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RESEARCH PAPER

A Global and Hemispheric Analysis of the Relationship between Environmental Sustainability and Economic Inequality

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Abstract: In this article, we examine how income distribution and energy use shaped per-capita CO_2 emissions between 1965 and 2022 at three spatial scales—world, northern hemisphere, and southern hemisphere. After re-scaling all the variables to the unit interval, we first estimate separate ordinary least squares regressions and then re-estimate the three equations jointly with Zellner's seemingly unrelated regression, a step warranted by the substantial contemporaneous error correlation. Across both emission channels—aggregate CO_2 and the land-use component—energy consumption emerges as the most consistent and statistically powerful predictor. Inequality effects are heterogeneous. The Gini coefficient amplifies emissions in the southern hemisphere and in the global system but is negligible in the northern fossil-fuel equation, while the Palma ratio reduces land-use emissions once overall inequality is held constant. Temperature anomalies display a further asymmetry, reducing land-use emissions everywhere, yet coinciding with higher fossil-fuel emissions in the south. Joint estimation raises the system-wide goodness of fit to 0.97 for land-use emissions and 0.99 for total emissions and yields more precise coefficients than the separate regressions. The results indicate that decarbonizing energy systems is a universal mitigation priority,

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whereas distributional reforms and land-governance measures are likely to deliver the greatest additional benefits in the southern hemisphere.

Keywords: CO_2 Emissions, Economic Inequality, Energy Consumption, Temperature Anomaly, Regional Analysis.

1. INTRODUCTION

Global climate change, primarily driven by anthropogenic CO_2 emissions, has become a major international concern (Wang *et al.* 2015; Wang and Feng 2017). A large literature links emissions to energy systems and macro-structural drivers—including energy mix and energy intensity (Wang *et al.* 2015; Wang and Feng 2017), industrial structure (Romero and Gramkow 2021; Wang, Kuang, and Huang 2011), economic activity and population scale (Le Quéré *et al.* 2019; Oreggioni *et al.* 2021), and financial/spatial structures shaping carbon intensity (Yan *et al.* 2022). While rising incomes and populations are often associated with higher emissions, they are neither necessary nor sufficient conditions; energy structures and emission intensities frequently emerge as crucial determinants. The relationship between warming and human activities is complex, encompassing energy consumption, human development, and economic activity; yet their relative importance, particularly for less developed countries, continues to be debated (Hao 2022). In recent years, research has increasingly linked socio-economic inequality to environmental outcomes, raising questions about whether—and through which channels—income distribution determines emission intensity (Khan, Yahong, and Zeeshan 2022).

Beyond cross-country averages, who emits within a country matters. Recent assessments have documented that upper-income groups account for a growing fraction of emissions—including in emerging economies—and that within-country emissions inequality now rivals or exceeds between-country gaps (Chancel, Bothe, and Voituriez 2023; Chancel *et al.* 2022; UNEP 2023). This further motivates the use of a lens that can distinguish structural north–south patterns while remaining sensitive to distributional dynamics. However, two gaps remain. First, most of the evidence is national or sub-national—informative for within-country dynamics but not designed to reveal hemispheric asymmetries that may arise from systematic differences in industrial composition, energy intensity, technological diffusion, and policy capacity (Dong, Dou, and Jiang 2022). Second, cross-country comparisons typically rely on a single inequality index—most often Gini—which is less sensitive to tail dynamics than the Palma ratio. Consequently, it is unclear whether conclusions hinge on the chosen inequality metric and whether the inequality–emissions nexus is symmetric across hemispheres over multiple decades.

This article addresses these gaps with a long-horizon global and hemispheric assessment of the association between environmental pressure and income distribution. We link CO_2 emissions per capita (including land-use change emissions) and primary-energy use per capita over the years 1965–2022 with two complementary inequality measures—Gini (overall dispersion, 0–1) and Palma (top 10% over bottom 40%)—using transparent, population-weighted aggregation from country data. Our analysis is guided by three questions: (1) How are inequality and environmental pressure related globally and by hemisphere over the long run? (2) Do these relationships differ meaningfully between the northern and southern hemispheres? (3) Are the main patterns robust to using Gini versus Palma as the inequality proxy?

A rich, theoretical, and empirical literature motivates these questions. Greater inequality can amplify emissions via luxurious consumption by high-income groups and consumption/behavioural channels in developing economies (Ahmad, Muslija, and Satrovic 2021; Pata *et al.* 2022), the political economy of regulation, and unequal access to land and credit, which influences land-use change; conversely, concentrated capital and faster diffusion of clean technologies could mitigate emissions in some settings (Duarte, Miranda-Buetas, and Sarasa 2021; Munasinghe 1999; Ray, Baland, and Dagnelie 2007; Sovacool *et al.* 2022; Sinha *et al.* 2023; Wang, Li, and Li 2023; Wang, Uddin, and Gong 2021). Empirically, results are mixed: Some studies report negative or non-linear links, or neutrality, underscoring the role of context and timing (Ghazouani and Beldi 2022; Mehmood *et al.* 2022; Ngankam 2024; Guo, *et al.* 2022). Over the long run, inequality often appears intertwined with emissions through macro-energy channels (Santillán Salgado, Valencia-Herrera, and Venegas-Martínez 2020).

We bring these strands together in a single comparative framework spanning nearly six decades and three aggregates—global, northern hemisphere, southern hemisphere—and include the global temperature anomaly to characterize the climatic backdrop. Missing values are handled transparently via an iterative machine-learning imputation (Random Forest, 500 trees; internal gaps only), after which country series are aggregated using population weights, with equatorial countries assigned based on majority landmass. We anticipate that energy use per capita will be the most pervasive correlate of emissions across all aggregates. Inequality here signifies hemispheric asymmetries—which are stronger and sign-differentiated in the south—and these patterns are robust to using either

Gini or Palma. Because many series trend over time, we assess unit roots (using the augmented Dickey–Fuller [ADF] test and the Kwiatkowski–Phillips–Schmidt–Shin [KPSS] test) and co-integration (Johansen, Engle–Granger) and estimate error correction models (ECMs) or first-difference models; the core associations persist once common trends are accounted for.

Throughout, coefficients are read as conditional associations rather than causal effects. The global average temperature anomaly is included as an ancillary control—it can influence energy demand and land-use practices in the short run—but we do not assign a causal interpretation to the coefficient of this factor, given its simultaneity with cumulative emissions. The hemispheric lens is informative for large-scale patterns but may mask within-hemisphere heterogeneity. Future work could deploy country or sub-national panel designs with stronger identification to unpack mechanisms. Taken together, our analysis clarifies where inequality appears most associated with emissions, and where energy system transformation is the dominant lever for mitigation.

Finally, to situate our contribution, Table 1 synthesizes representative studies on inequality and emissions—summarizing regions, periods, outcome variables, inequality metrics, and methods alongside headline findings. This comparison clarifies how our hemispheric, dual-metric (Gini and Palma), long-horizon approach—combined with machine learning–based imputation and co-integration-centred estimation—extends the literature.

2. DATA

This study uses a dataset from 1965 to 2022 that examines the relationships between environmental indicators and economic inequality on the global, northern hemisphere, and southern hemisphere scales. The variables analysed include per-capita GHG emissions, annual CO_2 emissions from land-use change per capita, energy use per person, the Gini coefficient, the Palma ratio, the Human Development Index (HDI), and the global average temperature anomaly.

Per-capita GHG emissions are calculated by combining CO_2, CH_4, and N_2O from all sources, including land-use change, measured in tonnes of CO_2 equivalent over a 100-year timescale. The data are sourced from the

Table 1. Selected Studies on Inequality and Emissions: Regions, Methods, Key Findings, and How the Present Study Advances the Field

Study	Regions/ coverage	Period	Scale	Outcomes	Inequality metric(s)	Methods	Key findings	How the present study advances the field
Le Quéré *et al.* (2019)	18 developed economies	2005–2015	National, multi-country	CO_2 emissions	—	Decom-position of drivers	CO_2 reduction linked to efficiency improvements and fuel switching (plus structural changes and consumption demand)	Adds hemispheric comparison; tests inequality channels jointly with energy
Oreggioni *et al.* (2021)	Global (EDGAR v. 5.0)	CO_2 emissions up to 2018 (non-CO_2 emissions up to 2015)	Global	Greenh ouse gas (GHG) trends	—	Trend synthesis	Global GHG trends shaped by socio-economic transitions, technology diffusion, and regulation	Quantifies inequality–emissions relations and north–south asymmetry
Romero and Gramkow (2021)	~67 countries	≈1995–2014	National	GHG emissions	—	Panel econo-metrics	Higher economic complexity associated with lower GHG intensity and per-capita emissions	Jointly models energy per capita and inequality metrics; provides

								hemispheric contrast
Ajide and Ibrahim (2022)	G7 economies	1990–2019	National	CO_2	Inequality (various types)	Panel models	Evidence of inequality–environment associations in advanced economies	Spans global/northern hemisphere/southern hemisphere with dual inequality indices
Ghazouani and Beldi (2022)	7 Asian countries	1971–2014	National	CO_2 emissions per capita	Income inequality	Non-para-metric panel	Non-linear, time-varying relationship; "equity–pollution dilemma"[*]	Tests with Gini coefficient vs. Palma ratio; documents hemispheric heterogeneity
Mehmood *et al.* (2022)	BRICS countries	1988–2017	National	CO_2 emissions; renewables	Income distri-bution	Causality tests	Lower inequality associated with higher renewables; bidirectional links with CO_2	Places inequality alongside energy-use and land-use CO_2
Santillán Salgado,	134 countries	1971–2014	National	CO_2 emissions	Gini	Co-integration	Gross domestic product (GDP),	Implements unit root/co-

[*] In this context, the expression refers to the (somewhat uncomfortable) trade-off where policies that reduce income inequality or redistribute income toward poorer households can increase aggregate emissions.

