

Article

Modeling Absolute CO₂–GDP Decoupling in the Context of the Global Energy Transition: Evidence from Econometrics and Explainable Machine Learning

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Abstract

This study investigates the feasibility of absolute decoupling—where economies expand while CO₂ (Carbon Dioxide) emissions decline in absolute terms—by identifying its key macro–energy drivers across 79 countries (2000–2025). We construct a comprehensive panel of energy-system indicators and estimate the probability of decoupling using two complementary classifiers: a penalized logistic regression and a gradient-boosted decision tree model (GBM). The non-parametric GBM significantly outperforms the linear baseline (ROC–AUC ~0.80 vs. 0.67), revealing complex non-linearities in the transition process. Explainable AI analysis (SHAP) demonstrates that decoupling is not driven by GDP growth rates alone, but primarily by sharp reductions in energy intensity and the active displacement of fossil fuels. Crucially, our results indicate that increasing renewable capacity is insufficient for absolute decoupling if the fossil fuel share does not simultaneously decline. These findings challenge passive “green growth” narratives, suggesting that current policies are inadequate; achieving climate targets requires targeted mechanisms for active fossil fuel phase-out rather than merely relying on renewable additions or economic modernization.

Keywords: absolute decoupling; CO₂ emissions; energy intensity; green growth; sustainability transitions

1. Introduction

Growing concern about climate change and environmental degradation has renewed scrutiny of the sustainability of traditional economic expansion. The concept of green growth—the idea that economies can grow while reducing environmental impacts—has become central in policy debates. A crucial element of green growth is decoupling, meaning that the link between Gross Domestic Product (GDP) and environmental pressure is weakened or broken. In particular, absolute decoupling requires that emissions fall in absolute terms even as GDP rises, which is considered necessary to meet Paris Agreement targets and the Sustainable Development Goals [1–3]. If absolute decoupling can be achieved, it validates strategies relying on technological innovation, efficiency improvements, and deliberate energy transitions. By contrast, if growth and deep decarbonization remain incompatible, then current economic paradigms may conflict with climate limits.

Empirical evidence on decoupling is limited and sometimes contradictory. Previous studies often focus on particular countries, regions, or sectors, and few offer a systematic,



Academic Editor:

Javier Cifuentes-Faura

Received: 25 November 2025

Revised: 20 December 2025

Accepted: 8 January 2026

Published: 12 January 2026

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cross-country analysis of absolute decoupling using multiple indicators. This paper narrows that gap by conducting a quantitative comparative study of 79 countries over 2000–2025. The main goal is to model and predict the occurrence of absolute decoupling—defined as positive real GDP growth with declining territorial CO₂ emissions—as a function of macroeconomic and energy-related factors (energy intensity, energy use per capita, and the primary energy mix). By identifying the statistical conditions under which decoupling has occurred historically, we contribute empirical evidence to the green-growth versus degrowth debate. Specifically, we ask whether green growth is attainable under current global energy and economic dynamics, or whether decoupling will remain rare without more radical changes.

1.1. Competing Views on Green Decoupling

Early work frequently relied on the Environmental Kuznets Curve (EKC), which hypothesizes an inverted-U relationship between income and pollution [4,5]. However, after decades of testing, there is no universal EKC for CO₂: estimated curves depend strongly on the pollutant and model specification, and many studies find no clear turning point for CO₂ even at high income levels [6–9]. Structural analyses additionally question whether aggregate environmental impacts can be decoupled from GDP growth under business-as-usual conditions [10,11]. In short, the expectation that economic growth eventually reduces environmental pressures is not supported as a general empirical rule.

A clearer conceptual framework is provided by the IPAT/Kaya identity, which decomposes emissions into population, affluence, energy intensity, and carbon intensity. Within this identity, relative decoupling occurs when energy or emissions intensity falls but total emissions may still rise, whereas absolute decoupling requires emissions to fall in absolute terms even as GDP grows. Decoupling elasticity metrics formalize this distinction, and empirical applications confirm that absolute decoupling is rare and context-dependent [12,13].

Two broad narratives emerge from this literature. Green-growth proponents argue that directed innovation, carbon pricing, and structural shifts can achieve sustained absolute decoupling [14,15]. In contrast, degrowth and ecological-economics scholars highlight rebound effects and biophysical limits to substitution, concluding that observed rates of decoupling are too slow to meet planetary boundaries and advocating sufficiency-oriented approaches [16–20]. Thus, the feasibility and drivers of absolute decoupling remain open empirical questions.

