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Article

Explainable Artificial Intelligence for Designing Country-Specific Climate Mitigation and Sustainable Development Pathways

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ABSTRACT

This study compares six machine-learning models for predicting per-capita CO_2 emissions in a panel of 118 countries over 2000–2020 and uses SHAP to examine the fitted XGBoost model. The test sample comprises 2019–2020. XGBoost achieved the lowest test RMSE (0.475) and highest R^2 (0.324), indicating limited to moderate predictive fit. GDP per capita had the largest means absolute SHAP value (0.2821), followed by the country effect (0.0361). Renewable-energy associations differed across observations and should not be interpreted as a uniform emissions reduction. Country profiles and four descriptive clusters illustrate possible areas for policy review; SHAP contributions are predictive associations, not causal effects or evaluated policy impacts.

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Research Highlights

- Across 118 countries over 2000–2020, XGBoost shows the best reported test performance among six models.
- GDP per capita was the largest global XGBoost SHAP predictor with other factors including renewable energy showing differennce.
- Country and four-cluster profiles can guide further investigation, but incomplete explained variation and the observational design preclude causal policy conclusions.
- Future work should incorporate additional energy and policy inputs and evaluate proposed interventions with designs suited to causal questions.

1. Introduction

Climate change threatens human health, economic development, and ecosystems [1, 2]. The Paris Agreement and Sustainable Development Goal (SDG) 13 motivate better evidence about variation in national emissions [2, 3]. This paper analyzes reported country-year CO_2 observations to compare predictive methods and describe model associations; it does not estimate the impact of climate policies. The IEA's assessment of energy-related CO_2 emissions provides context for national energy and emissions trajectories [4].

Machine-learning models can represent nonlinear predictive associations among economic, institutional, and energy indicators. Random Forest [5], XGBoost [6], and CatBoost [7] can be interpreted using SHapley Additive exPlanations (SHAP), which allocate individual predictions among model inputs [8]. Those allocations are conditional on a fitted model and do not identify causal effects. Given the test R^2 of 0.324, the analysis offers an exploratory account of predictive patterns. Reviews of explainable AI describe its concepts, taxonomies, and challenges for responsible use [9].

This study compares six machine-learning models and interprets the best-performing model using SHAP for 118 countries over 2000–2020. It reports no Method of Moments Quantile Regression (MM-QR) or feasible generalized least squares (FGLS) estimates. The analysis supports descriptive country comparisons and predictive interpretation, not causal policy effects.

2. Literature Review

2.1. Climate Change and Carbon Emissions

The environmental Kuznets curve (EKC) is a hypothesis that the relationship between income and environmental pressures may change with development [10, 11]. Its shape and interpretation depend on the pollutant, sample, specification, and identification strategy. This study does not test a causal EKC; it evaluates income as one predictor of a reported CO_2 measure. Prior work on emission modelling should be compared by outcome definition, study population, validation design, and treatment of confounding before drawing policy conclusions. Costantini et al. compared multivariate regression and random-forest approaches to national CO_2 forecasting across 117 countries [12]. Butt et al. combined panel econometrics with ANN, random-forest, and LSTM models for total CO_2 emissions in China, India, and the United States over 1992–2022; their outcome and validation design differ from the per-capita target and 118-country panel considered here [13].

2.2. Renewable Energy and Sustainable Development

Energy transition and trade are discussed in climate-policy research, but neither the existence nor the size of an intervention effect can be inferred from an observational model explanation. Renewable share and trade openness are model inputs here. The corresponding SHAP values show how those inputs contribute to predictions in this fitted model, with direction and magnitude varying across observations. Related research includes a cross-sectoral review of China's renewable-energy and energy-efficiency policies [14], an ARDL and machine-learning analysis of investment and emissions in China [15], and a study of governance, green finance, and mitigation technologies in European industrial economies [16]. Earlier work examined China's energy and carbon-emissions outlook to 2050 [17]. Butt et al. studied trade openness, energy intensity, technological innovation, and per-capita CO_2 in 40 Belt and Road Initiative countries over 2010–2022 using quantile methods [18]. Their separate China study examined ecological footprint over 1990–2021 using an ML-ARCH framework; ecological footprint is a broader environmental indicator and is not interchangeable with CO_2 emissions [19]. Energy-transition research emphasizes the joint roles of renewable energy, energy efficiency, and electrification [20], while the IPCC assesses mitigation options across sectors and development contexts [21].

