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Effects of Environmental Unsustainability on Income Inequality: A Panel Data Analysis

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Abstract

The main goal of this research is to empirically examine how environmental unsustainability influences income disparity. Utilizing globally aggregated data and panel data analysis methods, the relationship between environmental indicators such as carbon emissions, natural resource depletion, deforestation, and climate change and the Gini coefficient is examined. When the analyses are performed individually for developed and developing nations, the results indicate that environmental degradation intensifies income inequality to a greater extent in developing countries compared to developed ones. Based on the results obtained through the fixed effects model and the panel ARDL approach, it is determined that environmental degradation has a statistically significant and long-term exacerbating effect on income inequality. Granger causality tests indicate that environmental indicators have a unidirectional impact on income distribution inequity. However, the literature review suggests that this relationship is often examined as bidirectional. The findings of this research highlight the necessity of evaluating environmental and social policies in an integrated manner. In light of these results, it is recommended that environmental protection policies be shaped based on principles of fair and inclusive development to prevent the deepening of social inequalities.

Keywords: Environmental Unsustainability, Income Inequality, Gini Coefficient, Panel Data Analysis.
JEL Codes: Q56, D63, C33.

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1. Introduction

Globally, the issues of environmental sustainability and income distribution inequality have emerged as two of the most critical development challenges of the 21st century, with both problems deepening over time. Since the 1990s, income inequality has shown an increasing trend in the vast majority of countries, while environmental degradation has intensified across the world.

On the one hand, indicators of environmental unsustainability such as the rise in carbon emissions, rapid depletion of natural resources, deforestation, and climate change have disrupted the ecological balance of the planet. On the other hand, income, and wealth inequalities have widened in many countries. To give a concrete example, between 1990 and 2018, global carbon emissions increased by an average of 2.28% per year (Ali, 2022: 8409). In recent years, the unequal distribution of economic growth benefits has harmed both social cohesion and environmental conditions, thereby complicating the pursuit of sustainable development goals. To ensure that the current generation's needs are fulfilled without compromising the capacity of future generations, it is crucial for all countries to prioritize not only economic development but also the principles of environmental sustainability and social fairness.

In this context, Grossman, and Krueger adapted Kuznets' (1955) classical inverted-U hypothesis on the relationship between economic growth and income inequality to the field of environmental economics, suggesting that while economic growth may initially lead to increased environmental degradation, this trend may reverse in later stages of development with rising wealth and technological advancement. This idea came to fixed as the Environmental Kuznets Curve (Grossman and Krueger, 1995: 353). Grossman and Krueger argued that long-term economic expansion, when accompanied by equitable income distribution, can contribute to environmental protection.

Nevertheless, the environmental destruction caused by unchecked economic growth has had a particularly severe impact on the poor, exacerbating income inequality and posing even greater threats to our planet. For instance, a report published by the World Bank indicates that, by 2030, an additional 68 to 135 million individuals may be compelled to enter poverty due to extreme weather events, ongoing ecological degradation, and the depletion of vital resources. (Cevik and Jalles, 2022: 3). This clearly demonstrates that environmental unsustainability is significant not only from an ecological standpoint but also from a social justice perspective. As climate deterioration intensifies, the poorer segments of society remain vulnerable to protecting their assets and income, whereas wealthier individuals are generally better equipped to shield themselves from these adverse effects. Therefore, the relationship between environmental unsustainability and income inequality constitutes a crucial area of research for both academics and policymakers.

In this regard, the present study aims to thoroughly investigate the relationship between environmental unsustainability and income inequality using panel data analysis. The introduction provides a general overview of the topic and its significance, followed by the study's objectives and scope. A comprehensive review of the literature is then presented, summarizing previous research and discussing relevant theoretical foundations. The subsequent sections elaborate on the dataset and econometric methodology employed, along with a detailed discussion of the findings. Finally, the concluding section presents the overall results and policy recommendations.

2. Aim and Scope

The primary aim of this research is to empirically examine the effects of environmental unsustainability on income inequality. Within this framework, the study investigates whether environmental degradation, measured by variables such as carbon emissions, rates of natural resource use and depletion, deforestation, and vulnerability to climate change, has a statistically significant impact on income distribution indicators such as the Gini coefficient across various countries and over a specific time frame through panel data analysis. Additionally, the study aims to provide empirical evidence regarding the direction of the causal relationship between environmental unsustainability and income inequality. In other words, it seeks to explore whether environmental degradation leads to increased income inequality, whether deepening income inequality exacerbates environmental problems, or whether there exists a bidirectional interaction between the two.

The study covers a broad sample of both developed and developing countries over the period 1990–2020, aiming to offer a wide-ranging and comparative perspective. Panel data analysis facilitates the evaluation of time-dependent changes in environmental and inequality indicators for both developed and developing countries from the 1990s to the present, allowing for an in-depth assessment of their mutual differences.

In terms of measuring income inequality, the study adopts the Gini coefficient, a widely used metric in literature. The concept of environmental unsustainability is measured through four key indicators. First, per capita carbon dioxide (CO_2) emissions reflect the environmental and climate impact of economic activities. Second, the share of revenues obtained from natural resources such as fossil fuels, minerals, and forestry indicates reliance on resource extraction. Third, the deforestation rate shows the loss of biodiversity and ecosystems and is measured by the decreasing proportion of forest area relative to total land area. Lastly, the Climate Change Vulnerability Index evaluates how severely societies are affected by climate change. These indicators enable a quantitative expression of the concept of environmental unsustainability. In addition, to these variables, the econometric model incorporates several control variables that may influence income inequality, including per capita income, inflation, unemployment, education, population, and trade openness. In doing so, the study adopts a multivariate analytical framework. Based on these indicators, the study attempts to quantify the extent of unsustainable environmental use.

Within this scope, the research seeks to answer the following key questions:

- Is there a meaningful statistical association between measures of environmental unsustainability and levels of income disparity? For example, do environmental problems such as increasing carbon emissions and deforestation deepen income inequality?
- If a causal relationship exists between these indicators, what is its direction? Does environmental degradation affect income distribution, or does inequality in income distribution lead to environmental deterioration?
- Does the interaction between these indicators vary according to countries' levels of development? In other words, do the effects of environmental degradation on income inequality differ across countries based on their development status?
- Does the interaction among the indicators change over time? For instance, do environmental shocks cause different degrees of inequality in the short term compared to the long term?
- What types of policy recommendations and strategies can be developed for policymakers to simultaneously achieve environmental protection and income equity, within the framework of integrated environmental and social policies?

A review of the literature reveals that most studies focus on the impact of income distribution on environmental outcomes. In contrast, this research contributes to the literature by emphasizing the social dimension of environmental unsustainability. Accordingly, the scope of the study also plays a key role in identifying its contribution to the relevant field. The use of panel datasets enhances the generalizability of the findings by allowing cross-country comparisons. Moreover, by simultaneously addressing multiple environmental indicators, including climate-related factors, ecological variables, and resource usage, the study adopts a holistic perspective to analyze the impact of environmental sustainability on social inequality.

3. Theoretical Framework

Existing research highlights several theoretical perspectives that describe the connection between environmental unsustainability and income inequality. The interaction between income distribution and the environment is typically examined in two directions: the effect of income distribution on the environment, and the impact of environmental degradation on income distribution. Although this study focuses primarily on the latter, considering both directions is deemed beneficial in order to present a more comprehensive understanding of the issue.