1.2. Global and Regional Evidence

At the global scale, there has been no sustained absolute decoupling of CO₂ from GDP. From 2010 to 2019, world GDP grew by about 3% annually while global CO₂ emissions rose by ~1.3% per year, implying only relative decoupling [1]. Long-run data for 164 countries show that although the GDP–CO₂ link has weakened somewhat, it remains strongly positive and inconsistent with rapid decarbonization [9]. Worldwide panel studies likewise find that global economic growth remains tightly coupled to rising emissions despite gradual improvements in energy and carbon intensity [21].

At the country level, patterns are more mixed. Several advanced economies have experienced episodes of absolute decoupling in the last two decades, driven by energy-efficiency gains and cleaner energy mixes [22]. The European Union has reduced territorial GHG emissions substantially since 1990 while GDP continued to rise [23]. Decomposition analyses of major emitters and studies on Belt and Road Initiative (BRI) and Organisation for Economic Co-operation and Development (OECD) economies show that improvements in efficiency and fuel switching are common features of countries where absolute decoupling occurs [9,24]. Cross-national studies identify between 30 and 50 countries (mostly in

Europe and Oceania) that have achieved some form of decoupling, compared to more than 100 countries where emissions still rise with GDP [9,25]. Even in these “success” cases, the pace of decoupling is insufficient to meet Paris-aligned mitigation targets. Analyses of high-income countries that achieved absolute decoupling of consumption-based CO₂ show emission reductions far below what is needed under Paris-compliant pathways [26]. Scenario studies reach similar conclusions, indicating that efficiency gains alone are unlikely to offset growth-driven increases in emissions without additional sufficiency measures [11].

In most emerging and low-income economies, GDP and emissions remain tightly coupled. Rapid GDP and population growth in Asia, Africa, and Latin America frequently outweigh efficiency improvements, resulting in rising emissions despite falling carbon intensity [27–31]. China exemplifies this pattern: its carbon intensity has declined, but its rapid economic expansion has driven CO₂ emissions to new highs [32]. Many emerging economies show only relative decoupling—emissions rise more slowly than GDP but do not fall absolutely. International trade further complicates assessments of decoupling. High-income countries often outsource carbon-intensive production, displaying territorial decoupling while consumption-based emissions continue to rise. Multi-regional input–output studies find that consumption-based decoupling is weaker or absent compared to production statistics [33,34]. Only a subset of countries that decouple territorially also decouple on a consumption basis [25]. Recent decomposition work highlights that the carbon intensity of imports matters as much as domestic changes [35].

Across hundreds of studies, systematic reviews conclude that while relative decoupling of CO₂ and materials is common, rapid and sustained absolute decoupling aligned with climate targets is rare and highly context-specific [19,36]. This motivates our focus: rather than debating feasibility broadly, we examine the specific episodes and conditions under which absolute decoupling has occurred, with attention to energy-system dynamics.

1.3. Methodological Approaches and Research Gaps

The decoupling literature spans several methodological traditions. One approach computes decoupling indicators and elasticities to classify periods or locations as strongly/weakly decoupled or coupled [37–40]. These descriptive metrics are intuitive but sensitive to the length of the time window and do not explain underlying causes.

A second strand uses econometric models linking emissions to income and structural variables in time-series or panel settings [41–46]. More recent work incorporates heterogeneity, structural factors such as energy mix and trade, and non-stationary dynamics [24,29,47,48]. These analyses often identify energy intensity and fuel mix as key channels—variables central to our own modeling. A third strand applies decomposition techniques to attribute emission changes to population, affluence, energy intensity, and carbon intensity, with some studies including structural and trade effects [22,25,27–31,35,49]. While informative, decomposition approaches describe past contributions rather than predicting future decoupling events.

Other studies cluster countries into “decoupling clubs” or test for convergence in emission intensities, emphasizing the roles of institutional and structural factors beyond aggregate energy metrics [9,50–53]. Finally, machine-learning methods have recently been used to forecast emissions and identify key drivers, with tree-based ensembles and neural networks enabling the capture of non-linearities and interactions. Interpretability tools such as SHAP provide insight into variable importance and decision pathways within these models [54].

Together, these strands reveal significant methodological and empirical gaps. Few studies integrate multiple macro–energy covariates into predictive models of absolute decoupling across many countries, incorporating both linear econometric and modern

machine-learning tools. Our analysis addresses this gap by modeling the probability of absolute decoupling using a harmonized multi-country dataset and complementary predictive approaches.

