



Ecological Footprint and Income Inequality: A Cross-Country Analysis

Pinaki Das¹, Asikul Islam Mallik², Pabitra Adhikary³

¹Professor of Economics, ²Ph.D. Scholar of Economics, ³Ph.D. Scholar of Economics

Department of Economics

Vidyasagar University, Medinipur, West Bengal, India

Abstract: This research paper conducts a comprehensive cross-country analysis of the interplay between income inequality and ecological footprint, with a focus on their implications for Sustainable Development Goals (SDGs). Data from 55 economies, spanning 1995 to 2018 and representing developed, developing, and underdeveloped nations, is analyzed. The findings predominantly reveal a positive relationship between income inequality and ecological footprint, supported by the inequality measurements (Gini). However, some instances exhibit statistically insignificant relationships, particularly Gini in high-income countries. The economic rationale behind the positive relationship lies in heightened income inequality leading to resource disparities, where wealthier individuals can afford environmentally friendly goods, while the less privileged rely on natural resources, resulting in increased ecological footprint and environmental degradation.

The study also uncovers a positive correlation between GDP per capita growth and ecological footprint, as rising per capita income boosts purchasing power and increases the ecological footprint. Similarly, a positive relationship is observed between FDI inflows and ecological footprint, driven by increased foreign private investment stimulating urbanization and natural resource demand, amplifying the ecological footprint. However, inclusive growth from FDI inflows can contribute to income inequality, consequently increasing the ecological footprint. Significant variations are observed in income inequality across different country groups. Moreover, the ecological footprint is found to be higher in high-income countries and lower in low-income countries. Lastly, the Random Effects Model (REM) demonstrates the significant positive effect of income inequality on ecological footprint.

In light of these insights, the study emphasizes the need for government policies to prioritize initiatives that reduce income inequality, as such measures are likely to decrease ecological footprint and contribute to advancing SDGs.

Keywords: Income Inequality, Gini, Ecological Footprint, Panel Data

1. Introduction

In recent times, the world is facing three main problems: environmental sustainability, unequal distribution of wealth and income, and extreme levels of poverty. By increasing the level of income, a country may solve the problem of poverty, but the problem of unequal distribution of wealth may not be solved. If most of the increase in income is going to the rich people and the remaining income is going to the poor people, then the overall increase in income for every individual will increase, but the unequal distribution of income

will also increase. Due to an increase in economic activity, the pressure on the environmental ecosystem will also increase, which will lead to environmental degradation. The concept of the ecological footprint—the measure of humanity's demand on the planet's biocapacity—captures the extent to which current consumption and production patterns exceed ecological limits (Wackernagel & Rees, 1996). The Earth has its own carrying capacity, so raising the ecological footprint is not problematic at all, but if increasing the ecological footprint crosses the Earth's carrying capacity, then Earth overshooting is occurring. Our present study focuses on how unequal distribution of income impacts the environment and how unequal income distribution is not only problematic for society but also problematic for the environment.

Income inequality is the unequal distribution of income among the people in a society. Unequal distribution of income can impact the consumption pattern and consumption behaviour, which could impact the Ecological Footprint. Therefore, unequal resource distribution is not only a social or moral problem but also has a prominent impact on the environment. In the existing literature, there are several studies that have been done on this topic. Theoretical and empirical studies find that unequal societies tend to create higher environmental pressure due to several interrelated mechanisms: affluent groups drive resource-intensive consumption, poorer groups emulate these lifestyles, and unequal power structures often weaken environmental regulation (Boyce, 1994; Torras & Boyce, 1998). Some empirical investigations have been done on this topic. Knight et al. (2017) and Jorgenson et al. (2017) have found a positive relationship between income inequality and ecological footprint for developed countries. Grunewal et al. (2017) explored a "trade-off" relationship between income inequality and ecological footprint in a sample of developed and developing economies. Some literature focused on individual countries. Baloch et al. (2018) for Pakistan got a positive relationship, Demir et al. (2019) focused on Turkey, and Bhattacharya (2019) for India; both studies explored the negative relationship.

Our study focused on the cross-country differences and separated all countries into four groups: high, upper middle, lower middle, and low-income countries, which will help us to understand the nature of this relationship among heterogeneous income country levels. In high-income countries, higher awareness, stricter environmental policies, and technological advancement might mitigate the ecological burden of inequality. But in the case of upper-middle, lower-middle, and low-income countries, inequality often translates into unsustainable consumption patterns, deforestation, and energy overuse, magnifying their ecological footprints. Understanding this cross-country variation is crucial for formulating integrated policies that promote both equity and sustainability.

In the existing literature, there is a popular hypothesis, EKC, which shows the relationship between GDP per capita and environmental degradation, but the relationship between income inequality and environmental degradation is a very small amount of literature; some have reported positive, some have reported negative, and some have reported mixed results. Therefore, our motivation arises to do the research on this topic, to investigate the relationship between income inequality and ecological footprint in the heterogeneous income condition. The findings are expected to contribute to the broader debate on achieving inclusive and sustainable development, as envisioned in the United Nations Sustainable Development Goals (SDGs 10 and 13), where reducing inequality and combating climate change are inherently interconnected.

2. Literature Review

The literature review is structured thematically to capture the depth and diversity of the existing knowledge base.

The study delves into the nexus between income inequality and environmental degradation, examining EFP. Various authors have contributed to this field, and their studies have yielded different findings. Grunewal et al. (2017) explored a "trade-off" relationship between income inequality and ecological footprint in a sample of developed and developing economies. Zhang and Zhao (2014) investigated mixed results in China, while Jorgenson et al. (2017) found a positive relationship between income inequality and ecological footprint in the United States.

Knight et al. (2017) analyzed developed economies and found a positive relationship between income inequality and ecological footprint, while Ota (2017) observed mixed results in Asian developing economies. Baloch et al. (2020) studied Pakistan using ARDL and found a positive relationship. Masud et al. (2020) examined Vietnam, Thailand, Malaysia, the Philippines, and Indonesia, obtaining mixed results. Demir et al. (2019) focused on Turkey and found a negative relationship between income inequality and ecological footprint. Bhattacharya (2019) explored Indian data and found a negative relationship.