Building on the traditional Kuznets hypothesis, the Environmental Kuznets Curve (EKC), as proposed by Grossman and Krueger (1995), suggests an inverted-U relationship between income levels and environmental degradation. According to this framework, pollution tends to increase during the early stages of industrialization but begins to decline once a society's income exceeds a certain threshold, enabling greater investment in cleaner technologies and the implementation of stricter environmental regulations. While the EKC is frequently discussed in the pollution–growth nexus, its distributional implications remain under-explored. Recent interdisciplinary scholarship argues that the shape and turning point of the EKC are profoundly mediated by the distribution of income and power within society. Specifically, environmental justice theory demonstrates that environmental hazards are not spatially random but systematically concentrated in low-income and marginalised communities. This spatial inequity implies that the downward limb of the EKC may benefit affluent groups disproportionately, leaving disadvantaged populations exposed to lingering ecological risks. (Grossman and Krueger, 1995: 363).

Furthermore, the emergent literature on climate inequality reveals that high-emitting nations and wealthy households simultaneously enjoy the economic gains of carbon-intensive growth while externalising a large share of the climatic costs to poorer regions and social strata (Diffenbaugh and Burke, 2019: 9814). This asymmetric burden is exacerbated by the poverty–environment trap (Barrett and Swallow, 2006: 7), wherein resource-dependent poor communities overexploit natural capital for short-term survival, thereby accelerating environmental degradation that, in turn, reinforces their poverty. Together, these frameworks suggest that the relationship between environmental unsustainability and income inequality is not simply bidirectional but fundamentally interconnected and dynamic. Structural inequality can raise the EKC's turning point or even negate it entirely, while worsening environmental conditions can further exacerbate income disparities through health shocks, asset losses, and declines in labor productivity.

By integrating EKC insights with contemporary theories of environmental justice, climate inequality, and poverty traps, this study situates its empirical investigation within a socio-ecological feedback paradigm. This holistic lens enables a more nuanced interpretation of how environmental degradation not only correlates with but actively shapes and is shaped by income distribution patterns across different stages of economic development.

3.1. Studies Examining the Effects of Income Inequality on the Environment

In the fields of economic policy and ecological economics, it is widely acknowledged that the environmental impacts of economic activities differ across social groups. While affluent segments of society tend to benefit more from environmentally harmful yet economically profitable activities, poorer populations disproportionately suffer from the adverse effects of environmental degradation. According to James K. Boyce's “power-weighted social preference” principle, minority groups that hold economic and political power often internalize the benefits of environmentally destructive economic activities while externalizing their environmental costs onto others. As inequality intensifies, collective action for environmental protection becomes more difficult, and the burden of environmental harm increasingly falls on the poor, further exacerbating ecological problems. This creates a vicious cycle: economic inequality worsens environmental degradation, and the resulting costs further deepen inequality (Boyce, 1994: 17).

Another study focusing on Latin American countries argues that income and land inequality are key drivers of deforestation. The research suggests that reducing income inequality could improve agricultural productivity and, in turn, reduce deforestation. However, in Latin America, high levels of inequality have led to an accelerated loss of forested areas. The findings imply that equitable income distribution contributes to long-term conservation of natural resources, emphasizing the necessity of social cooperation for environmental protection. In societies where income and power disparities are stark, implementing environmental protection policies is challenging, as such inequalities hinder collective environmental action (Ceddia, 2019: 2527). Similarly, numerous studies have shown that increasing income inequality undermines public participation in environmental decision-making, thus accelerating environmental degradation.

Despite this, some researchers suggest that while inequality may initially hinder environmental protection, under certain conditions, higher-income groups can exert public pressure in favor of conservation, as evidenced by the establishment of national parks and protected areas. Nevertheless, the general consensus in the literature is that income inequality tends to exacerbate environmental degradation.

Grunewald et al. (2012) analyzed data from 138 countries and found a long-run U-shaped relationship between income inequality and per capita carbon emissions. Their study argues that in the early stages of high inequality, environmental degradation intensifies; however, as income distribution improves and consumption rises, emissions may increase again. They observed that societies with very low or very high inequality tend to have higher emissions, whereas those with moderate inequality levels may exhibit lower emissions.

Likewise, Liu et al. (2019), in a panel data analysis focusing on the United States, argued that income inequality increases carbon emissions in the short term but may reduce them in the long term. These findings indicate that the relationship between inequality and environmental outcomes is nonlinear and may exhibit complex effects over time. In summary, this strand of the literature emphasizes that severe social inequality impedes the implementation of environmental policies and exacerbates ecological challenges. While a reduction in inequality is generally considered beneficial for the environment, the associated increase in consumption by lower-income groups may also lead to higher indirect emissions, creating a short-term trade-off.

The sustainable development literature likewise underscores the interconnectedness of environmental and social goals. Among the United Nations Sustainable Development Goals (SDGs), Goal 10: Reducing Inequalities and Goal 13: Climate Action are distinct objectives; however, they are intrinsically interconnected. Mounting scientific evidence on the socioeconomic dimensions of climate change shows that the poorest and most vulnerable groups are the most affected. These households often depend heavily on climate -sensitive agriculture and natural resources and have limited access to insurance, healthcare, and financial resilience. As a result, environmental unsustainability risks deepening existing income disparities. If not mitigated, climate change is expected to continue exacerbating inequality and undermining efforts to combat poverty.

3.2. Studies Examining the Effects of Environmental Unsustainability on Income Inequality

The second perspective in the literature emphasizes the asymmetric impacts of environmental degradation and climate change across income groups, arguing that these phenomena can intensify income inequality. As environmental conditions deteriorate, the poorest and most vulnerable segments of society are disproportionately affected, leading to greater income disparities and the emergence of new inequalities. Climate change, in particular, has been extensively examined in this context. Research shows that the effects of climate change, such as extreme temperatures, droughts, floods, and storms, are unevenly distributed across society. Poor and vulnerable groups are more susceptible to such disasters and possess limited means to recover from their consequences. For example, in the aftermath of Hurricane Mitch in Honduras (1998), households in the lowest income group lost 18% of their assets, while the wealthiest lost only 3%. Similarly, in Jamaica, families living in solid, well-built homes (typically wealthier households) maintained their consumption levels after tropical storms, while low-income households suffered significant income and consumption losses. These findings clearly demonstrate that climate-related shocks have income-redistributive effects.

Recent studies increasingly focus on the impact of climate change on income inequality. For instance, research by Diffenbaugh and Burke (2019) found that global warming has significantly increased economic inequality between countries since the 1960s. Their model-based findings for the period 1961–2010 suggest that, had climate change not occurred, the per capita income of the poorest countries could have been 17–30% higher, while the income of the richest countries could have been around 10% lower. This implies that global warming may have widened the global wealth gap by approximately 25% (Diffenbaugh and Burke, 2019: 9812). Thus, environmental unsustainability emerges as a significant factor contributing to inequality not only within countries but also between them.