2.3. Explainable Artificial Intelligence and Machine Learning

Random Forest and gradient-boosted trees can capture nonlinear prediction patterns [5, 22]; interpretation tools such as SHAP describe how model inputs contribute

to fitted predictions [8, 23]. SHAP explanations depend on feature dependence, background data, and the chosen implementation [24]. They do not resolve confounding or establish that changing a predictor would change emissions by the SHAP amount [25]. Work on climate-policy classification likewise requires transparent category definitions and validation of any country assignment. Hamad et al. applied an optimized explainable-AI approach to environmental education and pollution, illustrating a related application outside national CO_2 prediction [26].

2.4. Research Gap

The specific contribution is a chronological six-model comparison for a reported 118-country panel, global and local XGBoost SHAP descriptions, and exploratory cluster profiles. The study does not estimate econometric or causal policy effects. Its novelty lies in bringing these descriptive analyses together for the stated sample, not in introducing a new learning algorithm or validated intervention-selection method.

3. Methodology

3.1. Research Framework

The workflow assembles country-year observations, prepares predictors, compares six regression models on a chronological split, explains XGBoost predictions using SHAP, and summarizes country and cluster profiles. Reported associations concern model predictions rather than causal emissions drivers.

SHAP explanations are used to describe global and country-level contributions to predictions. The results presented below do not report partial-dependence or LIME estimates; the methodological claims are limited accordingly.

3.2. Data Collection

The reported analysis uses 2478 observations from 118 countries over 2000–2020 (21 years per country). Per-capita CO_2 emissions are the target. Predictors are GDP per capita, renewable-energy share, industrial share, urbanization, trade openness, governance, year, and country. Table 1 lists the variables used in the reported models. The original source extracts, variable definitions, and any rescaling of the emissions target should be checked against the analysis data before submission. GDP per capita is shown in source-data units: the currency, price year, and purchasing-power adjustment are not documented in the supplied files. The definitions and denominators for renewable share, industrial share, trade openness, governance, and per-capita CO_2 must be verified from the source extract before the table can support cross-country comparisons.

3.3. Data Preprocessing and Feature Engineering

The data are described as a balanced panel. The supplied manuscript does not specify whether missing entries were imputed, how any imputation was fitted within the chronological split, or whether continuous predictors were standardized for each model. It also does not document tuning grids, cross-validation folds, or the precise encoding of country. These details must be retrieved from the analysis code; they cannot be reconstructed from the reported results. “Country effect” below denotes the model input representing country identity, not an estimated fixed effect. Figure 1 uses logarithmic display axes where labelled; the manuscript does not establish whether the underlying model inputs were transformed. The reported split implies 2006 training observations, 236 validation observations, and 236 test observations if the panel is complete in every year. Do not claim leakage-free imputation or scaling until the pipeline demonstrates that all fitted transformations use training data only and that validation and test years are transformed with the fitted training parameters. Software versions and random seeds are also unavailable. Validation design should account for temporal and country-level dependence [27].

Table 1. Variables and data sources.

Variable	Source
CO_2 emissions per capita, reported target	World Development Indicators (WDI)
GDP per capita	World Bank (WDI)
Renewable-energy share	International Energy Agency (IEA)
Industrial share	Source to verify from analysis dataset
Urbanization rate	World Development Indicators (WDI)
Trade openness	World Development Indicators (WDI)
Governance index	Worldwide Governance Indicators (WGI)
Year and country identity	Panel identifiers