Valencia-Herrera, and Venegas-Martínez (2020)				per capita			energy, urbanization, and Gini co-integrated with CO_2 per capita	integration and ECM/Δ at the hemispheric level
Khan, Yahong, and Zeeshan (2022)	Asian developing economies	1995–2018	National	Ecological footprint	Poverty and inequality	Panel models	Inequality associated with environmental pressure	Uses two inequality metrics and includes land-use emissions
Yan *et al.* (2022)	China (sub-national)	2000–2017	Sub-national	Emission intensity	—	Spatial/econometric	Financial and spatial structures affect carbon intensity with agglomeration effects	Adds global/hemispheric aggregation and transparent imputation
Nielsen *et al.* (2021)	OECD/high-income countries (conceptual)	≈1990–2019	National/synthesis	Energy-driven GHG emissions	Socio-economic status (SES)	Synthesis/review	High-SES lifestyles lock in or rapidly reduce emissions depending on choices and policies	Provides empirical north–south comparison with dual metrics

Source*:* Authors' compilation

2024 Global Carbon Budget,[†] and population figures are compiled from the 2024 material to calculate per-capita values. Per-capita annual CO_2 emissions from land-use change—which can be positive or negative depending on whether land-use changes emit or sequester carbon—are also obtained from the 2024 Global Carbon Budget and standardized using population data from 2024.

Energy use per person is measured in kilowatt-hours per person, representing primary-energy use calculated by the substitution method. Data for this variable come from the U.S. Energy Information Administration (2023) and the Energy Institute's *Statistical Review of World Energy* (2024), with population figures from 2023 used to derive per-capita values. The Gini coefficient and the Palma ratio, both measures of income inequality before taxes and benefits, are sourced from the World Inequality Database for 2024.[‡] The Gini coefficient ranges from 0 to 1, while the Palma ratio compares the income share of the richest 10% with that of the poorest 40%. We use the HDI from the United Nations Development Programme's (UNDP) *Human Development Report 2025* (UNDP 2025) as a broad, intuitive summary of human development (0–1 scale). HDI is the geometric mean of three dimension indices: health (life expectancy at birth), education (mean years of schooling and expected years of schooling—combined via their arithmetic mean), and standard of living (GNI per capita in PPP$).[§] Each indicator is normalized to [0,1] using UNDP's minimum–maximum bounds (life expectancy 20–85 years; expected schooling 0–18 years; mean schooling 0–15 years; GNI per capita Intl$100–75,000 at 2021 prices). Higher HDI reflects longer, healthier lives, better education, and greater command over resources; it does not capture inequality, sustainability, or subjective well-being. Given the substantial gaps in historical data at the country level, HDI enters our analysis post-imputation as a structural control in robustness specifications.

The average temperature anomaly, expressed in degrees Celsius, represents the deviation of the global mean surface temperature (land and ocean combined) from the 1961–1990 baseline. Temperature anomaly data for 2024 are obtained from the Met Office Hadley Centre.[**] All the variables are harmonized for unit consistency and aligned temporally to cover the

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† See the archive of the Global Carbon Budget Office: https://globalcarbonbudget.org/archive/ .

‡ See the World Inequality Database: https://wid.world.

§ Gross national income per person in international dollars, adjusted for purchasing power parity.

4 See the official website of Met Office Hadley Centre for Climate Science and Services: https://www.metoffice.gov.uk/weather/climate/met-office-hadley-centre/index.

period from 1965 to 2022. Data processing involves calculating per capita measures using reliable population figures, addressing missing data with imputation, and aggregating national data to hemispheric and global levels using standard methods.

Coverage differs markedly across sources (e.g., high historical sparsity for inequality and HDI vs. near-full coverage for emissions and energy). We quantify missingness and then address internal gaps using an iterative machine-learning imputation (IterativeImputer with a Random Forest regressor, 500 estimators, max_iter = 10), fitted at the country level and leveraging all available series (temperature, energy, CO_2, land-use CO_2, Gini, Palma, and sectoral pollutants NH_3/ BC/ CO/ CH_4/ NO_x/ N_2O/ NMVOC/ OC) plus calendar time (see Table 2). Terminal gaps and long data voids are left missing and excluded from the econometric estimations.

Table 2. Missing-Data Audit and Imputation Summary (Country Level, Then Aggregated by Hemisphere)

Variable	*N* observed	*N* missing	Percentage missing	*N* countries	*N* years	Years covered
hdi::World regions according to Our World in Data	54,144	53,873	100	314	235	1710–2023
hdi::HDI	54,144	47,680	88	314	235	1710–2023
hdi::GDP per capita, PPP (constant 2021 international dollars)	54,144	47,081	87	314	235	1710–2023
Gini coefficient	9,710	5,176	53	255	118	1820–2022
Palma ratio	9,710	3,182	33	255	118	1820–2022
hdi::Population (historical)	54,144	652	1	314	235	1710–2023
CO_2 emissions	26,182	0	0	231	229	1710–2023
CO_2 emissions from land use	36,434	0	0	211	174	1850–2023
Energy use per person	10,694	0	0	236	59	1965–2023
Per-capita GHG emissions	35,813	0	0	209	174	1850–2023

Source*:* Authors' analysis

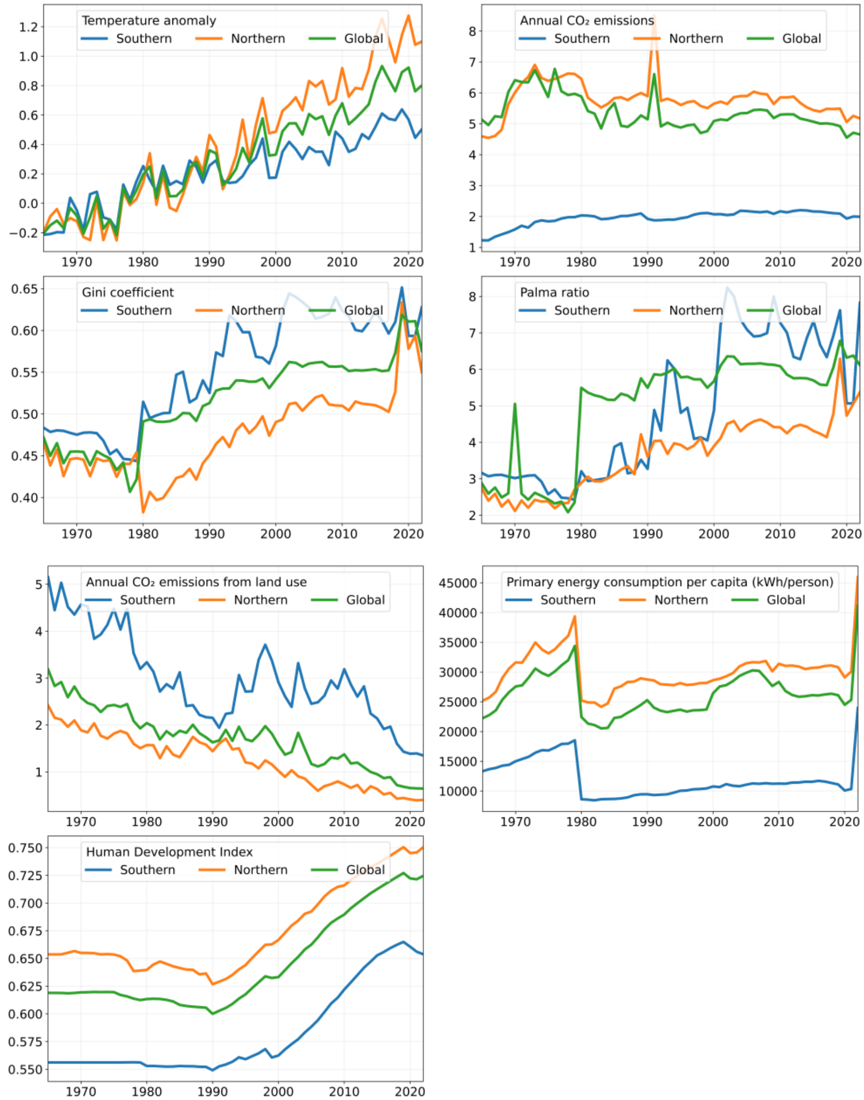
After the imputation, we compute hemisphere aggregates as population-weighted averages of country values; for per-capita variables, we weight by country populations, and for inequality indices, we apply the same weights. Countries intersecting the equator are not split; they are assigned to the hemisphere containing most of their territory. The global series is constructed as the sum of the northern and southern series, ensuring consistent country coverage and year alignment. This sequence (impute → aggregate) improves the reliability of the hemisphere series relative to aggregating raw sparse data.