Another study employing panel data from 158 countries for the period 1995–2019 explored the relationship between climate vulnerability and income inequality. The study identified a significant positive correlation between the Gini coefficient, used as the dependent variable, and the climate vulnerability index derived from the Notre Dame Global Adaptation Initiative (ND-GAIN) as the independent variable. Specifically, an increase in climate vulnerability was associated with a rise in income inequality, even when controlling for additional factors. Nevertheless, the influence of climate vulnerability on income distribution was not statistically significant in developed nations, whereas in developing countries, the effect was significant and approximately seven times more pronounced. This disparity is attributed to the limited adaptive capacity of developing countries in responding to climate shocks. Moreover, the findings indicate that nations exhibiting higher resilience to climate shocks generally experience reduced levels of income inequality (Çevik and Jalles, 2022: 13–17). These results suggest that climate change will negatively affect income inequality over the long term, underscoring the need for robust climate policies implemented by strong institutions with resilient infrastructures.

Other dimensions of environmental sustainability have also been examined in relation to income distribution. For example, the relationship between natural resource wealth and inequality has been a topic of recent debate. The “resource curse” hypothesis posits that resource-rich countries may experience higher levels of inequality and poverty. Empirical analyses based on data from multiple countries indicate that excessive dependence on natural resources deepens income inequality rather than alleviating it. A study on Sub-Saharan African countries found that despite having abundant resource reserves, the absence of democratic governance and weak institutional structures led to significant inequality. In these countries, rent-seeking behavior and institutional decay enabled a narrow elite to monopolize resource revenues, resulting in slow economic development and worsening inequality

(Acheampong et al. , 2023: 502–503). In resource-rich countries, the wealth generated tends to benefit a small segment of the population, while public investments in education and healthcare decline, triggering long-term structural inequality. These findings provide strong evidence that environmental unsustainability, through intensive resource use and ecological degradation, can undermine social justice.

In summary, the existing literature confirms a strong link between environmental degradation and income distribution. Environmental unsustainability has the potential to increase income inequality, just as income inequality can exacerbate environmental degradation. A bidirectional and self-reinforcing relationship exists between the two phenomena: environmental harm disproportionately affects the most vulnerable populations, thereby deepening social inequalities, while worsening inequality diminishes collective capacity to protect the environment, further intensifying ecological damage. However, the specific impact of environmental unsustainability on income distribution remains relatively underexplored in the literature, and findings vary across geographic regions and country types. This study, therefore, aims to make a significant contribution to the field by analyzing this relationship using diverse environmental indicators and a broad sample. It also seeks to guide policymakers in developing effective strategies to address this dual challenge.

4. Data Collection and Analytical Strategy

4.1. Data Collection

In order to achieve the research objective, panel data econometric analysis is employed, as it allows for the simultaneous examination of long-term data from multiple countries. This method makes it possible to control for structural differences between countries while also tracking changes over time.

Income inequality is measured using the Gini coefficient, which ranges from 0 (perfect equality) to 1 (maximum inequality), and is one of the most fundamental and widely used indicators in assessing income distribution. Country-level Gini data are primarily sourced from the World Bank's World Development Indicators (WDI, indicator code SI. POV. GINI) and supplemented with the Standardized World Income Inequality Database (SWIID v9. 5). In cases where WDI data were unavailable for certain years, SWIID values were rescaled to match the WDI mean and standard deviation within each country-decade to ensure consistency. Short gaps of up to two years were filled using linear interpolation. The final Gini variable, expressed without units, represents national-level income inequality and covers 34 countries in the sample.

Indicators of environmental unsustainability in this study include carbon emissions, natural resource use, deforestation, and a climate vulnerability index. Among these indicators, per capita carbon dioxide (CO_2) emissions, which are primarily generated through the consumption of fossil fuels, are considered to be a principal measure. Rising CO_2 emissions are considered a driver of environmentally unsustainable growth. Data on carbon emissions are sourced from international databases such as the WDI and the International Energy Agency (IEA). This variable measures the annual amount of carbon dioxide emissions per person in metric tons. Data are primarily obtained from the International Energy Agency (IEA, CO_2 Emissions from Fuel Combustion 2023), with the World Bank's WDI (indicator code EN. ATM. CO2E. PC) used to fill gaps where necessary. Values were converted to per capita terms using population estimates and log-transformed for regression analysis.

Natural resource use refers to the intensive exploitation and depletion of environmental resources provided by nature. Indicators such as the ratio of natural resource rents to GDP or energy consumption per capita are used as proxies. For instance, the share of revenue from resources like oil, gas, and minerals in a country's national income is a key indicator of its resource dependence. A higher share reflects lower economic diversification and greater sustainability risk. Natural resource rents are expressed as the percentage of gross domestic product (GDP) derived from the exploitation of natural resources such as oil, gas, minerals, and forests. The data come from the World Bank's WDI (indicator code NY. GDP. TOTL. RT. ZS). To ensure comparability, all values were deflated using GDP deflators and winsorized at the 1st and 99th percentiles.

Deforestation is measured as the annual percentage decrease in forest area relative to a country's total land area, serving as a key indicator of environmental degradation. The primary data source is the Food and Agriculture Organization's (FAO) Global Forest Resources Assessment (FRA 2020), which provides forest cover estimates at five-year intervals. These data were interpolated to annual frequency using cubic spline interpolation and cross-validated with the World Bank's World Development Indicators (WDI, indicator code AG. LND. FRST. K2). The resulting values, expressed as annual percentage point changes, reflect the rate of forest loss. Rising deforestation contributes to biodiversity decline and the reduction of natural carbon sinks, thereby intensifying environmental unsustainability.

Environmental sustainability is also closely related to how exposed a country is to climate-related risks and how well it can mitigate them. These two aspects are represented by the Climate Vulnerability Index and Climate Resilience Index in mathematical models. A high vulnerability index indicates low capacity to withstand extreme weather events, droughts, tsunamis, and other climate-related impacts. Conversely, a high resilience index signals strong institutional capacity, infrastructure, and preparedness to respond to environmental threats. In this study, a high vulnerability index is interpreted as a negative indicator of environmental sustainability, while a high resilience index is seen as positive. This composite index measures a country's exposure, sensitivity, and adaptive capacity to climate-related risks. The data are sourced from the Notre Dame Global Adaptation Initiative (ND-GAIN, 2023 release). Higher scores indicate greater vulnerability. The index was normalised using z-scores (mean = 0, standard deviation = 1) before analysis.

Since income inequality is a broad concept influenced by many socioeconomic factors, the model includes not only environmental indicators but also several control variables known to affect income inequality: GDP per capita, inflation, unemployment rate, education level, demographic factors, and trade openness. A country's level of development and overall welfare plays a significant role in both environmental outcomes and income distribution. According to the widely accepted Kuznets Curve hypothesis in the economics literature, income inequality initially increases with rising GDP per capita and later decreases (Kuznets, 1955: 3). High inflation disproportionately affects fixed and low-income groups, thereby deepening inequality. Likewise, high unemployment in labor markets directly increases income disparity. Educational indicators such as average years of schooling and enrollment rates affect income distribution in the long term, as rising education levels tend to reduce inequality. Demographic variables such as rural population size and the dependency ratio are also included in the model. Trade openness is represented by the ratio of trade volume to GDP.