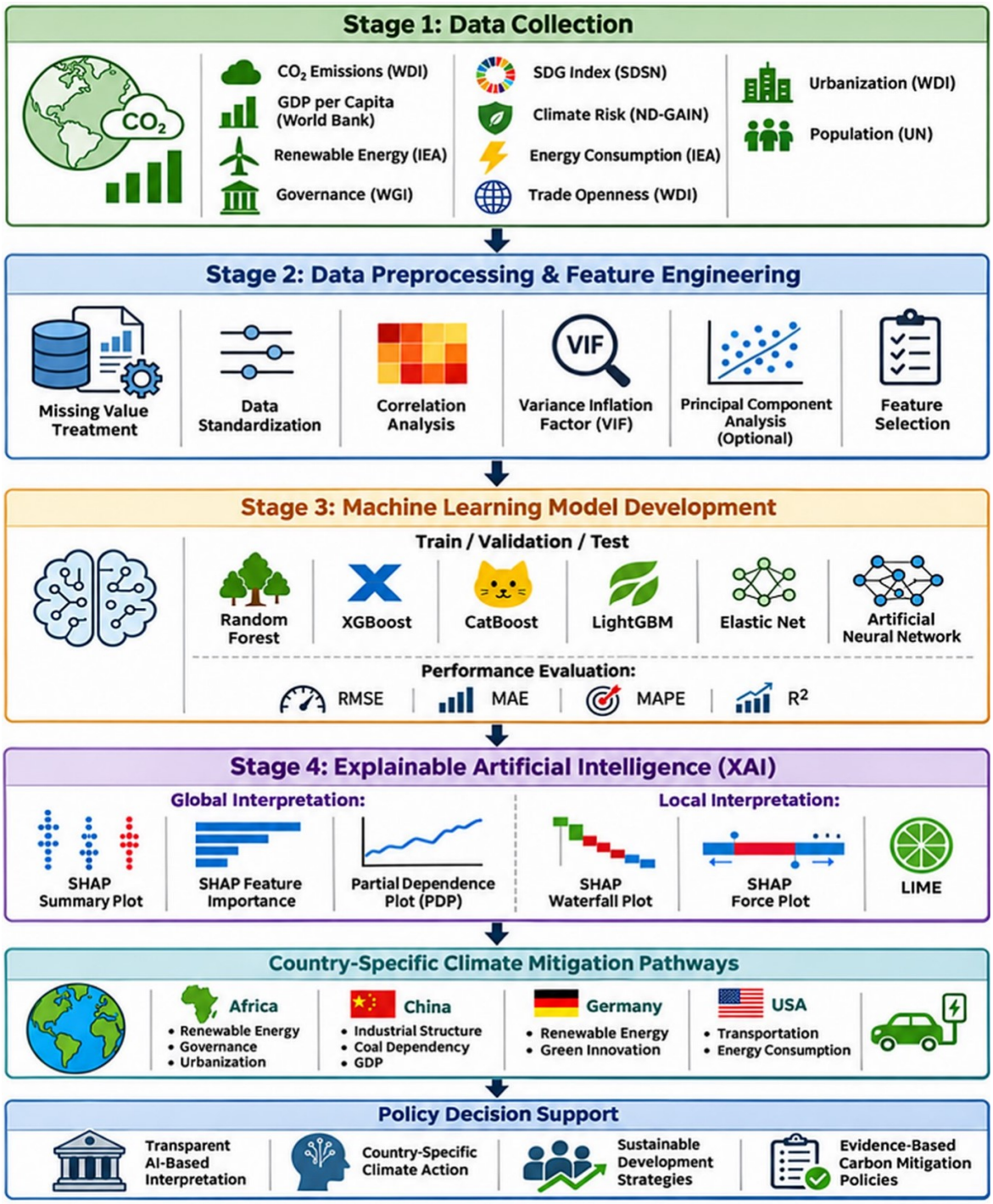


Figure 1. Proposed Explainable Artificial Intelligence (XAI) Framework for Country-Specific Climate Mitigation and Sustainable Development Pathways.

3.4. Machine Learning Models

Six regression models were compared:

- Random Forest (RF) [5]
- XGBoost, or Extreme Gradient Boosting [6]
- CatBoost [7]
- LightGBM [28]
- Elastic Net [29]
- ANNs, or artificial neural networks [30]

The reported splits are training (2000–2016), validation (2017–2018), and test (2019–2020), with 236 test observations. The available manuscript does not document a reproducible hyperparameter search or cross-validation protocol; these must be supplied from the training code before any tuning claim is made. A chronological split by

itself does not establish whether validation, model selection, and test evaluation were implemented without leakage. The original script must document the fit order and the untouched final test sample. The suitability of cross-validation for time-series prediction depends on the model and error structure; results for purely autoregressive models cannot be assumed to apply to this country panel [31].

3.5. Model Evaluation

Four commonly used regression measures are used to assess the model's performance:

- RMSE, or root mean square error
- MAE, or mean absolute error
- MAPE, or mean absolute percentage error
- Coefficient of Determination (R^2)

Root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R^2 summarize the reported held-out predictions. MAPE is especially unstable when actual outcomes approach zero [32]. Performance should also be compared with simple training-set mean, previous-year, or other prespecified baselines; those benchmark results have not been supplied and cannot be inferred.

3.6. Explainable Artificial Intelligence

The best-performing reported test model, XGBoost, was interpreted using SHAP.

The available results include global mean absolute SHAP values and local contributions. SHAP contributions sum with the model baseline to the prediction on the explanation scale [8]. The background distribution and treatment of correlated predictors [24] require confirmation from the analysis code.

Global interpretation:

- Global importance is summarized by the average absolute SHAP contribution of each input across the explained observations.
- No partial-dependence plot (PDP) analysis is reported as a separate validated result.

SHAP magnitude describes contribution to predicted values rather than physical emission shares or causal effects [8, 25].

Local interpretation:

Country profiles summarize SHAP contributions for selected observations and regions.