This dataset, spanning nearly six decades and two large geographical systems (north/south), enables an integrated assessment of how income distribution relates to environmental outcomes over time. Figure 1 displays the time series for the six core variables at the global and hemispheric scales.

We aggregate country series to the northern and southern hemispheres to operationalize the canonical north–south development framing. This partition is prompted by large, well-documented differences in industrial structure, energy intensity, technology diffusion, and policy capacity that map broadly onto the hemispheres and are central to our questions on inequality–emissions associations. A hemispheric lens is also geographically meaningful—countries share climatic regimes and land-use frontiers that shape both energy demand and land conversion pressures—while yielding non-overlapping, population-weighted aggregates whose sum equals the global series. Because income and population density correlate with emissions, we view geography as a parsimonious baseline that avoids mixing endogenous thresholds (e.g., income cutoffs) into the classification itself; nonetheless, income-based alternatives remain.

This geographically coherent partition captures the broad structural asymmetries (industrial structure, energy intensity, technology diffusion, and regulatory capacity) central to our questions, although we acknowledge that aggregation can mask within-hemisphere heterogeneity.

Figure 1. Annual Series (1965–2022) for CO_2 Emissions per Capita (Tonnes CO_2 per Capita), CO_2 Emissions from Land-Use Change per Capita (Tonnes CO_2 per Capita), Primary Energy Consumption per Capita (kWh per Capita), Gini Coefficient (0–1), Palma Ratio (Top 10%/Bottom 40%), and Global Temperature Anomaly (°C, Relative to 1961–1990) for the Global, Northern Hemisphere, and Southern Hemisphere Scales



Source*:* Authors' analysis

3. EMPIRICAL ANALYSIS AND METHODS

3.1. Variable Preparation

For all three geographical aggregates—global (*G*), northern hemisphere (*N*), and southern hemisphere (*S*)—the annual series 1965−2022 are re-scaled to the unit interval with a min–max transformation. Let

$$\left(\mathrm{CO}_{2,ht}, \mathrm{TemperatureAnomaly}_{ht}, \mathrm{PalmaRatio}_{ht}, \mathrm{EnergyUse}_{ht}\right) \in [0,1]^4, \qquad h \in \{G, N, S\}, \quad t = 1, \dots, T. \tag{1}$$

Because the transformed origin represents the empirical minimum of every variable, a regression without intercept preserves the economically intuitive mapping "zero inputs → zero emissions". We include the global temperature anomaly as an ancillary control to capture short-run climate variations affecting energy demand and land use. Because temperature is also an outcome of cumulative emissions, we do not assign a causal interpretation to its coefficient; all results are robust to excluding temperature.

Countries straddling the equator are assigned to the hemisphere containing the majority of their landmass; sensitivity checks with alternative splits yield similar patterns.

3.2. Stage I: Single–Equation Ordinary Least Squares

For each region *h*, we estimate,

$$\mathrm{CO}_{2,ht} \sim \beta_{1h}\mathrm{TemperatureAnomaly}_{ht} + \beta_{2h}\mathrm{PalmaRatio}_{ht} + \beta_{3h}\mathrm{Energy}Use_{ht} + \varepsilon_{ht}, \quad \mathcal{E}[\varepsilon_{ht}] = 0, \; \mathrm{Var}[\varepsilon_{ht}] = \sigma_h^2, \tag{2}$$

by ordinary least squares (OLS). Inference is based on HC1 heteroskedasticity-consistent standard errors, where HC1 is White's heteroskedasticity-robust variance estimator (Anselin 1988; White 1980) multiplied by the finite-sample correction $n/(n-k)$, where n is the sample size and k the number of regressors. The adjustment improves the small-sample coverage of confidence intervals while converging to White's original HC0 as $n \rightarrow \infty$. In this way, that coefficient tests remain valid even when σ_h^2 varies with t. Equation 2 yields preliminary slope estimates and residuals, which are later used to diagnose cross-equation dependence. The value 0 in the scaled version of the variables denotes the sample minimum, not a physical zero. We estimate models with and without an intercept. The main specification includes an intercept to allow for a baseline level of emissions, while the no-intercept version is reported as a robustness check that offers a weight-like interpretation of coefficients under min–max scaling. Conclusions are robust across both versions. Coefficients are interpreted as conditional associations, not causal effects. Potential endogeneity (reverse causality, omitted variables) motivates our ECM/Δ checks to mitigate spurious correlation from common trends.

3.3. Stage II: Seemingly Unrelated Regression

Seemingly unrelated regression (SUR) is an econometric technique used when several regression equations—each with its own dependent and explanatory variables—share contemporaneously correlated error terms. Although the equations may appear independent, their disturbances are linked, and treating them as a system allows the estimator to exploit this cross-equation correlation. By estimating all equations jointly through feasible generalized least squares, SUR delivers parameter estimates that are asymptotically more efficient than those obtained from separate OLS regressions, especially when the contemporaneous error correlations are substantial and the sets of regressors differ across equations.

Given the synchronized nature of global macro-shocks, the disturbance vectors $\varepsilon_t = (\varepsilon_{Gt}, \varepsilon_{Nt}, \varepsilon_{St})^T$ are unlikely to be contemporaneously independent. Zellner's (1962) SUR framework explicitly models that correlation and delivers feasible generalized least squares (FGLS) estimates that are asymptotically more efficient than equation-by-equation OLS.

System representation. Stacking the T observations for each region produces

$$y_h = \mathbf{X}_h \boldsymbol{\beta}_h + \varepsilon_h, \qquad h \in \{G, N, S\},$$

where X_h is the $T \times 3$ matrix of regressors in Equation 2.

$$y = (\boldsymbol{y_G}, \boldsymbol{y_N}, \boldsymbol{y_S}), \qquad X = \mathrm{diag}(X_G, X_N, X_S), \qquad \beta = \left(\beta_G^\top, \beta_N^\top, \beta_S^\top\right)^\top.$$

Assuming $\mathrm{Cov}(\varepsilon_t) = \Sigma$, constant across t, the covariance of the stacked errors is $\boldsymbol{\Omega} = \Sigma \otimes I_T$.

FGLS estimator. Let $\widehat{\boldsymbol{\Sigma}}_{\mathrm{OLS}} = T^{-1} \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t^\top$, where $\hat{\varepsilon}_t$ are the OLS residuals from Stage I. The FGLS estimator is

$$\widehat{\boldsymbol{\beta}}_{\mathrm{SUR}} = (\boldsymbol{X}^\top \widehat{\boldsymbol{\Omega}}^{-1} \boldsymbol{X})^{-1} \boldsymbol{X}^\top \widehat{\boldsymbol{\Omega}}^{-1} y, \qquad \widehat{\boldsymbol{\Omega}} = \widehat{\boldsymbol{\Sigma}}_{\mathrm{OLS}} \otimes \boldsymbol{I}_T, \tag{3}$$

which can be iterated once for convergence (iterative FGLS). The estimator is unbiased and, under standard regularity conditions, asymptotically efficient among the class of linear unbiased estimators when Σ is not diagonal.

Inference and cross-equation restrictions. Robust covariance estimates for $\widehat{\boldsymbol{\beta}}_{\mathrm{SUR}}$ follow directly from Equation 3. Wald statistics test linear hypotheses such as H_0: $\beta_{1N} = \beta_{1S}$ (equal Gini elasticities between hemispheres) or the joint null H_0: Σ is diagonal.

Interpretation of coefficients. Because every regressor varies from 0 to 1, each slope β_{jh} represents the change in scaled emissions associated with a full-range swing in the corresponding predictor *ceteris paribus*. Comparisons of β_{jh} across h therefore quantify how the inequality–emissions and energy–emissions associations differ between the northern and southern hemispheres and in the global aggregate.

Advantages of the two-stage approach. Estimating Equation 2 separately provides diagnostics and a baseline that is familiar to readers; transitioning to Equation 3 captures the efficiency gains from the empirically large ($\sigma_{GN}, \sigma_{GS}, \sigma_{NS}$) covariances documented in Section 4. The combination yields transparent, easily interpretable coefficients while addressing both heteroskedasticity and cross-equation dependence; it thus satisfies the econometric requirements for policy-relevant inference on the role of inequality and energy use in determining per-capita land-use CO_2 emissions.