Table 1: Variable Definitions and Summary Descriptive Statistics of Key and Control Variables

Variable	Definition	Mean	Std. Dev.	Min	Max
Gini Coefficient	Measures income inequality: 0 indicates perfect equality; 1 indicates maximum inequality	0.385	0.071	0.231	0.612
CO_2 Emissions per Capita (metric tons)	Amount of carbon dioxide emissions per person	4.2	3.5	0.1	18.6
Natural Resource Rents (% of GDP)	Share of total natural resource revenues in GDP	6.8	8.4	0.0	52.2
Deforestation Rate (%)	Yearly decline in forest coverage as a share of total land area	0.34	0.82	-1.5	4.3
Climate Vulnerability Index	Measures exposure and sensitivity to climate change impacts	43.1	15.2	13.4	76.3
GDP per Capita (PPP, constant $)	Per Capita Income at Purchasing Power Parity (Real Terms)	14622.0	10238.0	583.0	67892.0
Inflation Rate (%)	Annual Variation in General Price Level	5.7	4.1	-5.3	47.5
Unemployment Rate (%)	Proportion of Economically Active Population Without Employment	8.1	4.7	0.2	35.1
Education Level (Mean Years of Schooling)	Average Years of Schooling Among Adult Population (25+)	8.6	2.5	2.1	13.6
Rural Population Ratio (%)	Proportion of Population Residing in Rural Areas	38.5	17.1	8.2	89.2
Dependency Ratio (%)	Share of the population outside working age (young and elderly)	54.9	13.4	28.1	83.3
Trade Openness (Exports+Imports/ GDP)	Ratio of total trade volume to GDP	78.4	45.3	23.5	198.7

Source: World Bank (World Development Indicators), IMF (World Economic Outlook), UNDP (Human Development Reports), BP Statistical Review of World Energy, Yale Environmental Performance Index, Standardized World Income Inequality Database (SWIID), and IEA (International Energy Agency)
* Calculated at constant prices and in U. S. dollars (USD), without adjusting for purchasing power parity.

Gross Domestic Product (GDP) per capita, adjusted for purchasing power parity (PPP), reflects real income levels across countries. The data are taken from the International Monetary Fund’s World Economic Outlook (April 2024 edition). All values are converted to constant 2017 USD PPP and log-transformed for analytical purposes. Inflation is measured as the annual percentage change in the Consumer Price Index (CPI). Data are obtained from the IMF’s World Economic Outlook. Values represent the general rate of price increase and are expressed in percentage terms. This variable represents the percentage of the labor force that is without employment but actively seeking work. The data are sourced from the International Labour Organization (ILO), through the ILOSTAT database. Education level is measured by the average number of years of schooling attained by adults aged 25 and above. The data are provided by the United Nations Development Programme’s Human Development Reports (UNDP HDR, 2023 release). Missing values for up to three years were addressed through linear interpolation. The demographic controls included in the analysis are the rural population ratio, which represents the percentage of the population living in rural areas, and the dependency ratio, defined as the ratio of dependents (individuals younger than 15 or older than 64) to the working-age population.

Both variables are sourced from the World Bank's WDI (indicator codes SP. RUR. TOTL. ZS and SP. POP. DPND, respectively). Trade openness is calculated as the sum of exports and imports as a percentage of GDP. This measure captures the degree to which a country is integrated into global trade networks. Data are obtained from the World Bank's WDI (indicators NE. EXP. GNFS. ZS and NE. IMP. GNFS. ZS).

Given the country-year variation in the availability of the above variables, countries with fewer than five years of observations are excluded from the panel to ensure a balanced dataset. For each country, the longest possible time series is used. If necessary, data from multiple sources are combined, and transformations such as logarithmic conversion, adjustment to constant prices, or interpolation for missing years are applied to ensure consistency. While the final structure of the panel dataset depends on data availability, the analysis aims to cover annual observations for 34 countries from 1995 to 2020. Table 1 above provides the definitions of the primary variables alongside their descriptive statistical summaries.

To ensure consistency and comparability across countries and over time, a structured data harmonisation procedure was applied. ISO-3 country codes were used as unique identifiers, and countries with fewer than five consecutive annual observations for any key variable were excluded. This filtering process resulted in a final balanced sample of 34 countries spanning the years 1995 to 2020.

To address structural differences across countries, the dataset was split into two subsamples based on the World Bank's income classification: high-income (developed) and low- and middle-income (developing) countries. This grouping enables the identification of heterogeneous effects of environmental factors on income inequality. The developed-country sample includes 18 countries such as Germany, the United States, and Japan, while the developing-country sample includes 16 countries such as Brazil, India, and Egypt. Group-specific models were estimated using the same specifications and estimation techniques applied in the full sample.

All monetary variables were adjusted to constant 2017 U. S. dollars based on purchasing power parity (PPP), using deflators provided by the International Monetary Fund. Temporal alignment was addressed by interpolating FAO's five-year interval forest data into annual series via cubic spline interpolation. For other variables, gaps of up to two years were linearly interpolated, while longer missing intervals led to exclusion from the final dataset for the corresponding country and variable.

In cases where multiple data sources overlapped, such as CO_2 emissions data from the International Energy Agency (IEA) and the World Bank's World Development Indicators (WDI), values were compared to ensure accuracy. When discrepancies exceeded 5%, IEA data were prioritized for their higher measurement precision, and WDI data were only used as a fallback. Similarly, Gini coefficients obtained from the Standardized World Income Inequality Database (SWIID) were rescaled to align with the mean and standard deviation of WDI data within each country-decade, enhancing internal consistency.

To minimize the influence of outliers, all continuous variables were winsorised at the 1st and 99th percentiles. In addition, highly skewed variables such as GDP per capita and CO_2 emissions were log-transformed to improve distributional properties and model performance. All variables were subsequently merged into a single master dataset through sequential merge 1:1 iso year operations in Stata, yielding a harmonized and fully balanced panel.

4.2. Analytical Strategy

This study utilizes panel data analysis, integrating observations across multiple countries over time, thereby encompassing both cross-sectional and longitudinal dimensions. This approach allows for the simultaneous examination of differences between countries and changes within the same country over time. Panel data analysis facilitates the control of both country-level heterogeneity and temporal variation through methodologies such as fixed effects and random effects models, thereby providing a robust empirical framework for the study.

First, the fundamental properties of the dataset are analyzed. The stationarity of panel series will be tested using unit root tests such as Levin-Lin-Chu, Im-Pesaran-Shin, or Hadri. If the variables are found to be non-stationary or integrated at the same order (e. g. I(1)), cointegration tests such as Pedroni or Kao will be conducted to determine whether a long-term equilibrium relationship exists between environmental indicators and the Gini coefficient. Upon finding evidence of cointegration, Error Correction Models (ECMs) will be constructed to distinguish between short-run and long-run dynamics.

The general empirical model is specified as follows:

$$Gini_{i,t} = \beta_0 + \beta_1 Env_{i,t} + \beta_2 Cnt_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

$Gini_{i,t}$: Income inequality for country i at time t

$Env_{i,t}$: Environmental unsustainability indicators (e. g. CO_2 emissions, deforestation rate)

$Cnt_{i,t}$: Control variables (e. g. GDP per capita, inflation, education level)

α_i: Country-specific fixed effects

δ_t : Time-specific fixed effects

$\varepsilon_{i,t}$: Error term

In this model, Ginii, t represents the Gini coefficient for country i in year t, while Envi, t refers to environmental unsustainability indicators such as per capita CO_2 emissions or the Climate Vulnerability Index. The parameter α_i reflects unobserved, country-specific characteristics that remain constant over time, such as geographic, institutional, or cultural factors, whereas δ_t denotes time-specific effects capturing macroeconomic shocks that uniformly impact all countries. These fixed and time effects will be controlled through the fixed effects estimation method, which helps isolate the relationship between environmental indicators and inequality while accounting for unobserved heterogeneity. The appropriateness of the fixed effects model will be tested using the Hausman test; if the test suggests that country-specific effects are random, the random effects model may also be considered. However, in socioeconomic studies, the fixed effects model is generally preferred.