- A local contribution percentage can be defined as 100 $\times$ |SHAP value for input j|/sum over included inputs of |SHAP value| for the same prediction. The supplied materials do not document whether the existing percentage tables use this formula, which observations were aggregated, or how the baseline and residual categories were handled; verify these calculations before submission.
- No Local Interpretable Model-agnostic Explanations (LIME) estimates are reported.

These analyses describe variation in model predictions; they do not determine which mitigation policy would be effective.

3.7. Country-Specific Climate Mitigation Pathways

Illustrative countries and a regional group are used to describe model contributions. Table 2 lists evaluated inputs alongside policy topics requiring independent evidence. The existing profiles do not quantify policy outcomes.

Country-level SHAP contributions describe the fitted model and cannot by themselves determine effective interventions. Policy examples in Table 2 require separate sectoral and causal evidence [2, 21].

3.8. Specific contribution and scope

This paper compares six regression models on a chronological holdout and illustrates global, local, and cluster-level predictive summaries. The following statements should be read within that scope.

1. The study compares six specified models on the reported panel.
2. XGBoost SHAP supplies the reported global and local model explanations; standalone PDP and LIME analyses are not presented.
3. Country and cluster profiles organize exploratory, literature-informed policy questions; they are not evaluated intervention pathways.
4. The proposed use is descriptive decision support relevant to climate-action discussions, subject to limited predictive fit and incomplete methodological records.

Table 2. Illustrative country-level predictors and literature-informed mitigation topics.

Country	Main Variables Evaluated
African economies	Renewable energy, governance, urbanization
China	Industrialization, GDP
Germany	Renewable energy transition, industrial share
United States	GDP, trade openness, governance, country identity

4. Results and Discussion

Results from 2478 country-year observations for 118 countries (2000–2020) are summarized below. The target is the reported per-capita CO_2 measure. The model inputs are GDP per capita, renewable-energy share, industrial share, urbanization, trade openness, governance, year, and country identity. The split is chronological: training 2000–2016, validation 2017–2018, and test 2019–2020 (236 observations). The original data must be checked to identify the target unit or scaling before the numerical emissions values can be interpreted physically.

4.1. Descriptive Statistics

Table 3 summarizes the main characteristics of the dataset. The target values in Table 3 (maximum 2.734) do not establish conventional tonnes of CO_2 per person without a verified source unit or scaling factor. The table is therefore presented in the units of the supplied analysis; confirm the target construction against the raw dataset. The correlation matrix and Table 4 summarize pooled Pearson associations only. Near-zero pooled correlations involving governance and urbanization need not imply zero within-country or nonlinear associations; coding and scaling must also be verified before substantive interpretation.

The global distribution of per capita emissions (118 nations, 2000–2020) is depicted in Figure 2. Significant cross-country variation in economic development and environmental performance is shown by the descriptive statistics. Renewable energy, urbanization, trade openness, governance, and industrial structure all show significant variance throughout the sample, as do GDP per capita and per-capita CO_2 emissions. The application of nonlinear machine-learning models and country-specific interpretation are supported by this diversity.

4.2. Correlation Analysis

Figure 3 presents the Pearson correlation matrix for the study variables.

Table 4 gives pooled Pearson correlations between each predictor and the reported emissions target. GDP per capita has the largest positive pooled correlation (0.250). The other listed correlations are small in this dataset. Pooled correlations should not be interpreted as causal effects or evidence of the absence of within-country associations.

4.3. Machine-Learning Model Performance

Random Forest, XGBoost, CatBoost, LightGBM, Elastic Net, and an artificial neural network were the six machine-learning models that were compared. RMSE, MAE, MAPE, and R^2 were used to evaluate performance on the unseen 2019–2020 test sample. The out-of-sample machine learning performance is displayed in Table 5.

Figure 4 shows out-of-sample RMSE by model.

Table 3. Descriptive statistics.

Variable	Mean	Standard Deviation	Minimum	Maximum
CO_2 emissions target (unit and scaling unverified)	0.880	0.559	0.100	2.734
GDP per capita	31,765.67	23,606.35	1,012.37	256,164.01
Renewable-energy share (%)	20.01	9.87	0.00	53.85
Industrial share (%)	30.40	9.98	5.00	60.00
Urbanization rate (%)	59.73	14.96	20.00	95.00
Trade openness (%)	69.97	19.98	20.00	136.02
Governance index	0.011	1.021	−3.299	3.544

Note: Statistics for the CO_2 emissions target are reported as supplied in the analysis. Its source unit, per-capita construction, and any transformation or scaling have not been verified; these values should therefore not be interpreted as tonnes of CO_2 per person. Verification against the raw dataset and preprocessing code is required before substantive interpretation.