Assessing non-stationarity and long-run co-movement. Because many series trend over 1965–2022, we first test for unit roots using the ADF and KPSS tests. The ADF test's null is a unit root (non-stationary); rejection indicates stationarity after controlling for low-order auto-regression. The KPSS test's null is the opposite—level (or trend) stationarity—so rejection there signals non-stationarity. We run both in levels and in first differences for each series (CO_2 per capita, energy per capita, and the chosen inequality metric), using Schwarz/Bayesian information criterion to select lags and including a constant (and a deterministic trend where visual inspection warrants it). Convergence warnings in the KPSS test are handled conservatively (reporting $p \geq 0.10$ when the statistic falls outside the tabulated ranges). Evidence of ADF non-rejection in levels combined with KPSS rejection, alongside ADF rejection and KPSS non-rejection in first differences, is interpreted as I(1) behaviour, meaning that the series is integrated of order one (it contains a unit root and becomes stationary after first differencing).

To test for long-run equilibria among the key variables, we apply two complementary co-integration procedures. (1) The Johansen trace test (vector error correction framework) jointly evaluates the co-integration rank among emissions, energy, and inequality while allowing for short-run dynamics; we report the trace statistics and 5% critical values under a restricted constant in the co-integrating relations. (2) The Engle–Granger two-step test estimates a levels regression and then tests the residuals for stationarity (ADF test on residuals), where rejection implies co-integration. When co-integration is present, we estimate a single-equation ECM in first differences with the lagged error correction term; otherwise, we use first-difference regressions. All the regressions use heteroskedasticity- and autocorrelation-consistent (Newey–West) standard errors, and the variables are linearly re-scaled to [0,1] for comparability.

4. RESULTS

This study provides associational evidence at high levels of aggregation (global, northern hemisphere, and southern hemisphere). As such, the results may mask within-hemisphere heterogeneity and country-specific or sub-national dynamics. Despite our checks for non-stationarity and co-integration, our regressions remain correlational and do not establish causal effects; coefficients should be read as conditional associations. Potential limitations include measurement error across sources and the use of single national proxies for inequality (Gini/Palma), which may not capture all the distributional nuances. Before turning to coefficients, note that temperature anomaly is included solely as an ancillary control for short-run climatic variation in energy demand and land use. Given its simultaneity with cumulative emissions, we do not assign a causal interpretation to its coefficient; all the results are robust to excluding temperature. Our hemisphere assignment for equatorial countries follows the "majority-landmass" rule and population-weighted aggregation; although these choices are standard, they can affect levels and timing.

Our hemispheric design emphasizes geography-linked structural asymmetries consistent with a North–south perspective. Alternative macro-regional splits (e.g., the International Monetary Fund's [IMF] advanced vs. emerging economies, World Bank income groups, or OECD vs. non-OECD countries) are complementary lenses that organize countries by income and policy regimes rather than by geography. Because income is itself a key covariate in emission dynamics, income-based partitions risk conditioning on an outcome-related criterion; we therefore keep hemispheres as the main specification and view income-based groupings as a robustness lens for future extensions of this study.

We first verify that the long time span does not drive spurious fits. Standard unit-root tests (ADF and KPSS) indicate that emissions, energy use, and the inequality metric behave as I(1) processes in the global, northern, and southern aggregates. We then test for long-run co-movement using the Johansen and Engle–Granger procedures and find evidence of co-integration among the three variables; this justifies estimating ECMs rather than relying only on levels. For global, north, and south, the core series behave as I(1) (e.g., global ADF levels: CO_2 per capita $p = 0.324$, energy per capita $p = 0.400$, Palma $p = 0.306$; ADF in first differences: $p \leq 1.9 \times 10^{-4}$; KPSS in first differences: $p \geq 0.10$). The Johansen test indicates rank = 1 for global (trace = 129 > 107) and north (117 > 107) and rank = 2 for south (128 > 107, 83.6 > 79.3). The Engle–Granger test confirms co-integration for global ($p = 1.3 \times 10^{-4}$) and south ($p = 0.007$). We therefore estimate ECMs; the error correction coefficients are negative and significant (global $\phi = -0.612$, north $\phi = -0.587$, south $\phi = -0.132$), implying annual speeds of adjustment of 61%, 59%, and 13%, respectively (half-lives ≈ 0.73, 0.78, and 4.91 years, respectively). First-difference specifications have substantially lower explanatory power ($R^2 \leq 0.043$), indicating that the high R^2 in levels partly derives from common trends, while ECMs document a stable long-run relation (see Tables 3 and 4). These diagnostics support I(1) behaviour with co-integration among emissions, energy, and inequality, justifying ECM specifications and mitigating concerns that the high R^2 in levels could be driven by common trends alone.

Table 3. Unit-Root Test Applied to Individual Datasets in This Study

Aggregate	Time-series variable	ADF_level_*p*	KPSS_level_*p*	ADF_diff_*p*	KPSS_diff_*p*
Northern	CO_2 emissions	0.021	0.100	3.43×10^{-9}	0.100
	Energy use per person	0.273	0.100	1.96×10^{-6}	0.100
	Palma ratio	0.922	0.001	2.32×10^{-12}	0.100
	HDI	0.984	0.001	0.06	0.018
	Temperature anomaly	0.995	0.001	0.000	0.100
Southern	CO_2	0.002	0.001	7.08×10^{-10}	0.023
	Energy use per person	0.519	0.100	0.000	0.100
	Palma ratio	0.599	0.001	7.75×10^{-6}	0.100
	HDI	0.045	0.001	0.233	0.048
	Temperature anomaly	0.664	0.001	5.80×10^{-5}	0.100
Global	CO_2	0.324	0.022	3.10×10^{-10}	0.100
	Energy use per person	0.400	0.100	0.000	0.100
	Palma ratio	0.306	0.001	1.19×10^{-15}	0.100
	HDI	0.989	0.001	0.025	0.017
	Temperature anomaly	0.987	0.001	0.000	0.100

Source: Authors' analysis

Table 4. Engle–Granger, Johansen, and ECM Tests Applied to Individual Datasets in This Study CV5 denotes the 5% critical value of the corresponding trace statistic.

Test	Characteristic	Northern hemisphere	Southern hemisphere	Global
Johansen	Trace r_0	117	128	129
	CV5 r_0	107	107	107
	Trace r_1	73.8	83.6	77.9
	CV5 r_1	79.3	79.3	79.3
	Rank ≥ 1	True	True	True
	Rank ≥ 2	False	True	False
Engle–Granger	p	0.0632	0.0071	0.0001
ECM	ϕ_{ECM}	–0.587	–0.132	–0.612
	t_{ECM}	–2.77	–3.31	–3.34
	p_{ECM}	0.0056	0.00009	0.0008
	Speed (adjusted)	0.587	0.132	0.612
	Half-life years	0.784	4.91	0.733
	R^2_{EMC}	0.36	0.146	0.34

Note: CV5 denotes the 5% critical value of the corresponding trace statistic.
Source*:* Authors' analysis

4.1. Correlation Analysis and Economic Implications

Analysing the correlation matrices (Figure 2) reveals distinct patterns across regions. In the northern hemisphere, temperature anomaly strongly correlates with the Gini coefficient (0.645) and Palma ratio (0.752), indicating that higher inequality aligns with greater temperature deviations. It also shows a strong negative correlation with CO_2 emissions from land-use change (–0.753), while its association with global CO_2 emissions (–0.261) and energy consumption (0.162) is weaker. The strong correlations between inequality measures and temperature anomalies suggest that higher income disparity may drive consumption patterns that exacerbate climate variability, as wealthier segments of society typically engage in energy-intensive consumption, leading to increased emissions.

In the southern hemisphere, temperature anomaly is positively correlated with inequality measures—though the correlations are slightly lower than in the north (Gini: 0.586, Palma: 0.562). Notably, temperature anomaly has a moderate positive correlation with global CO_2 emissions (0.578) and a strong negative correlation with land-use change emissions (–0.557). Energy consumption shows a negligible correlation with temperature anomaly in this region. The moderate positive association between temperature anomaly and global CO_2 emissions in the south implies a more direct emission–climate connection, potentially due to different industrial or land-use practices from the north.

Globally, temperature anomaly correlates strongly with the Gini coefficient (0.721) and moderately with the Palma ratio (0.584), reinforcing the link between inequality and climate change. It is negatively correlated with CO_2 emissions from land-use change (–0.740) and shows modest associations with global emissions (–0.336) and energy consumption (0.124). The observed global patterns underscore that rising inequality is consistently associated with higher temperature anomalies, but the nature and strength of these relationships vary by region (Dang, Hallegatte, and Trinh 2024; Huynh and Phan 2024; Paglialunga, Coveri, and Zanfei 2022).