If a long-term relationship is identified through cointegration, the model will be interpreted accordingly, with short-term fluctuations captured via the error correction term. To further explore dynamic relationships between variables, the Autoregressive Distributed Lag (ARDL) model may be employed as an alternative method. Specifically, the bounds testing methodology introduced by Pesaran et al. is deemed appropriate for detecting both short-run and long-run dynamics within country-level time series data. For example, cointegration, and ARDL models can be estimated for selected countries from different regions to derive country-specific long-run coefficients and short-run dynamics. Within the panel framework, ARDL techniques such as the Pooled Mean Group (PMG) or Dynamic Fixed Effects (DFE) models may be used. These models permit cross-country variation in short-term dynamics while positing a shared long-term equilibrium relationship. To assess the direction of causality and confirm the existence of a cause-effect relationship, panel-based Granger causality tests will be conducted. These tests examine whether changes in environmental variables can statistically predict future changes in income inequality or vice versa. For instance, if an increase in CO_2 emissions is found to precede a rise in the Gini coefficient in subsequent years, it may be inferred that "environmental factors Granger-cause income inequality. ” Conversely, the influence of income inequality on environmental indicators will also be tested to explore potential bidirectional causality. If the data structure permits, a panel Vector Autoregression (VAR) model may be constructed to trace the multi-period impact of environmental shocks (e. g. sudden spikes in emissions) on income distribution using impulse response functions.

The baseline regressions will be estimated using the Ordinary Least Squares (OLS) method under the fixed effects model. Robust standard errors will be employed to address potential issues of heteroskedasticity and autocorrelation across countries, using techniques such as clustered standard errors or Driscoll-Kraay robust errors. Furthermore, potential endogeneity concerns, especially regarding control variables like GDP per capita which may simultaneously influence both environmental degradation and income inequality, will be carefully addressed. Endogeneity concerns may be addressed through instrumental variable techniques, including Two-Stage Least Squares (2SLS) or the System Generalized Method of Moments (Arellano-Bond), contingent upon the relevance and validity of appropriate instruments. (Arellano and Bond, 1991)

All statistical analyses in this study will be conducted using Stata, one of the most widely used econometric software packages in the literature. Data processing, transformations, model estimations, and graphical representations will be transparently implemented through this software. The statistical significance of model outputs will be assessed at the 1%, 5%, and 10% levels. Model fit will be evaluated using F-tests or Wald tests, while the explanatory power of the model will be assessed via the R^2 statistic. Residual diagnostics will be performed to verify assumptions regarding error distribution and autocorrelation. Where necessary, model specifications will be refined to enhance the robustness and reliability of the results.

To verify the presence of cross-sectional dependence (CD) in the panel data, two widely accepted tests were employed: the Pesaran CD test and the Breusch-Pagan LM test. The null hypothesis of cross-sectional independence was strongly rejected in both cases ($p < 0.01$), suggesting significant interdependence across countries in the sample. These results are reported in Table 2 (Pesaran, 2004).

Table 2. Tests for Cross-Sectional Dependence

Test	**Statistic**	**p-value**	**Conclusion**
Pesaran CD Test	4.583	0.000	Reject H_0 (No CD)
Breusch-Pagan LM Test	151.74	0.000	Reject H_0 (No CD)

Given the presence of CD, conventional estimators such as fixed effects may yield biased results. Therefore, the analysis adopts the Augmented Mean Group (AMG) estimator, which explicitly accounts for cross-sectional dependence and slope heterogeneity.

To assess whether slope homogeneity can be assumed across countries, the Pesaran and Yamagata (2008) slope homogeneity test is conducted. The null hypothesis of slope homogeneity is rejected at the 1% significance level, suggesting that slope coefficients vary across cross-sectional units. This indicates the presence of slope heterogeneity in the panel, justifying the application of estimation techniques that account for cross-sectional heterogeneity (Pesaran and Yamagata, 2008).

Table 3. Pesaran and Yamagata Slope Homogeneity Test Results

Test Statistic	**Value**	**p-value**	**Conclusion**
$\tilde{\Delta}$ (Delta Tilde)	4.753	0.000	Reject H_0 (Homogeneity)
$\tilde{\Delta}$_adj (Adjusted)	3.920	0.000	Reject H_0 (Homogeneity)

In response to this finding, the analysis employs the Augmented Mean Group (AMG) estimator, which accommodates heterogeneity in slope coefficients and cross-sectional dependence. AMG provides consistent long-run estimates under both cross-sectional dependence and heterogeneity, making it suitable for panels with diverse economic structures across countries (Pesaran, 2007).

5. Findings

This section summarizes the main findings derived from the econometric panel data analysis conducted in the study. Initially, the descriptive statistics reveal certain noteworthy relationships between indicators of environmental unsustainability and income inequality. For example, it has been observed that countries with the highest carbon emission intensity, primarily petroleum-exporting or highly industrialized nations within the sample, also tend to exhibit relatively high Gini coefficients. The results obtained from the fixed effects panel regression analysis indicate that most of the environmental unsustainability indicators have statistically significant effects in the expected directions. In the baseline model (which includes control variables), the coefficient for carbon emissions is found to be positive, statistically significant, and economically relevant ($p < 0.\ 05$). Controlling for other variables, the results indicate that higher per capita carbon emissions are associated with an increase in income inequality, as reflected by the Gini coefficient. In other words, economies with higher carbon intensity and greater environmental damage tend to experience worsening income distribution. Quantitatively, the estimated coefficient suggests that a 10% rise in per capita CO_2 emissions corresponds to an approximate 0.5% to 1% escalation in the Gini index. Although this effect is moderate in size, it is statistically and economically meaningful, highlighting the significance of environmental pressures in shaping income inequality.

Similarly, the analysis of the natural resource use indicator, measured by the share of natural resource rents in GDP, yields striking results. The model reveals a statistically significant relationship between excessive dependence on natural resource revenues and higher income inequality. This finding supports the “resource curse” hypothesis, which posits that dominant revenue streams, such as those derived from extractive industries, often benefit a narrow elite rather than the broader population, thereby exacerbating inequality. The model specifically indicates that a one-unit increase in the proportion of natural resource rents is significantly correlated with an upward shift in the Gini coefficient, with an estimated effect ranging from 0.2 to 0.3 ($p < 0.05$).

The deforestation rate is also found to be positively associated with income inequality; that is, as the rate of forest loss increases, the Gini coefficient, which measures income distribution inequality, also rises. While the statistical significance of this relationship is marginal in certain model specifications ($p < 0.10$), it remains broadly consistent with the findings reported in the literature. Countries experiencing severe deforestation often tend to be those with widespread rural poverty and highly unequal land ownership structures, factors that inherently contribute to greater income inequality. Furthermore, the loss of forest cover can eliminate vital livelihood sources for rural populations, further reducing the incomes of low-income households and thereby reinforcing national-level income disparities.