Table 4. Correlations with per-capita CO_2 emissions.

Predictor	Correlation with CO_2 Emissions
GDP per capita	**0.250**
Renewable-energy share	0.015
Industrial share	−0.000
Urbanization rate	−0.044
Trade openness	−0.026
Governance index	−0.006
Year	0.005

Table 5 reports the numerical test-set model comparisons: XGBoost RMSE 0.475, MAE 0.383, R^2 0.324; CatBoost RMSE 0.479, MAE 0.386, R^2 0.315. The test R^2 of 0.324 indicates substantial unexplained variation. Figure 5 must be regenerated from these same test predictions if its labels disagree with Table 5. Large MAPE values, especially with small target values, also limit its usefulness for model comparison.

4.4. Actual and Predicted Emissions

Figure 6 compares observed per-capita emissions with the predictions generated by XGBoost.

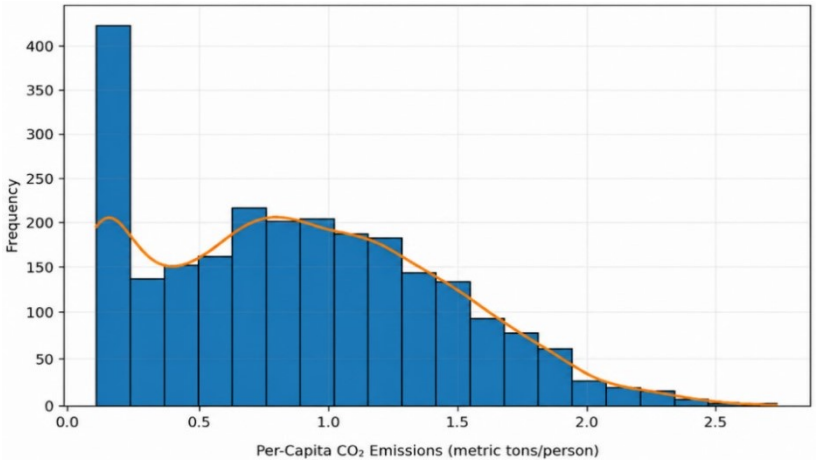


Figure 2. Global distribution of per-capita CO_2 emissions (118 countries, 2000–2020).

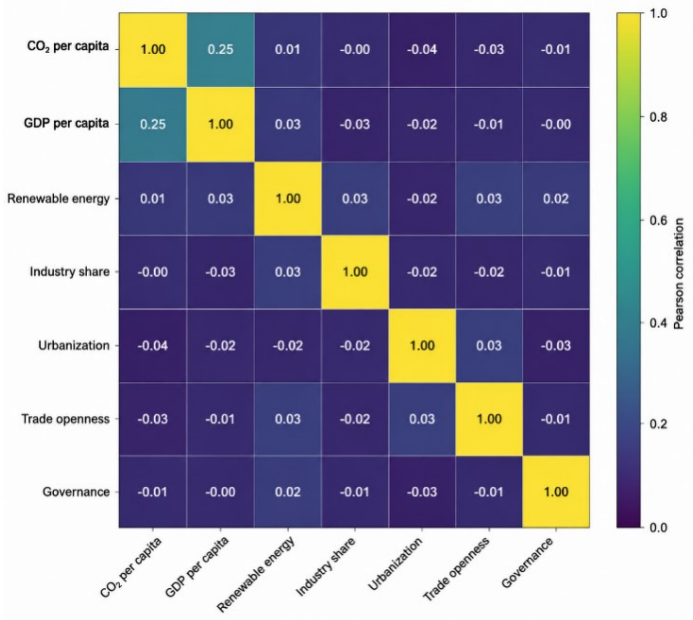


Figure 3. Correlation matrix of study variables.

Table 5. Out-of-sample machine-learning performance.

Model	RMSE	MAE	MAPE (%)	R^2
XGBoost	0.475	0.383	121.84	0.324
CatBoost	0.479	0.386	118.35	0.315
Random Forest	0.492	0.406	145.92	0.275
LightGBM	0.496	0.398	122.75	0.263
Neural Network	0.525	0.426	147.18	0.177
Elastic Net	0.668	0.507	220.86	−0.334