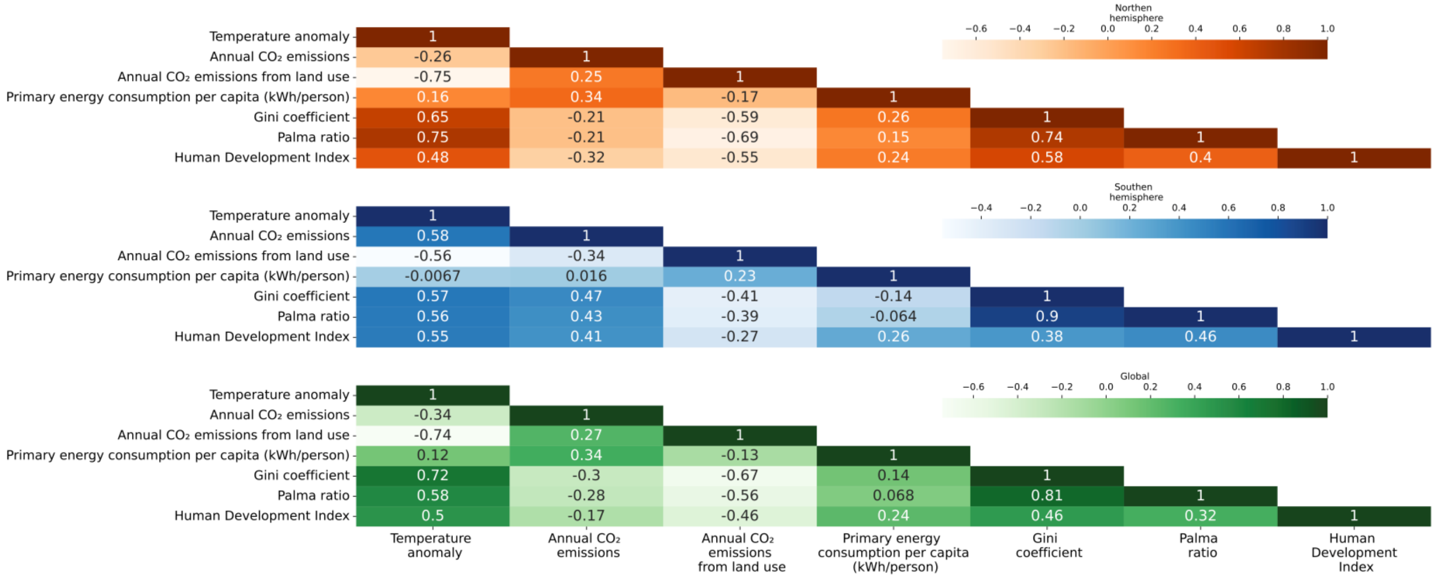
4.2. Regional Differences and Policy Insights

The northern hemisphere exhibits the strongest associations between inequality and temperature anomaly, highlighting the potential for socio-economic factors to influence environmental outcomes in industrialized regions. The strong negative relationship across both hemispheres between temperature anomaly and CO_2 emissions from land-use change may reflect periods of effective carbon sequestration or reduced deforestation, coinciding with warming trends. These findings suggest that addressing income inequality could contribute to mitigating climate variability; regional policies should consider local economic and environmental contexts to effectively tackle both socio-economic disparities and climate change (Dwarkasing 2023; Silva, Matyas, and Cunguara 2015).

4.3. Region-Specific OLS Results

Annual time-series regressions were estimated separately for each hemisphere and for the global aggregate to gauge the marginal contributions of income distribution and energy use to CO_2 emissions. All the variables are entered in the min–max scaleand the regressions are estimated without an intercept; heteroskedasticity-consistent (HC1) standard errors accompany every coefficient. Table 5 gives the full set of estimates. The temperature anomaly behaves as a small ancillary control—insignificant in the north and modest in the global and south scales—while the core conclusions hinge on energy use and inequality.

Figure 2. Heat Map of Correlation Matrices for Key Variables across the Northern Hemisphere, Southern Hemisphere, and Global Scales.



Note*:* Warmer colours indicate stronger positive correlations while cooler colours represent stronger negative correlations between temperature anomalies, inequality measures, CO_2 emissions, and energy consumption.
Source*:* Authors' analysis.

Table 5. Regression Results for Six OLS Models Predicting CO_2 Emissions (Global and from Land-Use Change) across the Northern Hemisphere, Southern Hemisphere, and Global Scales

Independent variable	Scale	Dependent variable	Coefficient	Standard error	*t* value	$p > \|t\|$	R^2	Akaike information criterion (AIC)	Bayesian information criterion (BIC)
Global CO_2 emissions	Northern hemisphere	Temperature anomaly	0.281	0.223	1.248	0.217	0.791	–36.40	–26.10
		Gini coefficient	0.159	0.273	0.582	0.563			
		Palma ratio	0.229	0.278	0.825	0.413			
		HDI	–0.577	0.150	–3.838	0.000			
		Energy consumption	0.874	0.132	6.613	0.000			
	Southern hemisphere	Temperature anomaly	1.056	0.162	6.541	0.000	0.958	–37.60	–27.30
		Gini coefficient	0.732	0.253	2.896	0.005			
		Palma ratio	–0.515	0.234	–2.201	0.032			
		HDI	–0.358	0.112	–3.207	0.002			
		Energy consumption	0.464	0.090	5.149	0.000			
	Global	Temperature anomaly	–0.690	0.335	–2.064	0.044	0.725	3.98	14.28
		Gini coefficient	0.214	0.457	0.459	0.641			
		Palma ratio	0.361	0.320	1.131	0.263			
		HDI	–0.110	0.230	–0.479	0.634			
		Energy consumption	1.236	0.154	8.038	0.000			

CO_2 emissions from land use	Northern hemisphere	Temperature anomaly	0.021	0.439	0.049	0.961	0.604	41.13	51.43
		Gini coefficient	1.701	0.532	3.196	0.002			
		Palma ratio	–0.476	0.531	–0.881	0.383			
		HDI	–1.071	0.294	–3.652	0.001			
		Energy consumption	0.936	0.258	3.630	0.001			
	Southern hemisphere	-	–0.066	0.231	–0.288	0.775	0.788	3.72	14.03
		Gini coefficient	1.194	0.361	3.307	0.002			
		Palma ratio	–0.886	0.334	–2.652	0.011			
		HDI	–0.417	0.159	–2.620	0.011			
		Energy consumption	1.210	0.129	9.390	0.000			
	Global	Temperature anomaly	–0.987	0.378	–2.612	0.012	0.718	18.08	28.38
		Gini coefficient	1.691	0.516	3.277	0.002			
		Palma ratio	–0.199	0.361	–0.553	0.583			
		HDI	–0.615	0.260	–2.368	0.022			
		Energy consumption	1.004	0.174	5.785	0.000			

Note*:* The table presents coefficients, standard errors, *t* values, *p* values, R^2, AIC, and BIC for models including the Gini coefficient, the Palma ratio, the HDI, and energy consumption as predictors.

Source*:* Authors' analysis

Global CO_2 emissions. For the northern hemisphere, per-capita primary-energy consumption is the dominant covariate ($\beta = 0.874$, $p < 0.001$). HDI is negative and significant ($\beta = -0.577$, $p < 0.001$). Gini and Palma are not significant ($p = 0.563$ and 0.413, respectively), and temperature anomaly is also not significant ($p = 0.217$). Model fit is high ($R^2 = 0.791$). For the southern hemisphere, all the blocks contribute, and the model fit is very high ($R^2 = 0.958$). Energy per capita is positive ($\beta = 0.464$, $p < 0.001$). For inequality, Gini is positive and significant ($\beta = 0.732$, $p = 0.006$), while Palma is negative and significant ($\beta = -0.515$, $p = 0.032$), indicating that overall dispersion and top-tail concentration capture distinct facets of the income distribution. HDI is negative ($\beta = -0.358$, $p = 0.002$), and temperature anomaly is positive ($\beta = 1.056$, $p < 0.001$). At the global level, energy per capita is the most robust predictor ($\beta = 1.236$, $p < 0.001$). Gini, Palma, and HDI are not significant ($p = 0.641$, 0.263, and 0.634, respectively), while temperature anomaly is small and marginal ($\beta = -0.690$, $p = 0.044$). The model explains $R^2 = 0.725$ of the annual variation.

CO_2 emissions from land-use change. For the northern hemisphere, energy per capita is the strongest driver ($\beta = 0.936$, $p < 0.001$). Gini is positive and significant ($\beta = 1.701$, $p = 0.002$), while Palma is not significant ($p = 0.383$). HDI is negative ($\beta = -1.071$, $p = 0.001$), and temperature anomaly is insignificant. The model explains $R^2 = 0.604$ of the variation, indicating that overall dispersion in incomes (Gini) relates to land-use emissions in the north whereas top-tail concentration (Palma) does not. For the southern hemisphere, the association is tighter ($R^2 = 0.788$). Energy is again strongly positive ($\beta = 1.210$, $p < 0.001$). Gini is positive and significant ($\beta = 1.194$, $p = 0.002$), and Palma is negative and significant ($\beta = -0.886$, $p = 0.011$), suggesting that overall inequality and top-end concentration affect land-use emissions through different channels (cf. Barbier 2008; Ceddia *et al.* 2014). HDI is negative ($\beta = -0.417$, $p = 0.011$), and temperature anomaly is not significant. At the global level, energy is once more the central predictor ($\beta = 1.004$, $p < 0.001$). Gini is positive and significant ($\beta = 1.691$, $p = 0.002$), while Palma is not significant ($p = 0.583$). HDI is negative ($\beta = -0.615$, $p = 0.022$), and temperature anomaly is negative and significant ($\beta = -0.987$, $p = 0.012$). Overall fit is high ($R^2 = 0.718$)—mirroring the hemispheric pattern in which energy and overall inequality (Gini) matter systemically—whereas Palma contributes only in the south.