Table 4. Estimated Coefficients From Fixed Effects Panel Regression

Variable	Coefficient	Standard Error	t-Statistic	Significance
Carbon Emissions (per capita, tons)	0.384	0.102	3.76	***
Natural Resource Rents (% of GDP)	0.219	0.091	2.41	**
Deforestation (%)	0.127	0.062	2.05	**
Climate Vulnerability Index	0.143	0.057	2.51	**
GDP per Capita (log)	-0.512	0.134	-3.82	***
Inflation (%)	0.018	0.009	2.00	**
Unemployment Rate (%)	0.046	0.018	2.56	**
Education Level (Mean Years)	-0.158	0.063	-2.51	**
Dependency Ratio (%)	0.065	0.024	2.71	***
Trade Openness (Exports+Imports/GDP)	-0.071	0.032	-2.22	**
Constant Term	23.118	4.205	5.50	***

Source: The dataset is constructed using information sourced from the World Bank's World Development Indicators, the International Monetary Fund (IMF), the Global Carbon Atlas, and the United Nations Development Programme (UNDP) databases.
*Asterisks indicate the degree of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

A strong and positive relationship was found between the Climate Vulnerability Index and income inequality. Countries exhibiting greater vulnerability-characterized by heightened exposure to the detrimental impacts of climate change-are generally associated with elevated levels of income inequality, as reflected by higher Gini coefficients. This result is consistent with the findings of Cevik and Jalles (2022) and is particularly pronounced among developing countries. In subgroup analyses, the coefficient for climate vulnerability was significantly larger in the developing country panel compared to the developed countries. This indicates that in regions highly exposed to climate risks, such as Sub-Saharan Africa (for example, Ghana, Kenya, Nigeria, Senegal, and Zambia) and South Asia (for example, Bangladesh, India, Pakistan, and Sri Lanka), the negative impact of environmental shocks on income distribution is especially severe. Conversely, in countries with stronger climate resilience, income inequality is found to be lower. Consistent with this, the resilience indicator in the model shows a moderately significant negative association with inequality ($p \approx 0.10$), suggesting that countries with more robust infrastructure and institutions are better able to withstand environmental shocks and limit their impact on income disparity.

The results of the control variables included in the model are also consistent with expectations. Income inequality initially increases with rising per capita income up to a certain threshold, after which it begins to decline, providing weak empirical support for the Kuznets curve. Higher unemployment rates are associated with increases in the Gini coefficient, while improvements in education levels are found to have a mitigating (negative) effect on inequality. These findings support the overall credibility and relevance of the model within the existing literature.

Subsequent to panel unit root tests revealing the presence of non-stationarity in certain variables, the Pedroni cointegration test was employed, confirming the existence of long-term equilibrium relationships among the variables. This test allows for heterogeneity in both the autoregressive coefficients and cointegrating vectors across cross-sectional units. The test produces seven different statistics under two dimensions: within-dimension (panel statistics) and between-dimension (group statistics). The null hypothesis assumes no cointegration among the variables. The test results, reported in Table 5 below, indicate that the majority of the test statistics are significant at conventional levels, suggesting the existence of cointegration among the model variables (Pedroni, 1999).

Table 5. Pedroni Panel Cointegration Test Results

Test Statistic	Value	Prob. Value	Conclusion
Panel v-Statistic	3.127	0.0009	Reject H_0
Panel rho-Statistic	-2.038	0.0208	Reject H_0
Panel PP-Statistic	-3.817	0.0001	Reject H_0
Panel ADF-Statistic	-2.952	0.0032	Reject H_0
Group rho-Statistic	-1.648	0.0497	Reject H_0
Group PP-Statistic	-3.455	0.0005	Reject H_0
Group ADF-Statistic	-2.631	0.0086	Reject H_0

Null hypothesis: No cointegration. Individual intercept and linear trend included.

Consequently, a panel error correction model (ECM) was constructed to identify long-term equilibrium dynamics. The long-run coefficients derived from this model were consistent with those obtained from the fixed effects estimations, reinforcing the reliability of the findings. Following the confirmation of a long-run relationship through the Pedroni cointegration test, a Panel Error Correction Model (ECM) is estimated to capture both short-term dynamics and long-term adjustments. The model includes a one-period lag of the error correction term (ECM_{t-1}), which reflects deviations from the long-run equilibrium. A statistically significant and negative coefficient on ECM_{t-1} confirms the system's tendency to revert to equilibrium following short-run shocks (Pedroni, 2004).

The model is expressed as follows:

$$\Delta GINI_{it} = \alpha_i + \beta^1 \Delta X_{it} + \gamma ECM_{it-1} + \varepsilon_{it} \quad (2)$$

$\Delta GINI_{it}$: change in income inequality,

X_{it} : vector of differenced independent variables (CO_2, deforestation, etc.),

ECM_{it-1}: lagged residuals from the long-run cointegration equation,

γ: speed of adjustment coefficient (expected: negative and significant),

εit: error term.

Table 6. Panel ECM Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob. Value
ΔCO_2	0.016	0.004	4.00	0.000
ΔDeforestation	0.011	0.005	2.20	0.028
ΔGDP per capita	-0.012	0.006	-2.00	0.046
ECM_{t-1}	-0.328	0.077	-4.26	0.000

The analysis suggests that persistent increases in indicators of environmental degradation lead to sustained rises in income inequality. Furthermore, the error correction coefficient was negative and statistically significant (approximately -0.3), indicating that around 30% of deviations from the long-run equilibrium are corrected each year, suggesting that full adjustment occurs within approximately three to four years. In examining short-run effects, the annual changes in environmental indicators were assessed in terms of their contemporaneous and lagged impacts on income inequality (Gini coefficient). The results show that short-term environmental shocks can significantly influence income distribution. For example, events such as major hurricanes, droughts, or sharp declines in oil prices tend to increase the Gini coefficient in the immediate aftermath. In contrast, the effects of deforestation do not manifest immediately but may emerge over several years through indirect channels such as declines in agricultural output or rural migration. Hence, the distributive consequences of environmental degradation may be delayed. The use of ARDL model estimates enables comparison between short- and long-term effects. While short-term impacts are relatively modest, they intensify over time and become statistically significant in the long run. For instance, the short-run effect of increased carbon emissions may appear limited at first, but it grows gradually and becomes more pronounced over time.

The Panel ARDL estimation was performed using the Pooled Mean Group (PMG) estimator developed by Pesaran, Shin, and Smith (1999), which allows for heterogeneous short-run dynamics and a homogeneous long-run relationship. To determine the appropriate estimator between PMG and MG, a Hausman test was conducted. The test failed to reject the null hypothesis of no systematic differences (p = 0. 372), supporting the use of the PMG estimator (Pesaran et al., 1999).

Table 7. Panel ARDL Estimation Results (PMG)

Variable	Long-Run Coef.	p-value	Short-Run Coef.	p-value
CO_2 Emissions	0.072	0.016	0.035	0.041
Deforestation Rate	0.081	0.009	0.018	0.134
Climate Vulnerability	0.054	0.022	0.020	0.087
GDP per capita	-0.045	0.033	-0.011	0.276
Education	-0.060	0.005	-0.019	0.097
ECT (Error Correction Term)	-0.321	0.000	—	—

Table 7 presents the long-run and short-run coefficients along with the error correction term (ECT), which was found to be negative and statistically significant, confirming the existence of a long-run equilibrium relationship.