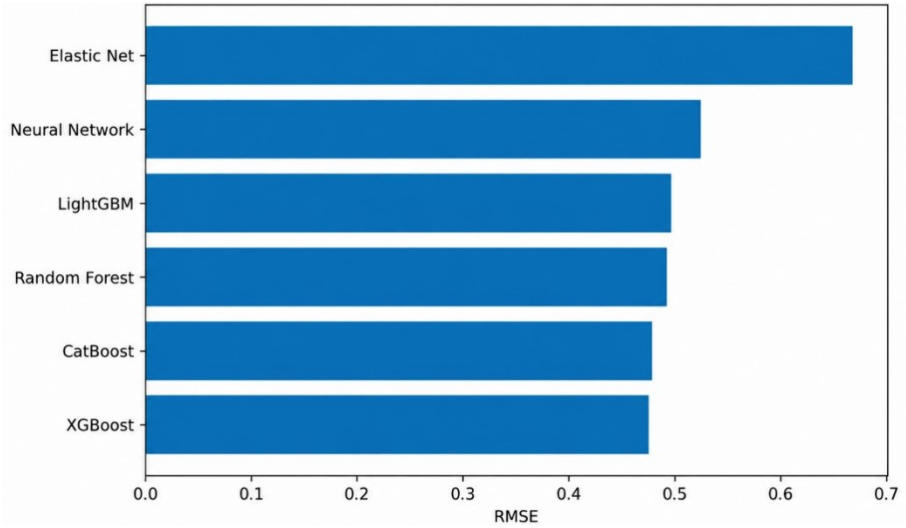


Figure 4. Test-set RMSE by model.

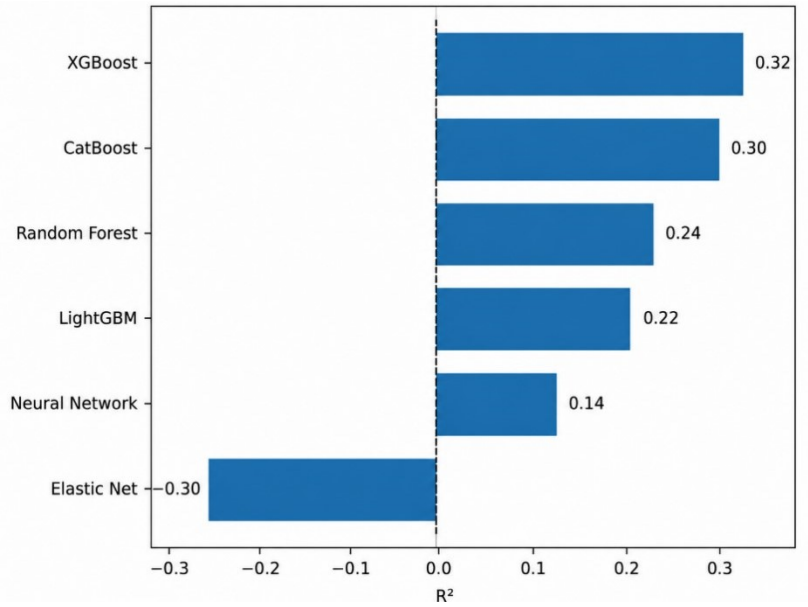


Figure 5. Test-set R^2 by model.

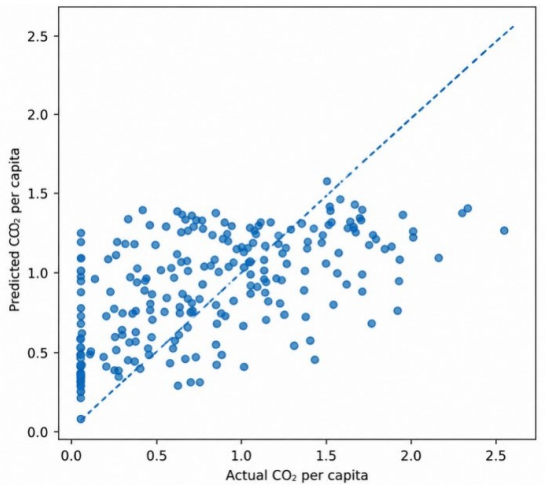


Figure 6. Actual versus predicted emissions from XGBoost.

Although predicted values are more concentrated around the sample means, they often follow the observed emissions trend, which results in greater errors for extreme observations. Overall, the model is more appropriate as a decision-support tool than an exact emissions-accounting system and works well for normal emission levels.

4.5. Residual Analysis

Figure 7 presents the distribution of the XGBoost residuals, defined as actual emissions minus predicted emissions.

The residuals appear approximately centered in the plotted sample, but visual inspection alone does not rule out systematic subgroup errors. Omitted energy-system and sectoral variables may contribute to residual variation.