Khan, Yanhong. et al. (2021) examine 18 Asian developing countries from 2006 to 2017, and want to show the nexus between income inequality, poverty, and ecological footprint. For analysis of this relationship, Driscoll-Kraay (D-K) standard error regression, for the detection of heteroscedasticity, serial correlation, and cross-sectional dependence. They have used the Ecological footprint as a dependent variable, the poverty headcount ratio, and the Gini coefficient for income inequality, GDP per capita, FDI, population growth, inflation, access to electricity, forest area, and manufacturing share of GDP. Poverty and income inequality are dangerous for the ecological footprint, and the EKC hypothesis does hold for selected countries. Inflation and Access to Electricity are negatively and significantly related; manufacturing value added is negatively but insignificantly related. FDI, forest area, and population growth are positively correlated. Ansari, Ahmad, et al. (2020) investigate their research on Gulf Cooperation countries (GCC) because these countries are highly energy abundant and use countries, taking long time periods from 1991 to 2017, and want to test EKC hypothesis holds for GCC or not. For this analysis, they have used ecological footprint as a proxy for environmental degradation, and GDP per capita, globalization, and energy consumption are used as independent variables. CADF, CIPS. Westerlund test, FMOLS (Fully Modified OLS), and DOLS (Dynamic OLS); these Econometrics techniques are used for analysis. Energy consumption and globalization are positively related to ecological footprint, and the EKC does not hold for GCC countries. Khan, Yahong (2021), the research is based on the relationship between income inequality and environmental degradation (in terms of ecological footprint and CO₂ emission) for the years 2006 to 2021 of 18 Asian developing economies by using Driscoll & Kraay's standard error estimator. Dependent variables are used for EF and CO₂ emission, and income inequality (Gini coefficient), FDI, Population growth, GDP per capita, and Electricity access are used as independent variables. They have found that there is a bidirectional causality between income inequality, ecological footprint, and CO₂ emission. FDI, access to electricity, and population growth decrease income inequality but increase environmental degradation; the EKC hypothesis no longer holds. Dorn, Maxand & Kneib (2021) research is based on the relationship between carbon emissions and income inequality, focused on the non-linearity and bidirectional and country-specific differences. The theoretical logic behind the different relation between income inequality and ecological footprint is that for a positive relation status of lobbying consumption, a negative relation occurs if carbon-intensive goods consumption is less among the poor people. Methodology is used in bivariate distributional copula regression and panel data regression for 154 countries from 1960 to 2019. They divided all countries into three different income groups: High-income countries, Middle-income countries, and Low-income countries. According to Çatık et al. (2024), the scope of research is for 49 countries from 1995 to 2018, and aims to show the impact of globalization, energy consumption (renewable and non-renewable energy consumption), and income inequality on ecological footprint. The innovativeness of this article is that an innovative methodology has been used in this article; they have used the second-generation Panel data regression model (like Common Correlated Effects (CCE) estimator, dynamic common correlated effects, factor-augmented model, and cross-sectionally augmented ARDL, Panel Unit Root & Cointegration tests allowing CSD, CIPS, and Westerlund) and Panel Threshold Error Correction Models (PTECM). The Panel threshold model identifies the non-linearity of different independent variables' effect, for getting better result of threshold model author separated two growth regime upper and lower growth regime. They have found that income inequality and non-renewable energy significantly increase the ecological footprint, but renewable energy significantly decreases the ecological footprint, and for both, the EKC hypothesis does not hold (positively related). Wang, Yang. et al. (2024) studied 62 countries from 2012 to 2020, and corruption is often linked with income inequality and its impact on carbon emissions. They have used a Threshold panel regression model. They have found that corruption increases carbon

emissions driven by income inequality. P Das, S Bisai, and S Ghosh(2022) explore the impact of past pandemics on the distribution of income across income groups(high income group, upper-middle income group, lower-middle income group, and lower income group), covering the study periods from 1995 to 2017 for the 70 countries. They have used a panel data regression model (GLS method) for the study. They have found that the past pandemic has had a negative impact on upper middle income country, a positive impact on high income country, and on all 70 countries. MA Baloch, SUD Khan, ULUCAK, A Ahmad (2020)examine the effect on CO₂ emission by the cause of income inequality, per capita income, and poverty for the 40 Sub-Saharan African countries over the period 2010 - 2016. They have used Driscoll Kray regression estimation technique, and they have found that income inequality and poverty increase the CO₂ emission in the Sub-Saharan countries. G Wan, C Wang, J Wang, X Zhang (2022),they work on 217 countries from 1960 to the present, the instrumental variable approach shows that there is a trade-off relationship between income inequality and CO₂ emission for the selected countries. Hayat Khan, Liu Weil, Itbar Khan, and Lei Han (2021)interpret how income inequality and institutional quality affect the CO₂ emissions for the 180 sample countries for the years 2002 to 2019. The study used OLS, Fixed Effects, and System Generalized Method of Movement and got the result that income inequality, institutional quality, financial development, and economic growth have a direct positive relation with carbon emission, but carbon emission is reduced by the increase of trade openness and renewable energy consumption. Sohail Abbas, Shazia kousar and Amber Pervaiz (2021) studied two dimensions: the effect of traditional energy use, ecological footprint, urbanization, renewable energy, and transportation on CO₂ emission in Pakistan, which is one dimension, and interpreted the correlation between temperature and CO₂ emission over Pakistan. They have found no short-run significant relationship between CO₂ emission and traditional energy, renewable energy, and ecological footprint, but have a long-run positive relationship with the traditional energy and ecological footprint, and a negative relationship with the renewable energy use. And they also found that CO₂ emissions, urbanization, and transportation increase the average temperature significantly in the short run and in the long run in Pakistan. Wajahat Ali, Azrai Abdullah, and Muhammad Azam (2017)investigated the EKC hypothesis for Malaysia for a long period of time. ARDL and causality tests are used for testing the long-run causality, but for the robustness check Dynamic Ordinary Least Squares (DOLS) method is used. According to the causality test, there is no bidirectional causality in the short run among the variables, but in the long run, bidirectional causality between energy consumption and CO₂ emission, and unidirectional causality among others variables with CO₂ emission, the EKC hypothesis is valid for Malaysia for the corresponding time periods. Salim Khan and Wang Yahong (2021)work on the symmetric and asymmetric impact of poverty, income inequality, along with population, economic growth, on carbon emission.

3. Theoretical background

The Ecological Footprint measures the total human demand on biological productive land and water required to meet the human demand and absorb waste. It is the composite indicator to measure the pressure on the environment (Wackernagel & Rees, 1996). A high ecological footprint means a high level of environmental degradation and more pressure on the environment. Income Inequality is the unequal distribution of income among individuals and households within a society. Several methods are available for measuring income inequality, such as the Gini coefficient, income shares, or the Theil index.

There is a different theoretical background that shows how income inequality relates to the ecological footprint, the Consumption-Inequality hypothesis: Rich people always consume more in an unsustainable way, but poor people's consumption is less, and the consumption pattern is unsustainable, and middle-income people always emulate the rich people's unsustainable lifestyle. Relative income hypothesis: Individuals emulate consumption patterns of higher-income groups ("keeping up with the rich"), which escalates ecological damage. Therefore, an unequal society will lead to a larger ecological footprint. But this type of positive relationship does not always hold; if rich people follow a sustainable lifestyle and consumption, and middle-income and poor people emulate the rich people's consumption pattern, then an unequal society will lead to less ecological footprint consumption. In that case ecological footprint will be

negatively correlated with income inequality, Dorn, Maxand & Kneib (2021), because of lobbying consumption patterns, a positive relation happens, a negative relation will happen if carbon-intensive goods consumption is less among the poor people.

