enlightened decision-making to boost resilience and prosperity in the area going forward by advocating approaches that support conserving the environment and equitable growth.

The finding of a U-shaped correlation between GDP and environmental sustainability in the Nordic region carries significant implications for policy. At first, higher income levels might have a detrimental consequence on ecological health since they lead to greater consumption and industrial activity. Nevertheless, once a specific income level is surpassed, higher earnings result in more investments in sustainable technology and practices heightened environmental consciousness, and more stringent regulatory requirements. To expedite this shift, policymakers should provide incentives for green investments and sustainable inventions, especially during the initial phases of economic expansion. Introducing progressive environmental levies and subsidies for clean technologies can help alleviate the adverse effects of increasing wealth. In addition, promoting collaborations between the public and commercial sectors and allocating resources towards environmental education can bolster public backing for sustainability endeavors. By employing strategic management techniques, it is possible to ensure that rising earnings contribute to enhanced environmental sustainability. This involves effectively balancing economic expansion with the preservation of ecological resources.

This study found that the application of AI technology and the implementation of a green tax contribute to the advancement of environmental sustainability in the Nordic region. Policymakers should give utmost importance to the incorporation of AI technology in order to improve environmental management, increase efficiency, and promote sustainability in many sectors. In order to accomplish this, governments can offer incentives, subsidies, and grants to both startups and existing enterprises that are engaged in developing AI advancements that have positive consequences on the environment. Simultaneously, the implementation and modification of environmental levies to accurately represent the actual cost of pollution can efficiently deter environmentally detrimental practices and produce income for sustainability initiatives. The taxation system should be structured in a progressive manner, with the aim of specifically targeting large-scale polluters while minimizing the financial strain on low-income populations. Proceeds derived from environmental levies might be allocated towards the development of eco-friendly infrastructure, advancement of clean technology through research and development, and promotion of public awareness initiatives. In addition, authorities should promote collaboration between the public and private sectors in order to establish a conducive environment for the development of AI advances. Nordic nations can strengthen their environmental sustainability, create economic growth, and continue their leadership in global sustainability efforts by strategically using AI innovation and implementing environmental levies.

The findings also indicated that the growth of financial accessibility and urbanization have a negative impact on environmental sustainability in the Nordic region. Policymakers should prudently oversee financial accessibility to prevent excessive borrowing and uncontrolled economic growth. This can be accomplished by allocating financial resources to green investments and sustainable projects rather than industries with significant emissions. Enforcing rigorous environmental norms and standards for urban development is essential to minimize the negative impacts of urbanization. Encouraging sustainable urban planning methods, such as implementing green construction rules, establishing efficient public transit networks, and preserving green spaces, can effectively mitigate the environmental consequences of expanding urban areas. Moreover, providing incentives to encourage the use of environmentally friendly technologies in urban infrastructure and housing can effectively improve sustainability. Nordic nations may achieve long-term sustainability by including sustainability standards in their financial and urban development policies. This approach allows them to strike a balance between economic growth and environmental preservation, even while financial accessibility and urbanization continue to rise.

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