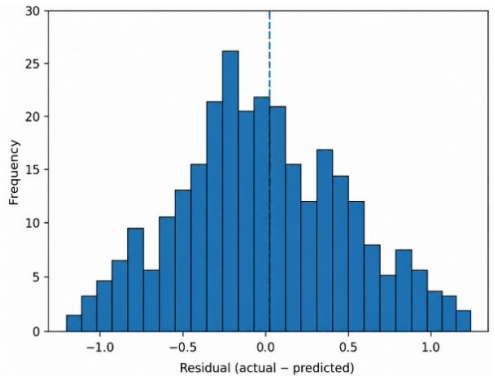


Figure 7. Test sample residual distribution.

4.6. Global SHAP Results

XGBoost was chosen for explainable-artificial-intelligence analysis since it had the best overall test results. The mean absolute SHAP values were used to calculate global relevance. Global SHAP feature relevance is displayed in Table 6.

Table 6 ranks average absolute XGBoost SHAP contributions. GDP per capita ranks first and country identity second; the latter may encode stable differences between countries, but its construction is undocumented. A model refit without country identity is needed to assess whether performance and feature rankings depend on it; this comparison is not available.

4.7. SHAP Beeswarm Results

Figure 8 shows the distribution and direction of SHAP values for the numerical predictors.

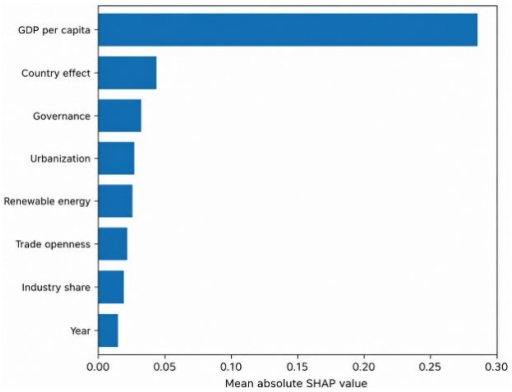


Figure 8. Global SHAP feature importance.

Figure 9 shows both positive and negative SHAP contributions for several predictors. In particular, the renewable-energy pattern should be described as heterogeneous; a positive SHAP value means a higher prediction relative to the model baseline for that observation and does not imply a causal increase in emissions.

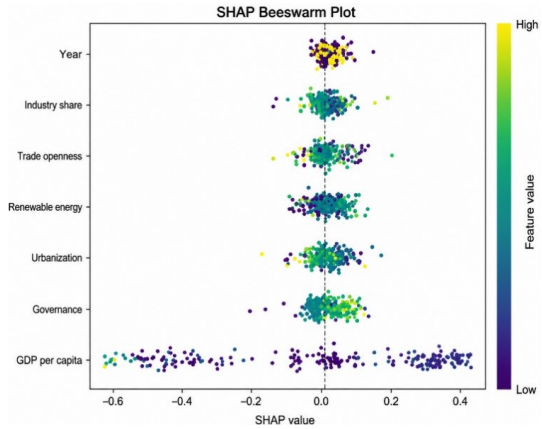


Figure 9. SHAP beeswarm plot.

4.8. Regional and Country-Level Explanations

Local SHAP profiles were reported for the United States, China, Germany, and a group of African countries. The tabulated percentages should represent shares of absolute model contributions only after their denominator and aggregation rule are confirmed. They are not national shares of CO_2 emissions or causal effects.

Figure 10 depicts associations in the fitted XGBoost model. GDP per capita shows a nonlinear predicted pattern, while the renewable-energy panel includes observations with slightly positive contributions as well as negative ones. Thus the plot does not support a general claim that higher renewable share lowers predictions in every country. Neither plot establishes a causal Environmental Kuznets Curve or the effect of increasing renewable generation.

4.8.1. Africa

The available test-period observations for the 25 African nations included in the dataset were used to compute the African regional profile. The main factors influencing the test-period projections for Africa are displayed in Table 7.

Table 6. Global SHAP features importance.

Rank	Predictor	Mean Absolute SHAP Value
1	GDP per capita	0.2821
2	Country effect	0.0361
3	Governance index	0.0271
4	Urbanization rate	0.0234
5	Renewable-energy share	0.0223
6	Trade openness	0.0191
7	Industrial share	0.0178
8	Year	0.0143