2. Materials and Methods

We assemble an unbalanced panel of 79 countries for the period 2000–2025. The data combine harmonized sources from Our World in Data (OWID), which collects consistent information on economic and energy indicators across countries and time. Specifically, we use (i) total territorial CO₂ emissions (metric tons), (ii) real GDP (constant prices, PPP), and (iii) energy-system indicators (total primary energy use, energy intensity, energy use per capita, and energy mix shares for fossil fuels and renewables). The OWID dataset synthesizes inputs from the Global Carbon Project, World Bank, International Energy Agency (IEA), and others, ensuring comparability.

After restricting to valid ISO3 countries, the 2000–2025 window, and dropping the first year for each country (to allow computation of lags), the final sample has 5232 country–year observations. We define an absolute decoupling episode (binary outcome, *decouple_abs*) at the country–year level: it equals 1 if real GDP grows and CO₂ emissions decline from $t-1$ to t , and 0 otherwise. By construction, in decoupling years, CO₂ falls while GDP rises, capturing the strongest notion of green growth. Approximately 27% of our observations satisfy this definition; the rest are “coupled” (GDP and emissions both rising) or cases of economic contraction. Table 1 lists all variables and units.

Table 1. Summary of all variables and their sources.

Variable	Description	Unit/Scale
<i>decouple_abs</i>	Absolute decoupling indicator	Binary (0/1)
<i>year</i>	Calendar year	Year
<i>iso3c</i>	Country code	Categorical
<i>gdp</i>	Real GDP level	Constant PPP currency
<i>gdp_lag</i>	Real GDP ($t - 1$)	Same as <i>gdp</i>
<i>gdp_growth</i>	GDP growth rate	Fraction per year
<i>co2</i>	CO ₂ emissions level	MtCO ₂
<i>co2_lag</i>	CO ₂ emissions ($t - 1$)	MtCO ₂
<i>co2_change</i>	Change in CO ₂ emissions	MtCO ₂
<i>energy_per_gdp</i>	Energy intensity	Energy per unit GDP
<i>energy_per_gdp_chg</i>	Δ Energy intensity	Same as <i>energy_per_gdp</i>
<i>energy_per_gdp_ma3</i>	Energy intensity (3-year avg.)	Energy per unit GDP
<i>energy_per_capita</i>	Energy use per capita	Energy per person
<i>energy_per_capita_chg</i>	Δ Energy use per capita	Same as <i>energy_per_capita</i>
<i>energy_per_capita_ma3</i>	Energy use per capita (3-year avg.)	Energy per person
<i>fossil_share_energy</i>	Fossil fuel share	% of primary energy
<i>fossil_share_energy_chg</i>	Δ Fossil fuel share	Percentage points (p.p.)
<i>fossil_share_energy_ma3</i>	Fossil fuel share (3-year avg.)	% of primary energy
<i>share_renewables_energy</i>	Renewables share	% of primary energy
<i>share_renewables_energy_chg</i>	Δ Renewables share	Percentage points (p.p.)
<i>share_renewables_energy_ma3</i>	Renewables share (3-year avg.)	% of primary energy

Descriptive statistics (Table 2) show that in decoupling years average GDP growth is slightly higher (4.3%) than in non-decoupling years (3.9%), while CO₂ declines on average (−4.5 Mt) in decoupling years but rises (+6.0 Mt) otherwise. Decoupling years also tend to have higher energy use per capita (~30,000 vs. 24,700 units) and slightly higher energy intensity (1.35 vs. 1.32 units of energy/GDP). Their energy mix is somewhat cleaner: the fossil-fuel share averages 81.3% in decoupling years (versus 85.0% in coupled years), and

the renewables share 1.99% (vs. 1.46%). These raw differences suggest that decoupling is more common in relatively energy-intensive, mid-to-high-income economies, but also that yearly shifts in intensity and fuel mix may be critical. We now formalize our modeling strategy using these variables.

Table 2. Standardized coefficients of top predictors in the pooled logistic regression model.