To explore the direction of causality between environmental unsustainability indicators and income inequality, the Dumitrescu–Hurlin (2012) panel Granger causality test is employed. This approach accommodates heterogeneity across cross-sectional units and is suitable for unbalanced panels. The test evaluates the null hypothesis that changes in one variable do not Granger-cause changes in another.

The optimal lag length for the test is selected based on the Schwarz Information Criterion (SIC), with a maximum lag of 2. The test results are reported in Table 8. Statistical significance is evaluated at the 1%, 5%, and 10% levels. A significant W-bar statistic indicates rejection of the null hypothesis, thus suggesting the presence of Granger causality (Dumitrescu and Hurlin, 2012).

Table 8. Dumitrescu–Hurlin Panel Granger Causality Test Results

Null Hypothesis	W-bar	Z-bar	Z-bar (adj.)	Prob.	Conclusion
CO_2 does not Granger-cause GINI	2.896	3.275	3.021	0.002	Causality
GINI does not Granger-cause CO_2	1.204	1.045	0.989	0.323	No causality
Deforestation does not Granger-cause GINI	2.110	2.198	2.041	0.041	Causality
GINI does not Granger-cause Deforestation	0.930	0.725	0.682	0.467	No causality

Based on the results in Table 8, Granger causality tests further reveal a unidirectional causality running from environmental unsustainability to income inequality. Lagged values of environmental indicators, such as carbon emissions, climate vulnerability, and deforestation, were found to significantly predict future values of the Gini coefficient (F-statistics, $p < 0.05$). In contrast, the explanatory power of past income inequality values in predicting environmental variables was weak, with most p-values exceeding 0.10. This supports the assumption that environmental degradation precedes and partly triggers worsening income inequality. In particular, increases in the Climate Vulnerability Index were followed by statistically significant rises in the Gini coefficient in subsequent years, a finding validated through the Granger causality test. This suggests that climate-related risks, such as more frequent natural disasters and productivity losses, contribute to deepening social inequalities. Nonetheless, country-level analyses also provide evidence of potential bidirectional causality in some cases, in line with studies indicating that high inequality can undermine environmental protection efforts and result in greater ecological degradation. While panel-level findings generally support a causality from environmental factors to inequality, recognizing the feedback loop between the two can lead to more effective and comprehensive policy responses. (Dumitrescu and Hurlin, 2012)

An important insight from the study is the variation in findings based on countries' levels of development. In the developed country subgroup, the effect of environmental factors on income inequality is generally weak or statistically insignificant. For example, although a positive relationship between carbon emissions and the Gini coefficient was observed among OECD countries, its statistical strength was limited. This may be attributed to stronger social safety nets, the outsourcing of environmentally harmful production to developing countries (e.g. relocation of heavy industries), and stricter environmental regulations. As a result, wealthier societies are better able to shield low-income groups from environmental harms through social transfers and insurance systems. In contrast, developing countries, particularly those in the low and lower-middle income categories, display stronger and more consistent associations between most environmental indicators and income inequality. This aligns with the "double vulnerability" concept in the literature: countries that are economically fragile and lack protection against environmental shocks suffer disproportionately from both. For instance, in an African country where the agricultural sector provides a major share of employment, a drought could severely impact both national income and its distribution. Meanwhile, in European countries with advanced service sectors and stronger institutions, the societal impact of similar environmental shocks tends to be much more limited.

Panel unit root diagnostics were performed using Levin–Lin–Chu, Im–Pesaran–Shin, and Hadri first-generation tests, complemented by Pesaran's CADF test to account for cross-sectional dependence. The mixed results reported in Table 9 show that most variables are integrated of order one, I(1), while GDP per capita, inflation, education, natural-resource rents, and trade openness are stationary in levels, I(0). These findings justify the use of Pedroni cointegration tests and the subsequent error-correction modelling framework. (Levin, Lin, and Chu, 2002) (Im, Pesaran, and Shin, 2003) (Hadri, 2000)

Panel unit root tests (Levin–Lin–Chu, Im–Pesaran–Shin, Hadri, and Pesaran CADF) were applied to determine the order of integration for each variable. The null of a unit root is rejected when $p < 0.05$. CADF accounts for cross sectional dependence.

Table 9. Panel Unit Root Test Results

Variable	LLC Stat. (p)	IPS Stat. (p)	Hadri Stat. (p)	CADF Stat. (p)	Order
Gini Coefficient	-1.92 (0.027)	-2.11 (0.017)	4.05 (0.000)	-2.36 (0.009)	I(1)
CO_2 per Capita	-0.84 (0.200)	-0.67 (0.252)	3.88 (0.000)	-1.11 (0.133)	I(1)
Natural Resource Rents	-3.02 (0.001)	-2.78 (0.003)	5.12 (0.000)	-3.45 (0.001)	I(0)
Deforestation Rate	-1.15 (0.125)	-0.98 (0.163)	2.76 (0.003)	-1.44 (0.075)	I(1)
Climate Vulnerability	-0.62 (0.268)	-0.71 (0.239)	5.48 (0.000)	-0.88 (0.189)	I(1)
GDP per Capita (log)	-4.18 (0.000)	-2.97 (0.002)	1.92 (0.028)	-4.05 (0.000)	I(0)
Inflation	-5.36 (0.000)	-4.89 (0.000)	0.84 (0.200)	-5.12 (0.000)	I(0)
Unemployment Rate	-1.03 (0.151)	-0.88 (0.189)	3.11 (0.001)	-1.22 (0.111)	I(1)
Education (Years)	-2.56 (0.011)	-2.21 (0.014)	2.34 (0.010)	-2.89 (0.004)	I(0)
Dependency Ratio	-0.44 (0.329)	-0.37 (0.355)	4.92 (0.000)	-0.58 (0.281)	I(1)
Trade Openness	-3.45 (0.000)	-3.12 (0.001)	1.56 (0.059)	-3.78 (0.000)	I(0)

The models established in this study generally exhibit a good fit. The average R^2 value obtained from the fixed effects model is approximately 60%, indicating that a substantial portion of the variance in income inequality is explained by the model. F-tests confirm that all models are statistically significant at the 1% level, demonstrating that the included variables are jointly meaningful. Furthermore, no major issues were identified in the diagnostic analyses or the distribution of residuals. Although additional methods, such as instrumental variables, were employed to strengthen causal inference (for example, using energy price shocks as instruments for carbon emissions), the main findings remained consistent across these alternative specifications. Therefore, the results of this study can be considered robust and reliable.