From a political economy perspective, income inequality leads to more environmental degradation, and rich people always focus on more economic growth by using their political power, irrespective of concern with environmental sustainability, but the poor fall behind in political awareness and power; therefore, they are not able to demand sustainable environmental goods.

4. Database and Methodology

The current study utilizes cross-country panel data from 55 countries spanning the period from 1995 to 2018. These countries have been categorized into four distinct groups based on their income levels, namely higher-income countries, upper-middle-income countries, lower-middle-income countries, and lower-income countries. The key variables under investigation are environmental degradation, represented by Ecological Footprint (EF), and income inequality, represented by GINI. Additionally, control variables have been considered: GDP per capita (constant 2017 international \$) and FDI net inflows (% of GDP), Urban population(URB) (% of the total population), Population growth(POP) (annual %), Manufacturing, value added(MANF) (% of GDP), Inflation, consumer prices(CPI) (annual %), Forest area(FRST) (sq. km). The data on income inequality is sourced from the "Standardized World Income Inequality Database," while the EFP data is gathered from the "Global Footprint Network (GFN)." GDP per capita, and FDI net inflow, Urban population (% of the total population), Population growth (annual %), Manufacturing, value added (% of GDP), Inflation, consumer prices (annual %), Forest area (sq. km) are collected from "World Development Indicators". The unit of measurement for Ecological Footprint is global hectares (Gha), cropland, grazing land, forest land, fishing ground, and built-up land. Forest land serves two distinct and competing uses: Forest products and CO₂ sequestration.

It should be noted that the data on income inequality and Ecological Footprint are available for limited years and countries. While income inequality data is available for 69 countries from 1995 to 2020, EFP data is only available for 55 countries from 1995 to 2018. Thus, the analysis is focused on the 55 countries that have data for both income inequality and EFP during the period from 1995 to 2018.

In our research, we employ static panel data regression models to investigate the relationship between ecological footprint and income inequality over time. We estimate these models through a Pooled regression model, fixed and random effects model, using ordinary least squares (OLS) estimation, generalized least squares (GLS) estimation, and least squares dummy variables (LSDV) estimation for the parameters of the fixed and random effect models, respectively.

To ascertain the importance of decomposing the constant and error term, we apply the Wald test, the Breusch and Pagan Lagrange Multiplier test, and the Restricted F-test. Additionally, we employ the Hausman specification test to determine the best-fit model. The primary objectives of this study are to test whether income inequality significantly varies across different groups of countries and whether Ecological Footprint is significantly higher in high-income group countries compared to low-income group countries. To facilitate multiple comparisons among different country groups, we use the "ANOVA" technique.

The panel data regression model is represented as follows:

$$\ln EF_{it} = \alpha + \beta \text{Dummy}_i + \beta_{it} \ln X_{it} + t_i + \delta_i + \varepsilon_{it}$$

Where EF denotes the ecological footprint per capita, X represents the vector of independent variables, and the subscripts $i = 1, N$ denote the country, while $t = 1, T$ denotes the time. The vector X comprises macroeconomic variables, including the Gini coefficient of inequality (net of taxes), FDI (Net inflows (% of GDP)), and GDP per capita (constant 2017 international \$), Urban population(URB) (% of total population), Population growth(POP) (annual %), Manufacturing, value added(MANF) (% of GDP), Inflation, consumer prices(CPI) (annual %), Forest area(FRST) (sq. km). Three dummy variables, dummy1,

dummy2, and dummy3, are used to compare differences in per capita Ecological Footprint between the higher income group and lower income group, upper-middle income group and lower income group, and lower-middle income group and lower income group, respectively. δ represents the unobserved country-level fixed effect, tt represents the time-fixed effect, and ε represents the error term. The logarithmic transformation is applied to the concerned variables, and all variables except the dummy are converted into their logarithmic counterparts to address distributional properties and derive elasticities.

5. Results

5.1 Trends and Variation of Income Inequality Across Different Groups of Countries:

Fig. 1 displays the variability of Gini inequality in the recent year (2018) for different groups of countries. Among higher-income countries, Uruguay exhibited the highest Gini inequality at 49.0, while Australia demonstrated the lowest at 34.3. This indicates a substantial variability of Gini values among higher-income countries. In the case of upper-middle-income countries, South Africa displayed the highest Gini inequality of 66.9, and Brazil showed the lowest at 37.4, revealing considerable variability within this group. Similarly, among lower-middle-income countries, Tunisia had the highest Gini inequality at 60.9, while Bhutan had the lowest at 48.6, indicating significant variability. However, in the case of lower-income countries, there was relatively little variation in Gini inequality values. Overall, South Africa had the highest Gini value at 66.9, and Australia had the lowest at 34.3, highlighting substantial variability across all countries.