Variable	No Decoupling (D = 0) M (SD)	Decoupling (D = 1) M (SD)
Decouple_abs	0.00 (0.00)	1.00 (0.00)
Gdp_growth	0.039 (0.067)	0.043 (0.033)
Co2_chang	5.997 (46.973)	−4.505 (14.030)
Real GDP level	5.72×10^{11} (1.94×10^{12})	6.03×10^{11} (1.98×10^{12})
CO ₂ emissions	202.02 (871.85)	180.16 (759.98)
Energy_per_capita	24,729.84 (35,854.01)	29,986.87 (36,587.24)
Energy_per_gdg	1.315 (0.943)	1.350 (0.886)
Fossil_share_energy	85.02 (15.76)	81.31 (18.45)
Share_renewables_energy	1.459 (3.275)	1.985 (3.702)
Decouple_abs	0.00 (0.00)	1.00 (0.00)
Gdp_growth	0.039 (0.067)	0.043 (0.033)
Co2_chang	5.997 (46.973)	−4.505 (14.030)
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Energy_per_gdg	1.315 (0.943)	1.350 (0.886)
Fossil_share_energy	85.02 (15.76)	81.31 (18.45)
Share_renewables_energy	1.459 (3.275)	1.985 (3.702)
Decouple_abs	0.00 (0.00)	1.00 (0.00)

Note. Values are means and standard deviations. GDP is in constant PPP currency (levels); CO₂ in MtCO₂. Energy variables are in the native OWID units; fossil and renewables shares are expressed in percent.

2.1. Model Specification and Estimation Strategy

Dependent Variable: Defining Absolute Decoupling—Let Y_{it} and E_{it} denote real GDP (PPP) and territorial CO₂ emissions for country i at time t . We focus on the discrete growth of output, $g_{it} = \Delta Y_{it} / Y_{i,t-1}$, and the absolute change in emissions, ΔE_{it} . Following the “strong” sustainability framework [20], we construct a binary indicator D_{it} for absolute decoupling:

$$D_{it} = 1(g_{it} > 0 \wedge \Delta E_{it} < 0)$$

This indicator identifies “green growth” episodes where the correlation between economic scale and environmental pressure is structurally broken.

Explanatory Variables and Dynamics—To model the likelihood of decoupling, we assemble a vector of covariates $\mathbf{X}_{it}$ capturing the scale, efficiency, and carbon intensity of the energy system (summarized in Table 1). We characterize the system state using four core metrics: Energy Intensity $EI_{it} = \text{Energy}_{it} / Y_{it}$, Energy Use per Capita ($EC_{it} = \text{Energy}_{it} / \text{Pop}_{it}$), and the shares of fossil fuels (S_{it}^F) and renewables (S_{it}^R) in the primary energy mix. Crucially, decoupling is dynamic. For each structural variable $v_{it} \in \{EI, EC, S^F, S^R\}$, we compute two transformations to capture short-run shocks and medium-run baselines:

1. **Annual Change:** $\Delta v_{it} = v_{it} - v_{i,t-1}$
2. **Structural Baseline (3-year MA):** $\tilde{v}_{it} = \frac{1}{3} \sum_{k=0}^2 v_{i,t-k}$

This specification allows the model to distinguish between the level of efficiency (e.g., a historically clean grid) and the rate of improvement (e.g., a rapid shift to renewables). To preserve sample heterogeneity, we employ a hierarchical imputation. Missing

values for a covariate x are replaced by the country-specific median $\mu_i^{(x)}$; if undefined, the global sample median $\mu_{\text{global}}^{(x)}$ is used. We estimate the probability of decoupling, $\pi_{it} = P(D_{it} = 1 \mid \mathbf{X}_{it})$, using two complementary approaches.

2.2. Penalized Logistic Regression

As a parametric benchmark, we assume a linear index function on the standardized predictors $\mathbf{Z}_{it}$:

$$\text{logit}(\pi_{it}) = \alpha + \beta^\top \mathbf{Z}_{it} + \varepsilon_{it}$$

Given the class imbalance (−27% positive cases), we maximize a weighted log-likelihood function to ensure sensitivity to minority-class instances.

2.3. Gradient Boosted Decision Trees (GBM)

To capture non-linearities and threshold effects (e.g., tipping points in renewable adoption), we employ a gradient boosting ensemble [55]. The model approximates the log-odds through an additive expansion of M shallow trees:

$$F(\mathbf{X}_{it}) = \sum_{m=1}^M \nu \cdot h_m(\mathbf{X}_{it})$$

where ν is the learning rate and each tree h_m fits the negative gradient of the loss function. We tune hyperparameters (depth, ν , subsampling) on the training set (70%) and interpret the “black box” predictions using SHAP (Shapley Additive Explanations) values to isolate the marginal contribution of each energy driver.