Before turning to mechanisms, note that our OLS specifications report Gini and Palma jointly. Their correlation is high in some aggregates (especially the south) but not uniformly so, and the coefficients are sufficiently stable for inference in the pooled display. Still, to guard against multi-collinearity, we also re-estimate single-metric models (Gini only/Palma only) and obtain the same qualitative conclusions; hence, the joint tables are meant to provide transparency rather than depending on a particular pairing.

Energy use is the most pervasive and quantitatively important determinant of CO_2 emissions—both for total emissions and for the land-use component—across all scales. This underscores the central role of energy systems in mitigation: Shifting away from carbon-intensive fuels and improving efficiency are the most immediate pathways to reducing per-capita emissions, even when other fundamentals remain unchanged (Le Quéré *et al.* 2019).

The influence of income distribution is clearly asymmetric across hemispheres. In the South, higher overall inequality (Gini) is positively associated with both aggregate and land-use emissions, whereas, holding the Gini coefficient constant, the Palma ratio is negatively associated with emissions. A plausible interpretation is that avoiding further increases in top-end income concentration—that is, keeping the Palma ratio relatively low—coincides with weaker pressures for land conversion. This pattern is apparent in settings where broader coalitions or redistributive institutions demand stronger environmental safeguards. In contrast, in the north, neither overall inequality nor top-tail concentration shows a statistically detectable effect once energy use is controlled for; this is consistent with the context of mature, capital- and technology-intensive economies, which rely less on land-extensive production (Parks and Roberts 2008).

At the global level, these effects are largely offset because the correlations for each hemisphere differ in both sign and magnitude. This heterogeneity calls for geographically differentiated policy: redistribution programmes to curb extreme income dispersion may be particularly effective at reducing emissions related to land-use change in the south, while energy system transformations (efficiency and fuel substitution) are universally beneficial.

4.4. Linking Mechanisms to Real-World Contexts

In the southern hemisphere, commodity exports have often grown through land-extensive production under conditions of unequal asset structures and uneven access to finance. In the Brazilian Amazon, tightening rural credit to environmentally risky borrowers causally reduced deforestation, illustrating how distributional access to finance and enforcement of environmental policy interact with land-use outcomes (Assunção *et al.* 2020). Enforcement capacity itself matters: Satellite-driven DETER monitoring and related enforcement constraints explain the variation in clearing (Merkus 2024). Beyond Brazil, comparative evidence highlights weak governance as a persistent underlying factor in forest loss across Sub-Saharan Africa; where regulatory capacity is limited, the pressure to reduce deforestation is amplified (Nansikombi *et al.* 2020).

In the northern hemisphere, the limited incremental role of inequality—once energy use is controlled for—accords with evidence of declines in structural CO_2 in advanced economies since 2007 due to efficiency improvements, fuel switching/cleaner power, and binding policy regimes (e.g., carbon pricing) (D'Arcangelo *et al.* 2022; IEA 2024). Cross-country estimates suggest that a €10 increase in effective carbon prices is associated with an approximately 3.7% long-run reduction in CO_2 emissions from fossil fuels (D'Arcangelo et al., 2022).

Taken together, the six region-specific OLS regressions indicate that (1) carbon intensity and scale of energy use are the principal channels driving emissions everywhere and (2) inequality modulates those channels in ways that depend on regional structures. In the next sub-section, we show that these results persist—with tighter standard errors—when the three equations are estimated jointly as an SUR system.

4.5. System-wide SUR Estimates and Substantive Implications

Table 6 summarizes the FGLS estimates obtained from the SUR systems for (1) per-capita CO_2 emissions stemming from land-use change and (2) aggregate per-capita CO_2 emissions.

Because the unexplained shocks in the three equations are strongly correlated, estimating them jointly is more appropriate than running separate OLS regressions. Feasible GLS in the SUR framework raise the overall explanatory power to overall $R^2 = 0.61$ for land-use CO_2 per capita and 0.8815 for total CO_2 per capita, and reduce the standard errors. The residual-correlation matrix is informative. For land-use CO_2, disturbances in global–north move almost in lock-step ($\varrho_{GN} = 0.96$), with strong correlations for global–south (0.87) and north–south (0.83). For total CO_2, $\varrho_{GN} = 0.92$ is high, while the values for global–south and north–south are more moderate (0.33 and 0.45, respectively), indicating that common shocks are tighter for land-use processes than for fossil-fuel emissions.

Temperature anomaly loads negatively in all land-use equations (global −0.8013*,†† north −0.7979*, south −0.3421*), which is consistent with abnormally warm years coinciding with slower clearing or net re-growth. For total CO_2, the value is small and negative at the global level (−0.4227*), is not retained for the north (jointly insignificant in the SUR system), and

[5] The asterisk denotes significance.

turns positive in the south (0.9342*); this is consistent with heat- and drought-related shifts in energy use or land-use practices in the tropical belts (e.g., temporary reliance on diesel power, fire-based clearing). These contrasts support considering land and energy pathways separately when developing mitigation strategies for the tropics.

Table 6. SUR Coefficients by Hemisphere and Emission Type

	Land-use CO_2 (per capita)			**Total CO_2 (per capita)**		
	Global	North	South	Global	North	South
Temperature anomaly	–0.8013***	–0.7979***	–0.3421***	–0.4227*		0.9342***
Energy use (per capita)	0.9412***	0.9899***	1.0267***	1.1433***	0.7607***	0.4628***
Gini	0.7739***		0.8753***			0.8076***
Palma		0.9508***	–0.4413*		0.4694***	–0.5408***
R^2_{overall}	0.61			0.88		
Residual correlations (Σ_b)						
Land use: ρ_{GN} = 0.96, ρ_{GS} = 0.87, ρ_{NS} = 0.83						
Total: ρ_{GN} = 0.92, ρ_{GS} = 0.33, ρ_{NS} = 0.45						

Note*:* The blank cells indicate the regressors excluded from the joint system to alleviate multi-collinearity (Gini vs. Palma) or because they were jointly insignificant in SUR. The asterisks denote significance in the SUR covariance structure at 1% (***), 5% (**), and 10% (*); the blank cells indicate p > 0.10. Robust HC1 standard errors underlie all the t statistics. The lower panel shows the contemporaneous correlation matrix Σ_b of the equation residuals.
Source*:* Authors' analysis

Per-capita primary-energy use is uniformly positive and statistically decisive across all equations (land use: global 0.9412*, north 0.9899*, south 1.0267*; total: global 1.1433*, north 0.7607*, south 0.4628*); this corroborates the centrality of energy systems found in decomposition studies (Le Quéré *et al.* 2019). Although the coefficients are numerically small due to our [0,1] scaling, their precision indicates that even marginal efficiency gains and fuel switching are associated with measurable per-capita emission reductions.

Inequality exhibits a clear north–south asymmetry that persists under joint estimation. For land-use CO_2, Gini is positive and significant where included (global 0.7739*, south 0.8753*), while Palma is positive in the north (0.9508*) but negative in the south (−0.4413*). For total CO_2, Gini is positive in the south (0.8076*), whereas Palma is positive in the north (0.4694*) and negative in the south (−0.5408*). Taken together, overall dispersion (Gini) is associated with higher emissions in the south, while top-tail concentration (Palma) contributes positively in the north and negatively in the south; this is consistent with different institutional and land-use channels.

The SUR estimates confirm and sharpen the OLS patterns. Energy use per capita is the dominant correlate everywhere, but the magnitude and even the direction of the inequality associations hinge on geography and emission channel. The implications are threefold:

Rapid decarbonization and electrification are universally beneficial; their impact is magnified where inequality is addressed.

Redistribution or inclusive land governance may yield a double dividend in the south—curbing both fossil-fuel and land-use emissions—whereas in high-income northern economies, inequality policies alone are unlikely to deliver large short-run climate gains without energy system change.

Models that aggregate hemispheres risk masking these asymmetric elasticities; region-differentiated policy design is therefore empirically warranted.

5. CONCLUSIONS

The seemingly unrelated regressions show three empirically grounded regularities. First, per-capita primary-energy consumption is the most stable predictor in the dataset. It enters with a positive and significant coefficient in every equation except the northern land-use regression, where the estimate is positive but not distinguishable from zero. This pattern confirms that energy use explains an important share of annual variation in both total CO_2 emissions and the land-use component.