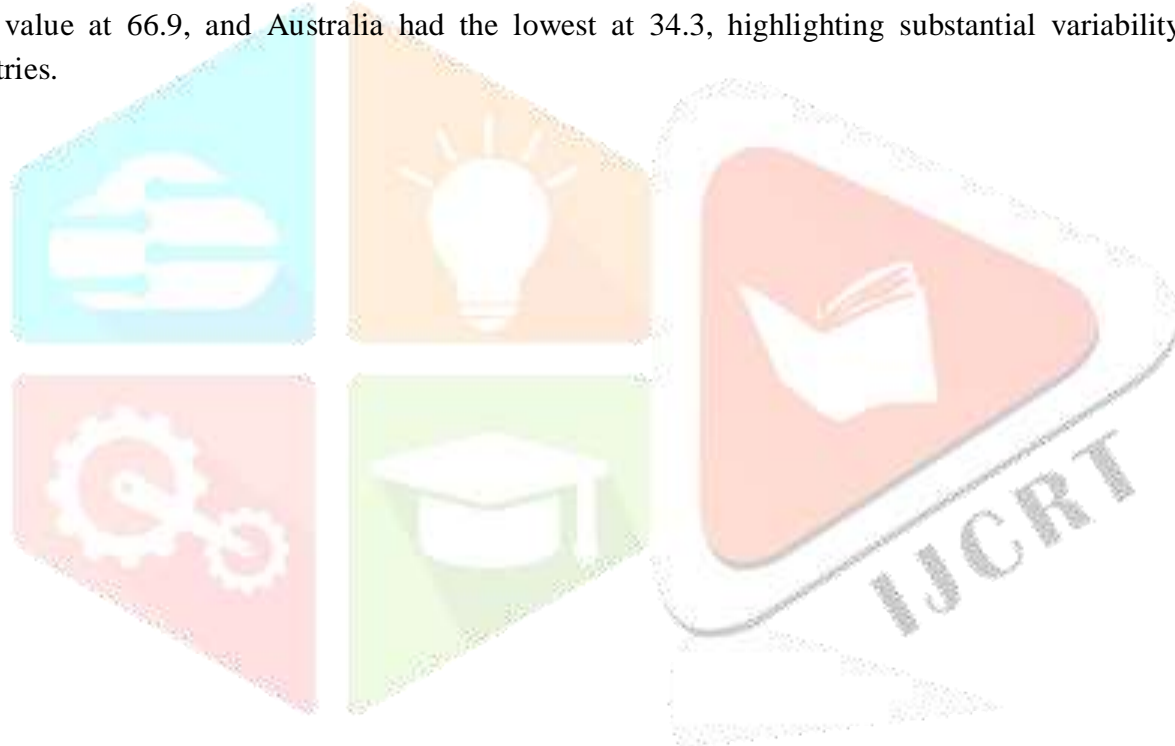
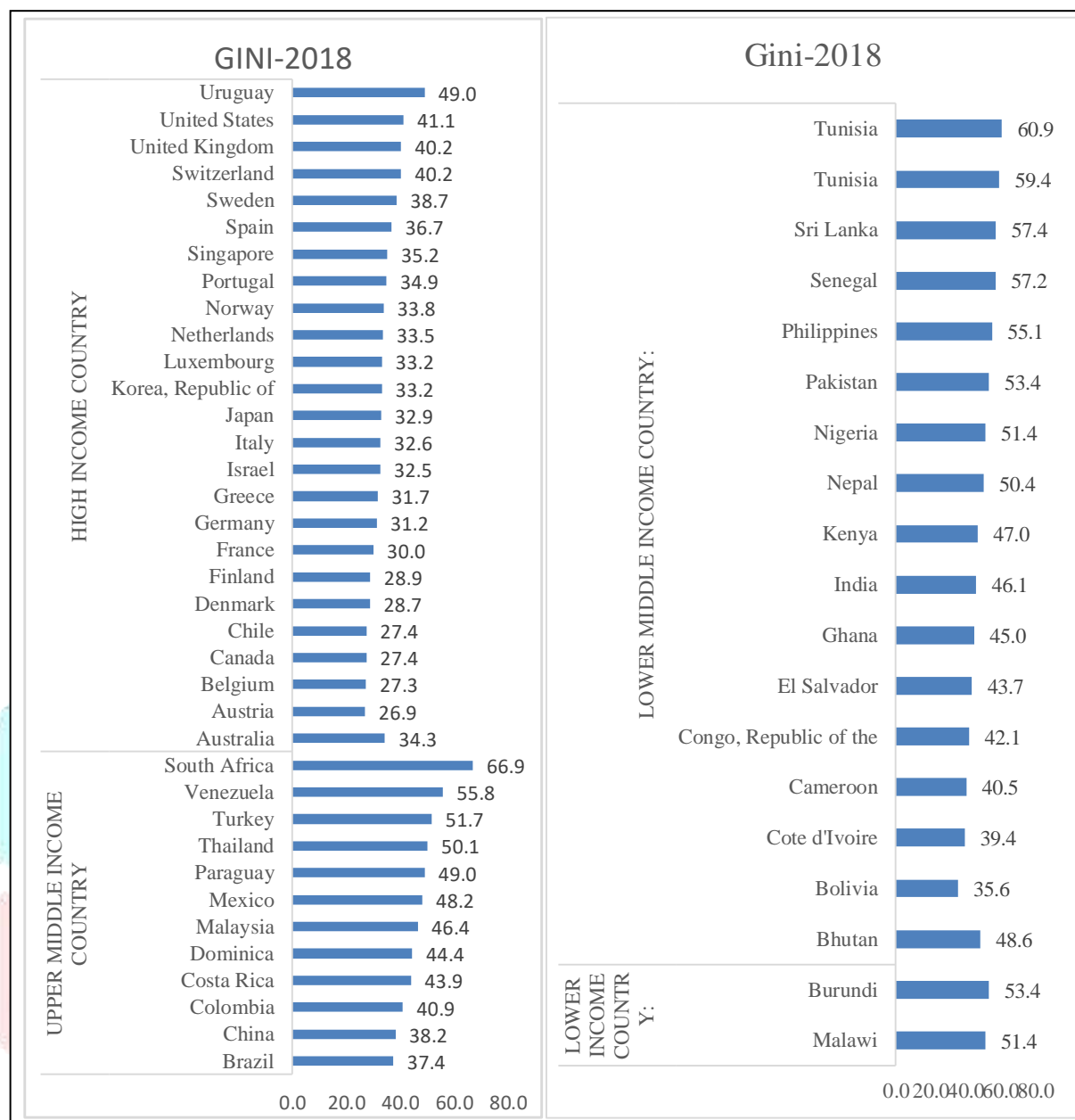


Figure 1: Gini across Countries, 2018



ANOVA table (Table 1A) indicates that the model is well-fitted, as the calculated value of the F-statistic is 809.46, significant at the 0% level. Tukey test (Table 1B) results allow for comparisons of mean Gini index values across different groups of countries. Specifically, comparing higher-income countries to upper-middle-income countries, we find a significant negative mean difference of "-16.02," signifying that higher-income countries have lower income inequality. Similarly, comparing higher-income countries to lower-middle-income countries, there is a significant negative mean difference of "-16.96," indicating lower income inequality in higher-income countries. Moreover, the mean difference in Gini index value between higher income and lower income countries is "-23.1," significant at the 0% level, signifying that higher income countries have lower income inequality than lower income countries. Regarding the comparison between upper-middle and lower-middle-income countries, the mean difference is "-0.93," significant at the 24.3% level, indicating no significant difference in income inequality. Finally, the mean difference between upper-middle and lower-income countries is "-7.07," significant at the 0% level, and the mean difference between lower-middle and lower-income countries is "-6.14," significant at the 0% level.

Table 1A: ANOVA of Gini among four groups of countries

Groups	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	102438.282	3	34146.094	809.5	0
Within groups	57538.688	1364	42.184		
Total	159976.97	1367			

Table1B: Gini Tukey HSD

(I) CG	(J)CG	Mean Difference (I-J)	Std. Error	Sig
1(High income country)	2	-16.02915*	0.46559	0
	3	-16.96207*	0.41677	0
	4	-23.10296*	0.81006	0
2(Upper-middle income country)	3	-0.93292	0.49986	0.243
	4	-7.07381*	0.85578	0
3(Lower-middle income country)	4(Lower income country)	-6.14089*	0.83023	0

*Denotes the level of significance at 1% level.