3. Results

Across the 5232 observations, about 27% are decoupling episodes (GDP↑ and CO₂↓). Table 2 (descriptive statistics) highlights a few patterns. On average, decoupling years have slightly higher GDP growth (4.3% vs. 3.9%), indicating that green growth can occur even in robust growth periods, not only low-growth times. By construction, CO₂ emissions fall in decoupling years (mean −4.5 MtCO₂) and rise in non-decoupling years (+6.0 Mt). The standard deviation of emissions change is much smaller during decoupling (14.0) than otherwise (47.0), suggesting that decoupling is associated with steady, moderate declines rather than extreme shocks.

Energy-system variables also differ on average. Countries experiencing decoupling tend to have higher energy use per capita (mean ~30,000 energy units vs. 24,700 in non-decoupling) and slightly higher energy intensity (1.35 vs. 1.32 energy units/GDP). This reflects that decoupling events are more common in middle-to-high-income, energy-intensive economies (which have the scale and resources to invest in transitions). Importantly, decoupling years feature a somewhat cleaner fuel mix: the average fossil fuel share falls from about 85.0% (non-decoupling) to 81.3% in decoupling years, while the renewables share rises from 1.46% to 1.99%. These raw means hint that both demand-side factors (energy intensity) and supply-side shifts (fuel mix) are relevant, but level differences alone do not fully explain decoupling. This motivates our formal modeling of both levels and dynamic changes.

Predictive Performance of the Models

Table 3 (reproduced below) compares the out-of-sample performance of the logistic regression and gradient boosting models on the test set. The gradient boosting classifier substantially outperforms the logistic model in all key metrics. Its receiver operating characteristic—area under curve (ROC–AUC) is ~0.80 (vs. 0.67 for logistic), and its

precision–recall area under curve (PR–AUC) is notably higher (around 0.45 vs. 0.40). Overall accuracy is 78.0% (balanced accuracy ~0.69) for boosting, compared to 68.6% (balanced 0.67) for logistic. At the 0.5 probability threshold, the logistic model achieves precision 0.44 and recall 0.63 for the decoupling class, meaning it correctly identifies most decoupling years but also has many false positives. The boosting model, by contrast, yields higher precision (0.62) albeit lower recall (0.48), indicating it is more conservative in flagging decoupling episodes but with fewer false alarms. Overall, these results suggest that decoupling episodes are not random; a fairly parsimonious set of macro–energy predictors can anticipate them with reasonably high accuracy when using a flexible non-linear model.

Table 3. Model performance on the test set.

Model	ROC–AUC	Accuracy	Balanced Accuracy	Precision	Recall	F1-Score
Logistic regression	0.673	0.686	0.668	0.443	0.631	0.520
Gradient boosting	0.798	0.780	0.686	0.620	0.480	0.541

The logistic regression coefficients shed light on the direction of effects. The largest (in magnitude) coefficients are associated with energy intensity and the energy mix. Specifically, a higher current energy intensity is linked to lower odds of decoupling ($\beta \approx -1.52$), while a higher fossil-fuel share also reduces decoupling odds ($\beta \approx -0.38$). On the other hand, improvements in intensity (negative Δ intensity) and rising renewables share (Δ renewables) are associated with higher decoupling probability (positive coefficients). These signs align with intuition: cleaner, more efficient systems favor green growth. Table 4 lists the top predictors by coefficient magnitude.

Table 4. Top predictors by coefficient magnitude of logistic regression.

Description	Logit Coefficient β
Energy intensity	−1.5176
Energy intensity (3-year avg.)	1.2141
Δ Energy intensity	−0.7324
Δ Fossil fuel share	−0.3742
Energy use per capita	0.1755
Renewables share	0.1672
Renewables share (3-year avg.)	−0.1091
Fossil fuel share (3-year avg.)	−0.0607
Δ Renewables share	0.0548
GDP growth rate	−0.0541
Fossil fuel share	−0.0478

Note. Coefficients from pooled logistic regression with standardized predictors and class-balanced weights; only the 10 predictors with largest $|\beta|$ are shown.

The gradient boosting model yields complementary insights via feature importance and SHAP analysis. Four variables emerge as most influential in the boosting model. First, GDP growth rate is a key predictor: moderate positive growth increases decoupling likelihood, whereas very low (recession) or very high growth both push against decoupling. In other words, decoupling tends to occur in “Goldilocks” years of steady expansion rather than booms or busts.