Second, the two indicators of income distribution show that its effect on emissions depends on both hemisphere and emission channel. The Gini coefficient is positive and highly significant in all southern equations and in the global system, yet it is statistically irrelevant for northern fossil-fuel emissions. Conditional on that broad measure of inequality, the Palma ratio is significantly negative for land-use emissions in the south and at the global level, while it is insignificant elsewhere. These differences indicate that the link between inequality and emissions is not uniform but instead varies with regional context and with the source of emissions examined.

Third, surface-temperature anomalies display contrasting signs across channels. Warmer-than-average years coincide with lower land-use emissions in all regions, whereas in the southern hemisphere they coincide with higher fossil-fuel emissions. The sign reversal suggests that warming affects emission pathways differently across regions.

Estimating the three equations jointly is statistically warranted. Contemporaneous residual correlations range from 0.20 to 0.85, and the SUR framework raises the overall goodness of fit to 0.61 for land-use emissions and 0.88 for total emissions while reducing standard errors relative to separate OLS. Each of these conclusions is directly supported by the coefficient estimates and diagnostic statistics reported in Sections 4.3 and 4.4.

6. POLICY IMPLICATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The empirical evidence points to a clear priority. Because per-capita energy use stands out as the most consistent and quantitatively important driver of both total and land-use CO_2 emissions, policies that help lower the carbon intensity of energy consumption—through efficiency gains, electrification from low-carbon sources, or both—are likely to yield the most immediate mitigation benefits. At the same time, the results reveal that income inequality modulates emissions in region-specific ways. The broader overall dispersion of incomes increases emissions in the southern hemisphere and, by extension, in the global aggregate, whereas inequality plays a limited role in the northern fossil fuel equation. These findings imply that mitigation strategies should be geographically differentiated. Energy system reforms are essential everywhere, but in regions where inequality significantly augments emissions—most notably the south—complementary measures to narrow income distribution gaps and reform land governance can reinforce the emission reduction strategies of energy policies.

Several avenues for further work emerge directly from the present results. First, the analysis is static and linear; extending it to dynamic specifications such as panel error correction models would clarify how quickly emissions adjust to energy-use, inequality, and temperature shocks and would help disentangle short-run fluctuations from long-run equilibria. Investigating possible endogeneity—for instance, via instrumental-variable SUR or dynamic panel methods—could refine causal interpretation, especially for the (coefficients. Second, the dataset aggregates emissions and energy use at the hemispheric scale. Future research could disaggregate by sector or by finer geographic units to examine whether the inequality–emissions nexus observed in the south is driven by particular industries (e.g., agricultural vs. extractive sectors) or by specific countries within the hemisphere. Incorporating institutional variables—such as land tenure security, environmental governance indices, or renewable energy adoption rates—would further illuminate the mechanisms behind the regional asymmetries documented here.

Taken together, these extensions would move the evidence base beyond correlation towards a richer understanding of the causal pathways linking energy systems, economic distribution, and carbon outcomes, thereby providing stakeholders with more precise input for designing region-appropriate climate policies.

Future research could leverage country- or sub-national panel designs with policy shocks or plausibly exogenous instrumental variables—variables that shift income distribution or carbon pricing but are otherwise unrelated to emissions, conditional on controls—incorporate spatial dependence, and examine distribution-sensitive measures of inequality (Kopp, Thomas, and Markus Nabernegg, 2022) and sectoral emissions to unpack the mechanisms we document here.

The results are associational and reported at high levels of aggregation (global/north/south), which may conceal country- or sector-specific dynamics and raises the usual ecological-fallacy caveat. We therefore interpret coefficients as conditional associations and explicitly address non-stationarity (ADF/KPSS) and long-run co-movement (Johansen/Engle–Granger, ECMs), using SUR to exploit cross-equation covariance. A country panel design with sectoral detail and identification strategies is a natural extension of this study. As a robustness lens for future work, regrouping countries by income or policy regime (e.g., World Bank/IMF classifications) and estimating panel ECMs with spatial dependence could uncover the heterogeneity that our hemispheric aggregates necessarily suppress.

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Data availability statement: The data used in this research are from publicly accessible sources. After conducting our own data mining and processing, we curated a refined dataset. This dataset can be made available to any interested party upon request.

Conflict of interest statement: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this article.

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REFERENCES

Ahmad, Munir, Adnan Muslija, and Elma Satrovic. 2021. "Does Economic Prosperity Lead to Environmental Sustainability in Developing Economies? Environmental Kuznets Curve Theory." *Environmental Science and Pollution Research* 28 (18): 22588–601. https://doi.org/10.1007/s11356-020-12276-9.

Ajide, Kazeem Bello, and Ridwan Lanre Ibrahim. 2022. "Environmental Impacts of Income Inequality: Evidence from G7 Economies." *Environmental Science and Pollution Research* 29 (2): 1887–1908. https://doi.org/10.1007/s11356-021-15720-6

Anselin, Luc. 1988. "Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity." *Geographical Analysis* 20 (1): 1–17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x.

Assunção, Juliano, Clarissa Gandour, Romero Rocha, and Rudi Rocha. 2020. "The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon." *The Economic Journal* 130 (626): 290–330. https://doi.org/10.1093/ej/uez060.

Barbier, Edward B. 2008. "Poverty, Development, and Ecological Services." *International Review of Environmental and Resource Economics* 2 (1): 1–27. http://doi.org/10.1561/101.00000010.

Boyce, James K. 1994. "Inequality as a Cause of Environmental Degradation." *Ecological Economics* 11 (3): 169–78. https://doi.org/10.1016/0921-8009(94)90198-8.

Ceddia, Michele Graziano, Nicholas Oliver Bardsley, Sergio Gomez-y-Paloma, and Sabine Sedlacek. 2014. "Governance, Agricultural Intensification, and Land Sparing in Tropical South America." *Proceedings of the National Academy of Sciences* 111 (20): 7242–47. https://doi.org/10.1073/pnas.1317967111.

Chancel, Lucas, Philipp Bothe, and Tancrède Voituriez. 2023. *Climate Inequality Report 2023*. World Inequality Lab. https://agritrop.cirad.fr/611813/1/611813.pdf.

Chancel, Lucas, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman, eds. 2022. *World Inequality Report 2022*. Harvard University Press. https://doi.org/10.4159/9780674276598.

Dang, Hai-Anh H, Stephanie Hallegatte, and Trong-Anh Trinh. 2024. "Does Global Warming Worsen Poverty and Inequality? An Updated Review." *Journal of Economic Surveys* 38 (5): 1873–905. https://doi.org/10.1111/joes.12636.

D'Arcangelo, Filippo Maria, Mauro Pisu, Anasuya Raj, and Kurt van Dender. 2022. *Estimating the CO2 Emission and Revenue Effects of Carbon Pricing: New Evidence from a Large Cross-Country Dataset*. OECD Publishing. https://doi.org/10.1787/39aa16d4-en.

Dong, Kangyin, Yue Dou, and Qingzhe Jiang. 2022. "Income Inequality, Energy Poverty, and Energy Efficiency: Who Causes Who and How?" *Technological*

Forecasting and Social Change 179: 121622. https://doi.org/10.1016/j.techfore.2022.121622.

Duarte, Rosa, Sara Miranda-Buetas, and Cristina Sarasa. 2021. "Household Consumption Patterns and Income Inequality in EU Countries: Scenario Analysis for a Fair Transition towards Low-Carbon Economies." *Energy Economics* 104: 105614. https://doi.org/10.1016/j.eneco.2021.105614.

Dwarkasing, Chandni. 2023. "Inequality-Determined Social Outcomes of Low-Carbon Transition Policies: A Conceptual Meta-review of Justice Impacts." *Energy Research & Social Science* 97: 102974. https://doi.org/10.1016/j.erss.2023.102974.

Energy Institute. 2024. *Statistical Review of World Energy*. https://www.energyinst.org/statistical-review.

Ghazouani, Tarek, and Lamia Beldi. 2022. "The Impact of Income Inequality on Carbon Emissions in Asian Countries: Non-parametric Panel Data Analysis." *Environmental Modeling & Assessment* 27 (3): 441–59. https://doi.org/10.1007/s10666-021-09811-4.

Guo, Yawei, Wanhai You, and Chien-Chiang Lee. 2022. "CO_2 Emissions, Income Inequality, and Country Risk: Some International Evidence." *Environmental Science and Pollution Research* 29 (9): 12756–76. https://doi.org/10.1007/s11356-020-09501-w.

Hao, Yuanyuan. 2022. "Effect of Economic Indicators, Renewable Energy Consumption and Human Development on Climate Change: An Empirical Analysis Based on Panel Data of Selected Countries." *Frontiers in Energy Research* 10: 841497. https://doi.org/10.3389/fenrg.2022.841497.