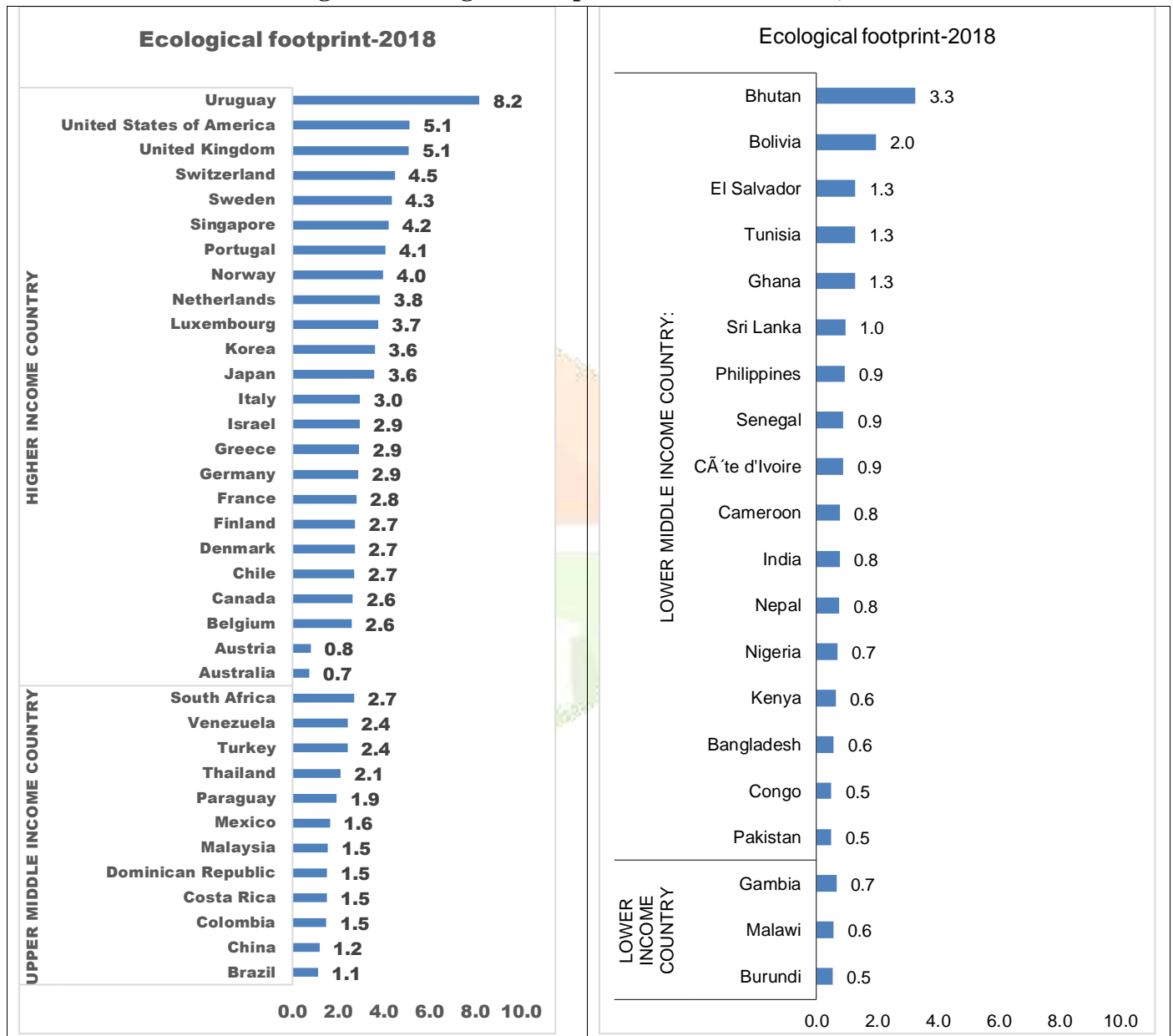
Source: Compilation Author

5.2 Trends and Variation of Ecological Footprint Across Different Groups of Countries:

To illustrate the trends of Ecological Footprint across different groups of countries, we present the Ecological Footprint (measured in global hectares) for the year 2018 for each group. The statistical bar diagram aids in comprehending these trends. Additionally, the ANOVA technique is utilized to examine the variation of the Ecological Footprint across the group. Fig. 2 demonstrates the Ecological Footprint values for different country groups in 2018. In the higher-income country groups, Uruguay achieved the highest position, 8.2gha, and Australia achieved the lowest ecological footprint, 0.7gha. South Africa's ecological footprint is 2.7gha, and Brazil's ecological footprint is 1.1gha, which are the highest and lowest ecological footprints in the upper middle-income country. There is a significant variation of ecological footprint across countries, in particular, income groups, and across income groups. This indicates that countries with the same level of income but different levels of economic activities that reflect the variation of ecological footprint or environmental degradation across countries in the same income group. In the lower-middle income group country Bhutan achieved the highest ecological footprint, 3.3gha, and Pakistan and Congo achieved the lowest ecological footprint, 0.5gha. Here, the ecological footprint also varies across countries. In the lower-income country Gambia ecological footprint is 0.7gha, and Burundi is 0.5gha, which are the highest and lowest ecological footprints in lower-income countries. In lower income country, there is less variation in ecological footprint values. The ecological footprint has emerged as a comprehensive indicator for assessing human pressure on the natural environment by measuring the biologically productive land and water required to sustain consumption and absorb waste. Over the past few decades, substantial variation and divergent trends in ecological footprint have been observed across different groups of countries, reflecting disparities in income levels, stages of development, population growth, and consumption patterns. At the global level, the total ecological footprint has increased continuously, primarily driven by rising population and expanding economic activity, although per-capita trends differ markedly across country

groups. High-income and developed countries consistently exhibit the highest per-capita ecological footprints. This pattern is largely attributable to energy-intensive lifestyles, high levels of material consumption, and dependence on fossil fuels. Although several developed economies have experienced stabilization or modest declines in per-capita ecological footprints in recent years due to technological efficiency, environmental regulations, and a transition toward renewable energy sources, their overall ecological pressure remains disproportionately high. These countries often operate under conditions of ecological deficit, where national consumption exceeds domestic biocapacity, leading to reliance on global resource trade and environmental externalization.

Figure 2 Ecological Footprints across Countries, 2018



The ANOVA table (Table 2A) indicates that the model is well-fitted, as the calculated value of the F-statistic is 702.32, significant at the 0% level. Tukey test results (Table 2B) enable comparisons of mean Ecological Footprint values across different groups of countries. Comparing higher-income countries to upper-middle-income countries, we find a significant positive mean difference of “1.89”gha, indicating a higher Ecological Footprint in higher-income countries. Likewise, comparing higher-income countries to lower middle-income countries, the mean difference is “2.64”gha, significant at the 0% level, suggesting a higher Ecological Footprint in higher-income countries compared to lower middle-income countries. Additionally, the mean difference between higher income and lower income countries is “2.97”gha, significant at the 0% level, implying a higher Ecological Footprint in higher income countries than in lower income countries.

However, the mean difference between upper-middle and lower-middle-income countries is “0.74”gha, significant at the 0% level, signifying a significant difference. Finally, the mean difference between upper-middle and lower-income countries is “1.07”gha, significant at the 0% level, and the mean difference between lower-middle and lower-income countries is “0.32”gha, significant at the 5.2% level, indicating an insignificant difference.