Second, the annual change in energy intensity (Δ EI) is critical. The SHAP summary (beeswarm) plot (Figure 1) shows a clear gradient: large negative Δ EI (strong efficiency gains) strongly increase decoupling probability, while increases in intensity reduce it. This

confirms that short-run improvements in energy efficiency are central to green growth. Third, the change in per-capita energy use (ΔEC) has a similar effect: decreases in per-capita energy use raise decoupling probability, suggesting that demand-side restraint (via efficiency or behavioral shifts) helps reconcile growth with emissions cuts.

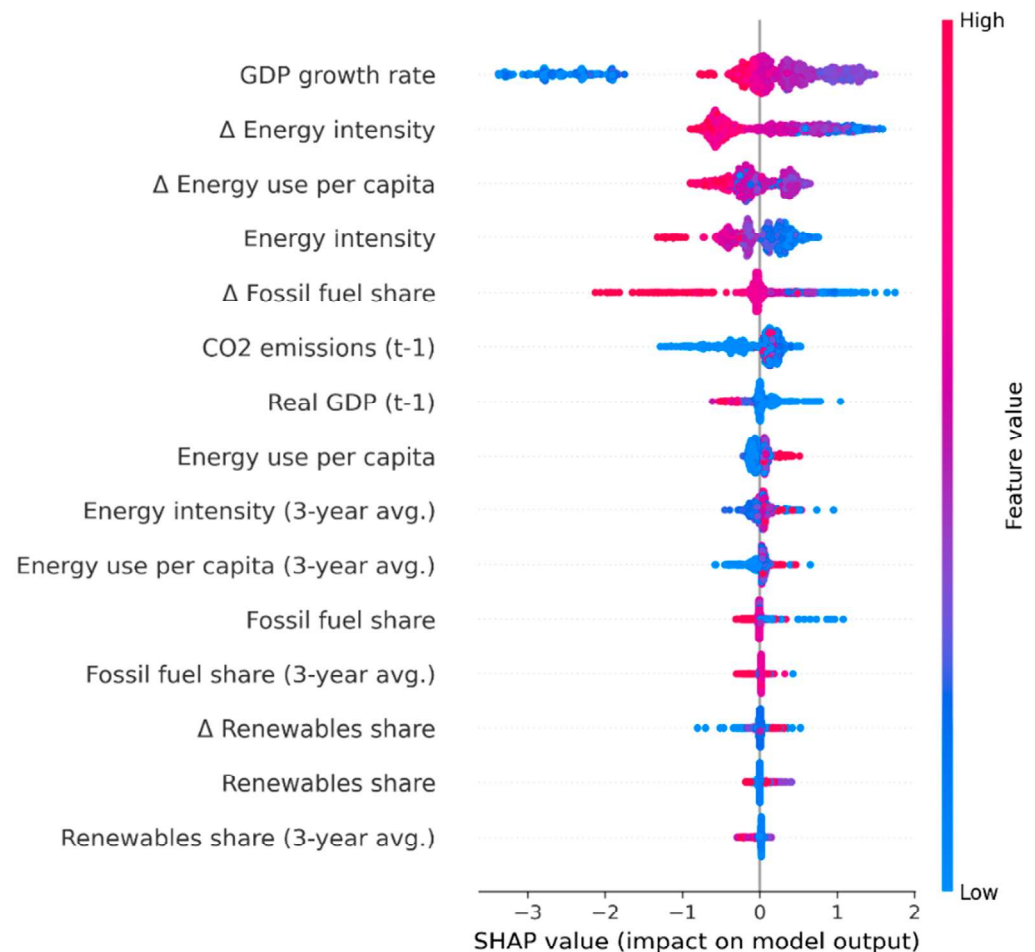


Figure 1. SHAP summary plot: feature contributions to the predicted probability of absolute decoupling. Source: own elaboration. Notes. Each point represents a country–year observation; colors indicate the feature value (low to high) and the horizontal position the SHAP value (marginal impact on the model's output).

Fourth, the annual change in fossil-fuel share ($\Delta Fossil$) is highly influential. Large negative $\Delta Fossil$ (rapid reductions in coal, oil, gas share) consistently push the model toward predicting decoupling. This implies that actively phasing down fossil fuels is strongly associated with green growth outcomes, more so than merely adding renewables on top of an unchanged fossil base. Beyond these dynamic factors, the level of energy intensity, lagged emissions, and lagged GDP also matter: very high levels of intensity or emissions tend to depress decoupling probabilities (as revealed by SHAP values), whereas intermediate levels are less inhibitory.