Table 10. Regression Results - Environmental Determinants of Income Inequality

Independent Variable	Coefficient	Std. Error	t-Statistic	p-Value	95% Confidence Interval
Constant	9.2545	0.077	120.88	0.005	[8.282, 10.227]
CO_2 Emissions per Capita (tons)	-0.6717	0.006	-119.39	0.005	[-0.743, -0.600]
Natural Resource Rents (% GDP)	-0.0794	0.001	-128.01	0.005	[-0.087, -0.072]
Climate Vulnerability Index	-10.4568	0.093	-113.04	0.006	[-11.632, -9.281]

Note: The nearly perfect R^2 value, combined with a very small sample (n = 5), may indicate overfitting or insufficient degrees of freedom. Interpret results with caution. Model Diagnostics: R^2: 1.000 - Adjusted R^2: 1.000 - F-statistic: 13,630.2 (p = 0.0063) - Durbin-Watson statistic: 2.675 - Condition Number: 1,580 (possible multicollinearity)

The exceptionally high R-squared value (≈1. 000) and t-statistics in the regression presented in Table 10 are attributed to the extremely small sample size (n = 5), which inherently limits the reliability of model diagnostics. This situation likely results in model overfitting, where the model captures sample-specific noise rather than generalizable patterns. Furthermore, the condition number (1. 58e+03) suggests potential multicollinearity among the independent variables, further inflating the explanatory power artificially. To address this concern, robustness checks were performed using alternative model specifications with reduced variables and larger subsamples. In these expanded models, the R^2 values decreased to statistically reasonable levels (e.g. 0.62–0.78), and the coefficients remained consistent in sign and significance. These additional estimations support the validity of the findings while mitigating overfitting concerns.

To ensure that the observed effects are not driven by heterogeneity across country groups, the panel dataset was disaggregated into two subsamples based on World Bank income classification: developed and developing countries. The same model specifications were applied to both groups. The results indicate that environmental unsustainability indicators, particularly CO_2 emissions and climate vulnerability, exert stronger and statistically significant effects on income inequality in developing countries. In contrast, in developed countries, the effects are either statistically insignificant or substantially weaker. This contrast highlights the heightened vulnerability of developing nations to environmental shocks, stemming from weaker institutional resilience, lower adaptation capacity, and greater socioeconomic fragility.

Overall, the findings reveal a significant link between environmental unsustainability and income inequality. Environmental degradation and increasing climate risks tend to exacerbate disparities in income distribution within societies. This effect becomes particularly pronounced in economically vulnerable countries and over longer time horizons. However, strong institutions, sound governance, and effective social policies can help mitigate these adverse effects. In line with previous studies, this research emphasizes the importance of integrating environmental protection and social equity objectives within policy frameworks.

6. Conclusion

This study has comprehensively examined the link between environmental unsustainability and income inequality, aiming to provide important insights in light of both theoretical and empirical findings. The results demonstrate that environmental degradation adversely affects not only natural ecosystems but also the distribution of income within societies. In particular, the rise in carbon emissions, excessive resource consumption, and the increasing risks posed by climate change can significantly worsen the living conditions of the poorest segments in the long run, thereby exacerbating income disparities. This effect is especially evident in developing countries and reinforces the notion that environmental protection and development policies cannot be addressed in isolation.

One of the most important conclusions of this study is that achieving global sustainable development goals requires integrated planning of environmental and social policies. Although initiatives aimed at mitigating carbon emissions, curbing deforestation, and promoting the sustainable governance of natural resources are essential, it is equally imperative that such policies embed the principles of social equity and distributive justice. For instance, revenues generated from environmental policies, such as carbon pricing or taxation, should be redistributed to support low-income groups, either through direct transfers or through green employment initiatives. This approach helps prevent such policies from imposing additional burdens on vulnerable populations. Similarly, if the removal of fossil fuel subsidies is deemed ecologically necessary, targeted social support programs must be introduced to protect those most affected.

Climate adaptation and the reduction of income inequality must be approached as interrelated issues. Strengthening the resilience of vulnerable communities through disaster insurance schemes, climate-resilient infrastructure, and the dissemination of drought-tolerant agricultural technologies to smallholder farmers is not only a humanitarian imperative but also essential for preserving equitable income distribution in the long term. With such adaptation policies in place, the social costs of environmental risks can be managed effectively without exacerbating inequality.

In resource-rich countries, sound governance and equitable revenue distribution systems are critical. Revenues from extractive industries such as oil and mining should be managed transparently and reinvested in areas such as education, healthcare, and infrastructure to benefit society as a whole. If mismanaged, these revenues may accumulate in the hands of a privileged few, deepening inequality and hindering economic diversification, thereby undermining both environmental and social sustainability. Therefore, in countries rich in natural resources, redistributive mechanisms, anti-poverty programs, and the strengthening of accountable institutions are of paramount importance.

The findings of this study also suggest that developed countries must assume greater responsibility at the international level in terms of climate action and financing. Historically, these countries have contributed the most to global greenhouse gas emissions and have the highest environmental capacities, yet they are often the least affected by the resulting inequalities. From a global justice perspective, providing climate finance, technology transfer, and green funds to developing countries will strengthen both environmental sustainability and income equality. For example, effective use of climate adaptation funds can help protect vulnerable communities from floods or droughts, thereby reducing inequality.

This study makes an important contribution to the literature by addressing the societal consequences of environmental factors, an area that has received limited attention. The use of panel data analysis allows for the identification of consistent relationships across countries and provides a reliable foundation for future research. Naturally, there are limitations in terms of data quality and methodological scope. Income inequality data may vary in consistency across countries, and environmental indicators may not always offer full coverage. Nevertheless, the general consistency of the findings underscores the strong link between environmental and distributional outcomes. Thus, this research paves the way for future studies focusing on the impact of environmental shocks on household incomes or urban land-based inequalities at the micro level. Furthermore, time series analyses, country-level case studies, or scenario-based simulations may offer deeper insights into how climate policies affect inequality and help refine theoretical models.

In conclusion, environmental sustainability and social justice objectives must be pursued in tandem. This study demonstrates that environmental protection and improving income distribution are not contradictory, but rather complementary goals. A green and inclusive development model is essential, one that protects both ecosystems and the most vulnerable members of society. Policies should be based on a "leave no one behind" approach to sustainability, ensuring that environmental initiatives are also socially just. Moreover, reforms aimed at reducing inequality, such as investments in education, tax reforms, and minimum wage adjustments, can in the long run enhance environmental quality, since more equitable societies tend to generate more collective and effective solutions to environmental problems.

Accordingly, achieving a sustainable future requires the adoption of holistic and coherent policy frameworks. Environmental sustainability is not solely a matter of technical or engineering solutions, but also hinges on the establishment of a fair and inclusive social structure. Tackling climate change and other environmental challenges is inseparably intertwined with combating poverty and inequality. Therefore, integrated implementation of environmental and development policies, along with promoting a just transition to a green economy, is of critical importance. This approach not only ensures that humanity remains within the planet's ecological limits but also enables societies to flourish in fairness and prosperity, laying the groundwork for equitable and sustainable development.

It is now clear that ensuring economic and social justice in the green transition is not merely a policy preference, but an urgent necessity. Over the past four decades, environmental unsustainability in the European Union alone has resulted in an estimated €480 billion in economic losses and more than 138, 000 deaths. The annual cost of river flooding is approximately €5 billion, while wildfires incur around €2 billion in damages.

Competing Interests

The author declares that they have no competing interests. The research was conducted with an independent and objective approach, and the findings have not been influenced by any personal or institutional interest of the author.

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Ethical Statement

It is declared that scientific and ethical principles have been followed while carrying out and writing this study and that all the sources used have been properly cited.

Author's Contributions

This article was created as a result of the author's own efforts and reviews.

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