Huynh, Cong Minh, and Thi Nga Phan. 2024. "Climate Change and Income Inequality: Does Renewable Energy Matter?" *Renewable Energy* 233: 121147. https://doi.org/10.1016/j.renene.2024.121147.

Khan, Salim, Wang Yahong, and Asma Zeeshan. 2022. "Impact of Poverty and Income Inequality on the Ecological Footprint in Asian Developing Economies: Assessment of Sustainable Development Goals." *Energy Reports* 8: 670–79. https://doi.org/10.1016/j.egyr.2021.12.001.

Kopp, Thomas, and Markus Nabernegg. 2022. "Inequality and Environmental Impact: Can the Two Be Reduced Jointly?" *Ecological Economics* 201: 107589. https://doi.org/10.1016/j.ecolecon.2022.107589.

IEA (International Energy Agency). 2024. "CO2 Emissions in 2023." https://iea.blob.core.windows.net/assets/33e2badc-b839-4c18-84ce-f6387b3c008f/CO2Emissionsin2023.pdf.

Le Quéré, Corinne, Jan Ivar Korsbakken, Charlie Wilson, *et al.* 2019. "Drivers of Declining CO_2 Emissions in 18 Developed Economies." *Nature Climate Change* 9 (3): 213–17. https://doi.org/10.1038/s41558-019-0419-7.

Mehmood, Usman, Ephraim Bonah Agyekum, Salman Tariq, *et al.* 2022. "Socio-economic Drivers of Renewable Energy: Empirical Evidence from BRICS." *International Journal of Environmental Research and Public Health* 19 (8): 4614. https://doi.org/10.3390/ijerph19084614.

Merkus, Erik. 2024. "The Economic Consequences of Environmental Enforcement: Evidence from an Anti-deforestation Policy in Brazil." *World Development* 181: 106646. https://doi.org/10.1016/j.worlddev.2024.106646.

Munasinghe, Mohan. 1999. "Is Environmental Degradation an Inevitable Consequence of Economic Growth? Tunneling through the Environmental Kuznets Curve." *Ecological Economics* 29 (1): 89–109. https://doi.org/10.1016/S0921-8009(98)00062-7.

Nansikombi, Hellen, Richard Fischer, Rubén Ferrer Velasco, *et al.* 2020. "Can de Facto Governance Influence Deforestation Drivers in the Zambian Miombo?" *Forest Policy and Economics* 120: 102309. https://doi.org/10.1016/j.forpol.2020.102309.

Ngankam, Bertrand Tessa. 2024. "Sustainable Development Goals Synergies/Trade-offs: Exploring Long- and Short-Run Impacts of Economic Growth, Income Inequality, Energy Consumption and Unemployment on Carbon Dioxide Emissions in South Africa." *Journal of Sustainable Development* 12 (4). https://ideas.repec.org/a/ibn/jsd123/v12y2024i4p40.html. https://doi.org/10.5539/jsd.v12n4p40.

Nielsen, Kristian S, Kimberly A Nicholas, Felix Creutzig, Thomas Dietz, and Paul C Stern. 2021. "The Role of High-Socioeconomic-Status People in Locking in or Rapidly Reducing Energy-Driven Greenhouse Gas Emissions." *Nature Energy* 6 (11): 1011–16. https://doi.org/10.1038/s41560-021-00900-y.

Oreggioni, Gabriel David, Fabio Monforti Ferraio, Monica Crippa, *et al.* 2021. "Climate Change in a Changing World: Socio-economic and Technological Transitions, Regulatory Frameworks and Trends on Global Greenhouse Gas Emissions from EDGAR v5.0." *Global Environmental Change* 70: 102350. https://doi.org/10.1016/j.gloenvcha.2021.102350.

Paglialunga, Elena, Andrea Coveri, and Antonello Zanfei. 2022. "Climate Change and Within-Country Inequality: New Evidence from a Global Perspective." *World Development* 159: 106030. https://doi.org/10.1016/j.worlddev.2022.106030.

Parks, Bradley C, and J Timmons Roberts. 2008. "Inequality and the Global Climate Regime: Breaking the North–South Impasse." *Cambridge Review of International Affairs* 21 (4): 621–48. https://doi.org/10.1080/09557570802452979.

Pata, Ugur Korkut, Veli Yilanci, Bilal Hussain, and Syed Asif Ali Naqvi. 2022. "Analyzing the Role of Income Inequality and Political Stability in Environmental Degradation: Evidence from South Asia." *Gondwana Research* 107: 13–29. https://doi.org/10.1016/j.gr.2022.02.009.

Ray, Debraj, Jean-Marie Baland, and Olivier Dagnelie. 2007. "Inequality and Inefficiency in Joint Projects." *The Economic Journal* 117 (522): 922–35. https://doi.org/10.1111/j.1468-0297.2007.02064.x.

Romero, João P, and Camila Gramkow. 2021. "Economic Complexity and Greenhouse Gas Emissions." *World Development* 139: 105317. https://doi.org/10.1016/j.worlddev.2020.105317.

Santillán Salgado, Roberto J, Humberto Valencia-Herrera, and Francisco Venegas-Martínez. 2020. "On the Relations among CO_2 Emissions, Gross Domestic Product, Energy Consumption, Electricity Use, Urbanization, and Income Inequality for a Sample of 134 Countries." *International Journal of Energy Economics and Policy* 10 (6): 195–207. https://doi.org/10.32479/ijeep.10070.

Silva, Julie A, Corene A Matyas, and Benedito Cunguara. 2015. "Regional Inequality and Polarization in the Context of Concurrent Extreme Weather and Economic Shocks." *Applied Geography* 61: 105–16. https://doi.org/10.1016/j.apgeog.2015.01.015.

Sinha, Avik, Stelios Bekiros, Nazim Hussain, Duc Khuong Nguyen, and Sana Akbar Khan. 2023. "How Social Imbalance and Governance Quality Shape Policy Directives for Energy Transition in the OECD Countries?" *Energy Economics* 120: 106642. https://doi.org/10.1016/j.eneco.2023.106642.

Sovacool, Benjamin K, Peter Newell, Sanya Carley, and Jessica Fanzo. 2022. "Equity, Technological Innovation and Sustainable Behaviour in a Low-Carbon Future." *Nature Human Behaviour* 6 (3): 326–37. https://doi.org/10.1038/s41562-021-01257-8.

UNDP (United Nations Development Programme). 2025. *Human Development Report 2025: A Matter of Choice: People and Possibilities in the Age of AI*. https://hdr.undp.org/system/files/documents/global-report-document/hdr2025reporten.pdf.

UNEP (United Nations Environment Programme). 2023. "Executive Summary." In *Emissions Gap Report 2023: Broken Record—Temperatures Hit New Highs, yet World Fails to Cut Emissions (Again)*. https://wedocs.unep.org/rest/api/core/bitstreams/ad8dea00-b147-49c9-aafc-9e070fafacd5/content.

US Energy Information Administration. 2023. "Total Energy." https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T01.07#/?f=A&start=1949&end=2023&charted=2.

Wang, Guokui, Xingpeng Chen, Zilong Zhang, and Chaolan Niu. 2015. "Influencing Factors of Energy-Related CO_2 Emissions in China: A Decomposition Analysis." *Sustainability* 7 (10): 14408–26. https://doi.org/10.3390/su71014408.

Wang, Miao, and Chao Feng. 2017. "Decomposition of Energy-Related CO_2 Emissions in China: An Empirical Analysis Based on Provincial Panel Data of Three Sectors." *Applied Energy* 190: 772–87. https://doi.org/10.1016/j.apenergy.2017.01.007.

Wang, Qiang, Lejia Li, and Rongrong Li. 2023. "Uncovering the Impact of Income Inequality and Population Aging on Carbon Emission Efficiency: An Empirical Analysis of 139 Countries." *Science of the Total Environment* 857: 159508. https://doi.org/10.1016/j.scitotenv.2022.159508.

Wang, Wenxiu, Yaoqiu Kuang, and Ningsheng Huang. 2011. "Study on the Decomposition of Factors Affecting Energy-Related Carbon Emissions in

Guangdong Province, China." *Energies* 4 (12): 2249–72. https://doi.org/10.3390/en4122249.

Wang, Yongming, Irfan Uddin, and Yingmei Gong. 2021. "Nexus between Natural Resources and Environmental Degradation: Analysing the Role of Income Inequality and Renewable Energy." *Sustainability* 13 (15): 8364. https://doi.org/10.3390/su13158364.

White, Halbert. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (4): 817–38. https://doi.org/10.2307/1912934.

Yan, Bin, Feng Wang, Mingru Dong, Jing Ren, Juan Liu, and Jing Shan. 2022. "How Do Financial Spatial Structure and Economic Agglomeration Affect Carbon Emission Intensity? Theory Extension and Evidence from China." *Economic Modelling* 108: 105745. https://doi.org/10.1016/j.econmod.2021.105745.

Zellner, Arnold. 1962. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57 (298): 348–68. https://doi.org/10.1080/01621459.1962.10480664.