The 3-year averages of intensity and energy per capita have smaller but non-negligible effects, indicating that the broader efficiency and demand context matters. The renewables share (level and change) also contributes positively when it increases, but it is less dominant than the fossil-share dynamics. In summary, the SHAP and feature-importance analyses reinforce the logistic results: short-term energy transitions are the main statistical markers of absolute decoupling. Rapid efficiency improvements (reducing energy intensity and

per-capita use) and swift fossil-fuel phase-out are associated with green growth, conditional on moderate GDP expansion.

Finally, we use the gradient boosting model to compute, for each country, the average predicted probability of decoupling over the test-set years and visualize these averages on a world choropleth map (Figure 2). The resulting spatial pattern aligns with the descriptive evidence. High predicted probabilities cluster in several advanced economies with well-documented decarbonization efforts, including Western European countries such as the United Kingdom, Italy, the Netherlands, Poland, and Lithuania, as well as high-income resource exporters like Canada and Australia.

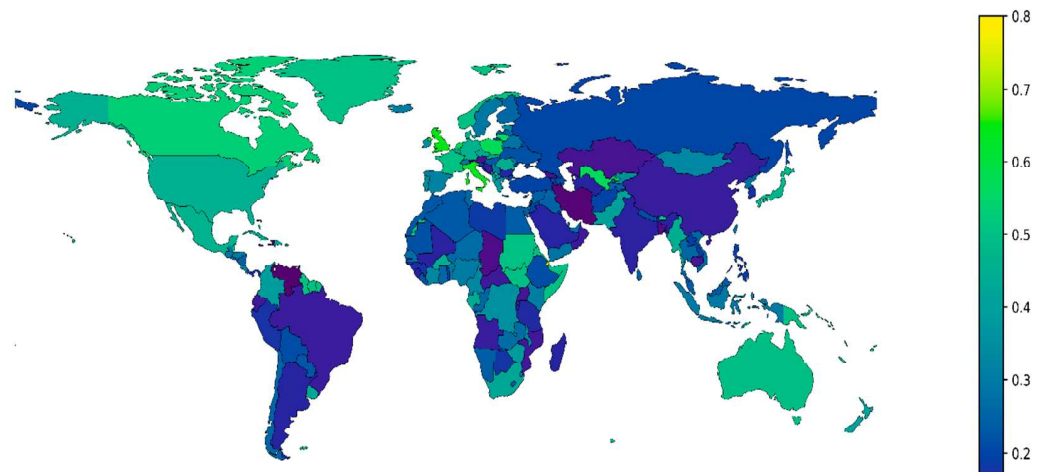


Figure 2. Average predicted probability of absolute decoupling by country.

Some smaller economies (for example Luxembourg, Uzbekistan, and Djibouti) also exhibit relatively high modelled propensity to decouple, reflecting idiosyncratic combinations of efficiency improvements and rapid fuel-mix shifts. By contrast, many coal- and oil-dependent economies, particularly in parts of Asia, the Middle East, and Latin America, display low average predicted probabilities. Large emerging emitters with high fossil shares and rising energy demand tend to be assigned a low likelihood of achieving decoupling in any given year, even when their GDP growth is strong. The map therefore offers a compact visual summary of the model-implied geography of green growth, highlighting both pockets of repeated decoupling and regions where decoupling remains rare.

4. Discussion

Our findings indicate that absolute decoupling is neither automatic nor universal, but it does occur repeatedly in some contexts. About one in four country–year observations in the sample is a decoupling episode, suggesting that green growth is attainable under certain conditions. This occurrence rate aligns with empirical work showing decoupling is generally rare, though we do not find it to be entirely exceptional. A key contribution of this study is highlighting the importance of dynamic energy-system variables over static country characteristics. While rich, energy-intensive economies do have more decoupling events on average, it is the year-to-year changes that drive most predictive power. In other words, the pace of transition matters more than the starting point. Large annual improvements in energy intensity or large shifts in the fuel mix are much more predictive of decoupling than whether a country is simply wealthy or large.

Consistent with the literature, we find that fossil fuel phase-down is more decisive for decoupling than renewables growth alone. Years marked by rapid declines in coal/oil/gas shares are strongly associated with decoupling, implying that adding renewables on top

of an unchanged fossil base is not sufficient. This contrasts with some studies that focus mainly on renewables; our results highlight that actively reducing fossil dependence is central to green growth.