Table 2A. ANOVA Results of EF among four groups of countries

Groups	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2054.676	3	684.892	702.323	.000
Within Groups	1329.172	1363	.975		
Total	3383.848	1366			

Table 2 B. Tukey HSD

(I) CG	(J) CG	Mean Difference (I-J)	Std. Error	Sig.
1(High income country)	2	1.89*	0.07	0.000
	3	2.65*	0.06	0.000
	4	2.97*	0.12	0.000
2(upper-middle income country)	3	.749*	0.07	0.000
	4	1.07*	0.13	0.000
3(Lower-middle income country)	4(Low-income country)	0.323	0.12	0.052

*Denotes the level of significance at 1% level.

Source: Compilation Author.

5.3 Relationship between Income Inequality and Ecological Footprint: A Panel Data Analysis Across Countries.

In our study, we aimed to investigate whether income inequality significantly affects the ecological footprint. To achieve this, we employed a regression model, specifically a Panel data regression model (Random Effects Model – REM and Fixed Effects Model – FEM, Pooled Reg Model).

Table-3 presents the results for higher-income, upper-middle-income, lower-middle-income, and all countries. Based on the Breusch and Pagan LM test, chibar2, which is significant at the 0% level, and the “F test that all $u_i = 0$: F()” being significant at the 0% level, we concluded that Random Effect GLS estimation is more appropriate than the pooled regression OLS model. Additionally, the Hausman chi2(0) test was insignificant, indicating that REM is a better model than FEM, but for lower income countries LM test and the Restricted F-test are statistically insignificant; therefore Pooled regression model is a better model for lower income countries.

For the higher income group, the R-squared values indicate that the variability of independent variables explains 39.7% of the variability of the ecological footprint (R-sq: overall), while 13% of the within-group variability and 49.5% of the between-group variability are explained (R-sq: within and R-sq: between, respectively). The estimated coefficient of Gini (main) suggests a negative relationship between income inequality and ecological footprint; it is statistically significant (significant at less than a 10% level). On the other hand, the coefficients of GDP (control) and FDI (control) indicate a positive relationship with the ecological footprint, with GDP being significant at less than 1% level and FDI being significant (significant at less than 10% level) and others variables like Forest area(FRST) (sq. km), Manufacturing, value added(MANF) (% of GDP) are negatively correlated with Ecological Footprint but FRST is insignificant (significant at 79%) and MANF is significant at less than 5% level. Population growth (POP) (annual %)

has a positive and significant relationship with ecological footprint (significant at less than 10% level), but Urban population (URB) (% of total population) has a positive and insignificant relation (significant at 16% level).

For the upper-middle-income group, the R-squared values show that the independent variables account for 35% of the ecological footprint's variability (R-sq: overall), with 74% and 24% of the within-group and between-group variability being explained, respectively. The estimated coefficient of Gini (main) indicates a significant positive relationship with the ecological footprint (significant at the 0% level), suggesting that a 1% increase in income inequality leads to a 40.52% increase in the ecological footprint. The coefficients of GDP (control), FRST, CPI, and POP are positive, with GDP being significant at the 0% level, while FRST at 0% level and CPI are insignificant, but POP is significant at 0% level. On the other hand, MANF and URB have a negative relationship with ecological footprint; MANF is significant at 0% level, but URB is insignificant.

For the lower-middle-income group, the R-squared values suggest that the independent variables explain 42% of the ecological footprint's variability (R-sq: overall), with 70.8% and 40% of the within-group and between-group variability being explained, respectively. The estimated coefficient of Gini (main) indicates a significant positive relationship with the ecological footprint (significant at 0% level), with a 1% increase in income inequality leading to a 16% increase in the ecological footprint. The coefficients of GDP (control), CPI, POP, and URB are positive, with GDP being significant at the 0% level, and CPI, POP, and URB are significant at 0%, 0%, and 30% level, while FDI, FRST, and MANF show a negative relationship with the ecological footprint, significant at 90%, 20%, 50% respectively.

Considering all countries in our analysis, the R-squared values indicate that the independent variables explain 80.5% of the ecological footprint's variability (R-sq: overall), with 37% and 82% of the within-group and between-group variability being explained, respectively. The estimated coefficient of Gini (main) shows an insignificant positive relationship with the ecological footprint, indicating that a 1% increase in income inequality leads to a 4.9% increase in the ecological footprint. The coefficients of GDP (control) and FDI (control), except MANF, are all variables that are positively related to Ecological Footprint, with GDP being significant at the 0% level, while FDI is insignificant (significant at 30% level).

The relationship between income inequality and ecological footprint has become an increasingly important theme in environmental economics and sustainability studies, particularly in the context of cross-country panel data analysis. Income inequality influences patterns of production, consumption, and resource use in ways that directly affect environmental pressure. Countries with high levels of income inequality often display polarized consumption structures, where affluent groups engage in resource-intensive lifestyles while poorer sections rely heavily on natural resources for survival. This uneven distribution of income tends to increase the overall ecological footprint, as luxury consumption, energy-intensive goods, and carbon-heavy transportation dominate economic activity, outweighing the relatively low ecological impact of poorer populations. The political economy perspective further explains how inequality shapes environmental outcomes. High income inequality often leads to unequal political influence, allowing wealthier groups to shape environmental policies in favor of continued resource exploitation. This weakens environmental governance and delays the transition toward sustainable production systems. Panel regression results frequently show that countries with lower income inequality tend to have stronger environmental institutions and lower ecological footprints over time, even when controlling for GDP growth, urbanization, and energy consumption. This suggests that equitable income distribution contributes indirectly to environmental sustainability by fostering collective action and long-term policy commitments.

At the same time, the relationship between income inequality and ecological footprint is not uniform across all countries. Panel data evidence reveals non-linear and context-specific effects, particularly between developed and developing nations. In low-income countries, inequality may initially be associated with lower ecological footprints due to limited overall consumption; however, as economic growth accelerates, inequality amplifies environmental degradation. This dynamic aligns with extensions of the Environmental Kuznets Curve hypothesis, where income distribution acts as a conditioning factor influencing the trajectory of environmental impact over time. The relationship between income inequality and ecological footprint has

gained increasing attention in environmental economics, as rising disparities in income distribution are believed to influence patterns of resource consumption and environmental pressure across countries. The ecological footprint, which measures the demand placed on natural ecosystems by human activities, provides a comprehensive indicator to examine how unequal income distribution affects environmental sustainability. Using panel data analysis across countries allows for capturing both cross-sectional and temporal variations, thereby offering a robust framework to analyze this complex relationship.