We also identify a “Goldilocks zone” of economic growth: moderate, sustained expansion is most conducive to decoupling. The model suggests that deep recessions or overheating booms both reduce decoupling likelihood, unless they coincide with extreme efficiency gains and fuel switching. This challenges any simplistic assumption that any positive growth inherently supports emissions declines.

Cross-country heterogeneity likely reflects broader institutional and structural factors beyond our model. The high-propensity countries in our map (Western Europe, Canada, Australia, etc.) all have long histories of climate and energy policies, strong technological capacity, and (in some cases) wealth to invest in cleaner infrastructure. In contrast, many developing or resource-dependent economies face persistent constraints: weaker institutions, limited clean-technology access, and economic structures tied to fossil industries. These factors likely explain why similar macro-energy changes may or may not occur in practice. In short, our results do not deny the role of GDP or policy environments; they complement them by showing what macro variables co-occur with decoupling given those contexts.

Several caveats are in order. We use production-based CO₂ at annual frequency and pool all country-year observations, which may obscure some multi-year transition dynamics or fixed country traits (like geography or climate policy). For example, some countries might achieve decoupling through structural shifts over a decade, which a year-on-year model may understate. Moreover, relying on territory-based emissions does not capture the carbon footprint of trade. Nevertheless, our approach provides a broad, quantitative perspective on the conditions associated with absolute decoupling. It highlights actionable levers: namely, continued efficiency improvements and active fossil fuel reduction.

5. Conclusions

Absolute decoupling of CO₂ from GDP growth is possible but remains an exceptional outcome, observed in roughly 25–30% of country-year cases in our sample. The main determinants of decoupling episodes are dynamic energy-system factors rather than GDP growth per se. In particular, sharp improvements in energy intensity, reductions in per-capita energy use, and most importantly rapid declines in the fossil-fuel share are associated with a significantly higher probability of green growth. Decoupling is most likely under moderate, sustained economic growth, rather than during recessions or uncontrolled booms, emphasizing a “Goldilocks” growth regime. Cross-country differences underscore that institutional and structural contexts matter: countries with long-standing climate policies tend to achieve repeated decoupling, whereas fossil-dependent economies face structural limits.

Overall, our results reinforce that green growth is not automatic. It requires the simultaneous alignment of moderate growth, improved energy efficiency, and active fossil fuel phase-out. These insights provide guidance for policymakers: focusing on efficiency gains and fuel switching can increase the chances of expanding the rare episodes of absolute decoupling.

Author Contributions: Conceptualization, R.T.-G. and R.T.-S.; methodology, R.T.-G.; software, R.T.-G.; validation, R.T.-G., P.F.d.A. and R.T.-S.; formal analysis, R.T.-G.; investigation, R.T.-G.; resources, R.T.-S.; data curation, R.T.-G.; writing—original draft preparation, R.T.-G.; writing—review and editing, R.T.-G., P.F.d.A. and R.T.-S.; visualization, R.T.-G.; supervision, R.T.-S.; project administration, R.T.-S.; funding acquisition, P.F.d.A. and R.T.-S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Instituto Politécnico de Setúbal, Escola Superior de Ciências Empresariais, Campus do IPS, Estefanilha, Setúbal, Portugal, and by the University Center of Defense, Polytechnic University of Cartagena. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset used in this study is publicly available from Our World in Data (OWID) and combines harmonized sources including the Global Carbon Project, the World Bank, and the IEA. All data supporting the findings of this study can be accessed at: <https://ourworldindata.org/co2-and-greenhouse-gas-emissions> (accessed on 7 January 2026). The new variables and model are available if the journal needs it.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CO ₂	Carbon Dioxide
GDP	Gross Domestic Product
GHG	Greenhouse Gas
EKC	Environmental Kuznets Curve
IPAT	Impact = Population × Affluence × Technology
BRI	Belt and Road Initiative
OECD	Organization for Economic Co-operation and Development
EU	European Union
PPP	Purchasing Power Parity
OWID	Our World in Data
IEA	International Energy Agency
GBM	Gradient Boosted Machine/Gradient Boosting Model
SHAP	SHapley Additive exPlanations
ROC–AUC	Receiver Operating Characteristic—Area Under Curve
PR–AUC	Precision–Recall Area Under Curve
Δ	Change ($\Delta x = x_t - x_{t-1}$)

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