Income inequality affects ecological footprint through multiple channels. In highly unequal societies, affluent segments of the population tend to consume disproportionately large quantities of energy, land, and natural resources, thereby increasing the overall ecological footprint. Luxury consumption, higher carbon-intensive lifestyles, and excessive material use among high-income groups significantly contribute to environmental degradation. At the same time, lower-income populations often lack access to clean technologies and efficient energy systems, leading to environmentally harmful coping strategies such as reliance on biomass fuels or informal resource extraction. This dual effect intensifies ecological pressure, particularly in developing and emerging economies. Panel data studies across developed and developing countries consistently indicate a positive association between income inequality and ecological footprint, though the magnitude and direction of this relationship vary across income groups. In high-income countries, inequality tends to amplify ecological footprint by reinforcing overconsumption patterns among the wealthy, even when overall economic growth stabilizes. In contrast, in low- and middle-income countries, income inequality often interacts with rapid urbanization, population growth, and weak environmental regulations, resulting in rising ecological footprints as economies expand. These findings challenge the assumption that economic growth alone can lead to environmental improvement without addressing distributional concerns.

Table 3: Results of Panel Data Regression Models (Random Effect Model).

Variables	High-income country		Upper-middle-income country		Lower-middle-income country		All country	
	Coeff	Prob	Coeff	Prob	Coeff	Prob	Coeff	Prob
Dependent variable LNEF								
dummy1	0	0	0	0	0	0	0.295	0
dummy2	0	0	0	0	0	0	0.199	0.1
dummy3	0	0	0	0	0	0	0.106	0.3
LNGDP	0.2645	0	0.5692	0	0.573	0	0.444	0
LNGINI	-0.1959	0.07	0.4052	0	0.169	0	0.049	0.5
LNFDI	0.0001	0.09	-4E-05	0.7	-5.52	0.9	3E-05	0.3
LNFRST	-0.0017	0.8	0.0359	0	-0.011	0.2	4E-04	0.9
LNCPI	0.0001	0.25	2E-05	0.9	2E-04	0	3E-05	0.3
LNMANF	-0.080	0.04	-0.057	0	-0.015	0.5	-0.004	0.8
LNPOP	0.0001	0.05	0.0004	0	3E-04	0	1E-04	0
LNURB	0.141	0.16	-0.028	0.4	0.027	0.3	0.062	0
Constant	-0.624	0.12	-2.93	0	-2.511	0	-2.057	0
Number of observations	576	0	264	0	408	0	1296	0
R-sq:overall	0.397	0	0.3528	0	0.423	0	0.805	0
R-sq:within	0.131	0	0.7397	0	0.708	0	0.374	0
R-sq:between	0.495	0	0.2372	0	0.401	0	0.822	0
Wald chi2()	94.79*	0	707.17*	0	947.33*	0	966.77*	0
Breusch and Pagan LM test,	2330*	0	1216.61	0	3975.01	0	10181.35*	0

chibar2()			*		*			
F test that all $u_i = 0$: F()	71.76*	0	129.3*	0	452.82*	0	149.32*	0
Hausman chi2(0)	0.000	0	0	0	0	0	0	0

*Denotes the level of significance at 1% level.

Source: Compilation Author.

In Table 3, we introduced three dummy variables for comparing per capita ecological footprints (gha) between different country groups. The coefficients of these dummies reveal significant differences in ecological footprints between higher and lower-income countries, upper-middle and lower-middle-income countries, and lower-middle and lower-income countries. Positive values suggest higher ecological footprints in the mentioned groups compared to lower-income countries.

In Table 4, we have applied Pooled regression OLS estimation for the lower-income country group, as the Breusch and Pagan LM test, chibar2(), is insignificant, indicating that the pooled regression OLS model is better than Random Effect GLS estimation. Additionally, the "F test that all $u_i = 0$: F ()" is also insignificant, which indicates the Pooled OLS is better than the restricted F-test.

For the lower-income group, the R-squared values indicate that the independent variables explain 45% of the ecological footprint's overall variability (R-sq: overall), with 42% of the within-group variability and 99.5% of the between-group variability being explained (R-sq: within and R-sq: between, respectively). The estimated coefficient of Gini (main) suggests a negative relationship with the ecological footprint, but it is statistically insignificant (significant at 44.9% level). The coefficient of GDP (control) is negative and significant at the 7.3% level, indicating that a 1% increase in GDP per capita leads to a 18.7% decrease in the ecological footprint.

Table 4. Pooled Regression Model estimation for the lower-income country group.

Variables	Lower-income country	
Dependent variable LNEF	Coefficient	Prob
LNGDP	-0.302	0.001
LNGINI	-0.617	0.328
LNFDI	-0.001	0.146
LNMANF	-0.446	0.003
LNFRST	-0.149	0.364
LNCPI	-0.0005	0.442
LNPOP	0.0021	0.101
LNURB	-0.081	0.131
Constant	2.922	0.008
R-squared:	0.722	0
Adj R-squared:	0.665	0
No of observations:	48.000	0
F-test	12.64*	0
Breusch and Pagan LM test, chibar2()	0.000	1
F test that all $u_i = 0$: F ()	3.250	0.0792

*Denotes the level of significance at 1% level.

Source: Compilation Author.

6. Conclusions

The present research study has shed light on the intricate connection between environmental quality and income inequality, emphasizing the significance of considering both factors in the pursuit of Sustainable Development Goals (SDGs). By meticulously analyzing data from 55 economies encompassing developed, developing, and underdeveloped nations spanning the years 1995 to 2018, the study has explored the relationship between environmental degradation and income inequality. To ensure comprehensiveness, several control group variables, including GDP per capita and FDI net inflows (% of GDP), Forest area (FRST) (sq. km), Manufacturing, value added (MANF) (% of GDP), Population growth (POP) (annual %), Urban population (URB) (% of total population) were incorporated in the analysis.

From the empirical findings, it became apparent that most inequality measurements, namely Gini, demonstrate a positive relationship between income inequality and ecological footprint. However, it is worth noting that this relationship proved to be statistically insignificant in certain instances. Specifically, in the Gini measurement for all countries and a negative, insignificant relation in lower income country. The underlying economic rationale for the positive relationship between income inequality and ecological footprint can be attributed to the fact that heightened income inequality often translates to a smaller cumulative percentage of the population having access to a disproportionately large share of resources, while a larger cumulative percentage faces resource scarcity. Consequently, affluent individuals are more capable of acquiring environmentally friendly goods, whereas impoverished individuals remain dependent on natural resources, leading to an increase in ecological footprint and environmental degradation.

Furthermore, the empirical results revealed a positive correlation between GDP per capita growth and Ecological Footprint. This is driven by the basic economic principle that rising per capita income augments individuals' purchasing power, subsequently increasing the ecological footprint.

Similarly, the findings indicated a positive relationship between FDI inflows and ecological footprint. This can be elucidated by the fact that increased foreign private investment tends to spur urbanization and escalates the demand for natural resources, thereby amplifying the ecological footprint. Additionally, while FDI inflows may boost GDP per capita and potentially alleviate poverty, inclusive growth can simultaneously contribute to income inequality, subsequently leading to an increase in ecological footprint. Except for Upper-middle income and Low-income countries, the urban population (URB) (% of the total population) has a positive and significant relationship with an ecological footprint. The rationale behind that positive relation is that if more people are going to urban areas, then resource demand will increase. Forest area (FRST) (sq. km) and ecological footprint are negatively related except in upper-middle-income countries. The rationale behind this relation is that more forest area will absorb more carbon pollution, which will reduce the ecological footprint. Population growth (POP) (annual %) is positively and significantly (Lower income country) related to the ecological footprint, because if population growth increases, then demand for resources will also increase, which will increase the ecological footprint.

In light of our analysis, it was observed that income inequality significantly varies across different groups of countries, thus corroborating our first hypothesis. Moreover, the ecological footprint was found to be higher in high-income countries and lower in low-income countries, affirming our second hypothesis. Lastly, both the Random Effects Model (REM) and Fixed Effects Model (FEM) demonstrated that income inequality has a significant positive effect on ecological footprint, lending support to our third hypothesis.

In light of these insights, governmental policies ought to prioritize initiatives that alleviate income inequality, as a reduction in income disparity is likely to yield a subsequent decrease in ecological footprint. And the government should also take initiatives to reduce population growth, % of the urban population, and increase the forest areas, which will possibly lead to a subsequent decrease in ecological footprint. By adopting such measures, the pursuit of Sustainable Development Goals (SDGs) can be effectively advanced.

References

1. Abbas, S., Kousar, S., & Pervaiz, A. (2021). Effects of energy consumption and ecological footprint on CO₂ emissions: an empirical evidence from Pakistan. *Environment, Development and Sustainability*, 23(9), 13381-13395.
2. Ali, W., Abdullah, A., & Azam, M. (2017). Re-visiting the environmental Kuznets curve hypothesis for Malaysia: Fresh evidence from the ARDL bounds testing approach. *Renewable and Sustainable Energy Reviews*, 77, 990-1000.
3. Ansari, M. A., Ahmad, M. R., Siddique, S., & Mansoor, K. (2020). An environmental Kuznets curve for ecological footprint: Evidence from GCC countries. *Carbon Management*, 11(4), 355-368.
4. Ansari, M. A., Ahmad, M. R., Siddique, S., & Mansoor, K. (2020). An environmental Kuznets curve for ecological footprint: Evidence from GCC countries. *Carbon Management*, 11(4), 355-368.
5. Baloch, M. A., Khan, S. U. D., Ulucak, Z. Ş., & Ahmad, A. (2020). Analyzing the relationship between poverty, income inequality, and CO₂ emissions in Sub-Saharan African countries. *Science of the Total Environment*, 740, 139867.
6. Baloch, M. A., Khan, S. U. D., Ulucak, Z. Ş., & Ahmad, A. (2020). Analyzing the relationship between poverty, income inequality, and CO₂ emissions in Sub-Saharan African countries. *Science of the Total Environment*, 740, 139867.
7. Bhattacharya, H. (2020). Environmental and socio-economic sustainability in India: evidence from the CO₂ emission and economic inequality relationship. *Journal of Environmental Economics and Policy*, 9(1), 57-76.
8. Çatık, A. N., Bucak, Ç., Ballı, E., Manga, M., & Destek, M. A. (2024). How do energy consumption, globalization, and income inequality affect environmental quality across growth regimes? *Environmental Science and Pollution Research*, 31(7), 10976-10993.
9. Das, Pinaki, Bisai, S., & Ghosh, S. (2022). Impact of pandemics on income inequality: lessons from the past. *International Review of Applied Economics*, 35(2), 1-19.
10. Demir, C., Cergibozan, R., & Gök, A. (2019). Income inequality and CO₂ emissions: Empirical evidence from Turkey. *Energy & Environment*, 30(3), 444-461.
11. Dorn, F., Maxand, S., & Kneib, T. (2021). *The dependence between income inequality and carbon emissions: A distributional copula analysis* (No. 413). Cege Discussion Papers.
12. Dorn, F., Maxand, S., & Kneib, T. (2021). *The dependence between income inequality and carbon emissions: A distributional copula analysis* (No. 413). Cege Discussion Papers.
13. Grunewald, N., Klasen, S., Martínez-Zarzoso, I., & Muris, C. (2017). The trade-off between income inequality and carbon dioxide emissions. *Ecological Economics*, 142, 249-256.
14. Hieu, V. M. (2022). Influence of green investment, environmental tax, and sustainable environment: Evidence from ASEAN countries. *International Journal of Energy Economics and Policy*, 12(3), 227-235.
15. Jorgenson, A., Schor, J., & Huang, X. (2017). Income inequality and carbon emissions in the United States: a state-level analysis, 1997–2012. *Ecological Economics*, 134, 40-48.
16. Kalina, M. (2021). As South Africa's cities burn, we can clean up, but we cannot sweep away inequality. *Local Environment*, 26(10), 1186-1191.
17. Khan, H., Weili, L., Khan, I., & Han, L. (2022). The effect of income inequality and energy consumption on environmental degradation: the role of institutions and financial development in 180 countries of the world. *Environmental Science and Pollution Research*, 29(14), 20632-20649.
18. Khan, S., & Yahong, W. (2021). Income inequality, ecological footprint, and carbon dioxide emissions in Asian developing economies: what effects what and how? *Environmental Science and Pollution Research*, 29(17), 24660-24671.
19. Khan, S., & Yahong, W. (2021). Symmetric and asymmetric impact of poverty, income inequality, and population on carbon emission in Pakistan: new evidence from ARDL and NARDL co-integration. *Frontiers in Environmental Science*, 9, 666362.

20. Khan, S., Yahong, W., & Zeeshan, A. (2021). Impact of poverty and income inequality on the ecological footprint in Asian developing economies: Assessment of Sustainable Development Goals. *Energy Reports*, 8, 670-679.
21. Knight, K. W., Schor, J. B., & Jorgenson, A. K. (2017). Wealth inequality and carbon emissions in high-income countries. *Social Currents*, 4(5), 403-412.
22. Masud, M. M., Kari, F., Banna, H., & Saifullah, M. K. (2020). Does income inequality affect environmental sustainability? Evidence from the ASEAN-5. In *Climate change mitigation and sustainable development* (pp. 27-42). Routledge.
23. Ota, T. (2017). Economic growth, income inequality, and environment: assessing the applicability of the Kuznets hypotheses to Asia. *Palgrave Communications*, 3(1), 1-23.
24. Rees, W., & Wackernagel, M. (2008). Urban ecological footprints: why cities cannot be sustainable—and why they are a key to sustainability. In *Urban ecology: an international perspective on the interaction between humans and nature* (pp. 537-555). Boston, MA: Springer US.