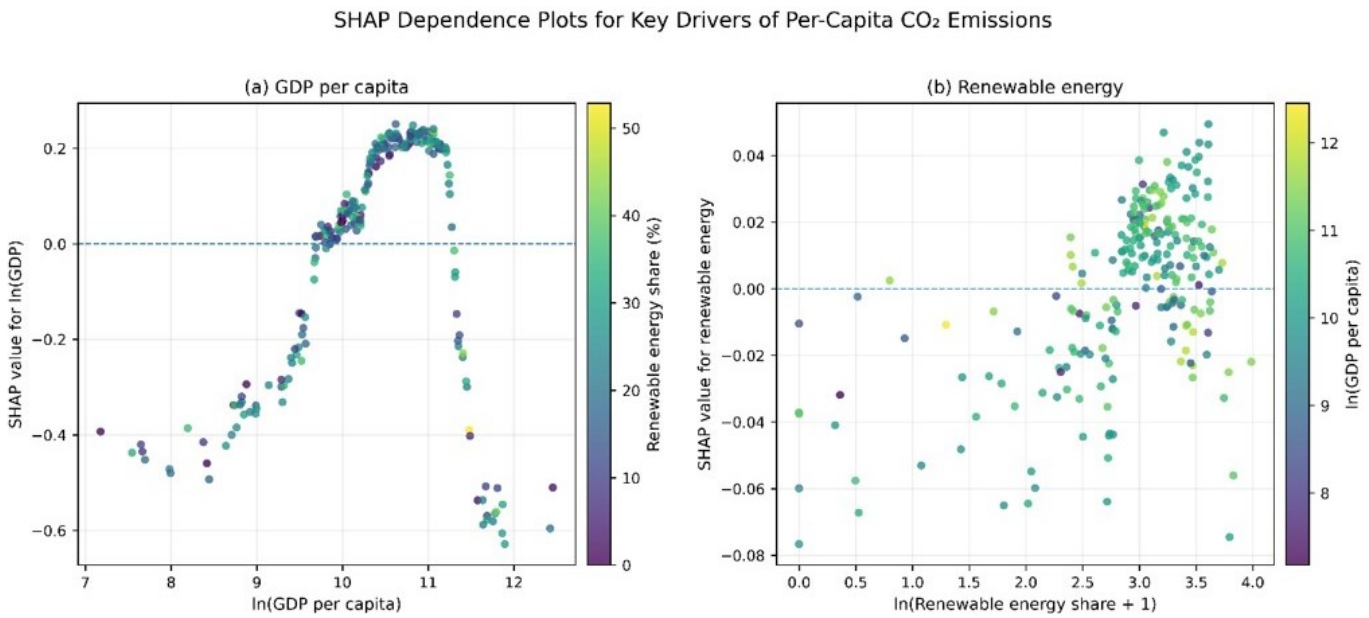


Figure 10. SHAP dependence plots for GDP per capita and renewable energy.

Table 7. Principal drivers of the African emission profile.

Predictor	Mean Direction	Share of Local Explanation (%)
GDP per capita	Reduces prediction relative to global baseline	67.36
Country effect	Reduces prediction	6.79
Urbanization	Slight increases prediction	4.96
Governance	Approximately neutral on average	4.92
Renewable-energy share	Slight increases prediction	4.74
Industrial share	Reduces prediction	4.41
Other features (combined)	Not reported	6.82

Africa's local emission driver profile is depicted in Figure 11. Africa's primary predictor is GDP per capita, and a negative SHAP effect indicates the region's comparatively low-income levels rather than a causative decrease in emissions. Smaller, nation-specific contributions are made by urbanization, governance, and renewable energy. The results indicate that in order to achieve low-carbon economic growth without repeating development routes that rely heavily on fossil fuels, Africa should prioritize renewable energy, sustainable urbanization, greater governance, and climate finance.

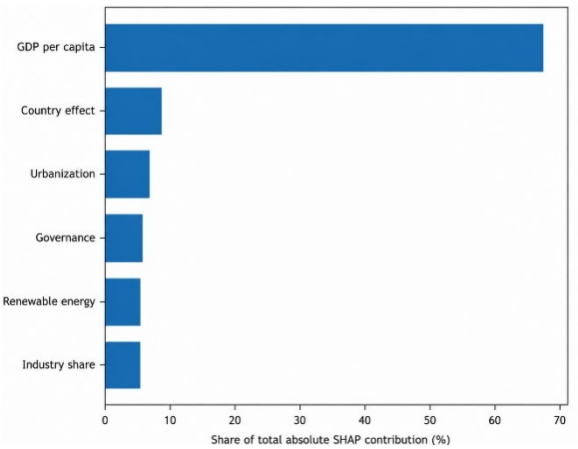


Figure 11. Local emission-driver profile: Africa.

4.8.2. China

Table 8 show principal drivers of China test-period predictions.

China's local emission driver profile is depicted in Figure 12. China's emissions are primarily predicted by GDP per capita, which reflects the impact of industrial activity and economic growth. While urbanization raises anticipated emissions, renewable energy and governance lower them. These results imply that low-carbon urban growth, clean manufacturing, renewable electrification, and industrial efficiency should be given top priority in China's mitigation strategy.

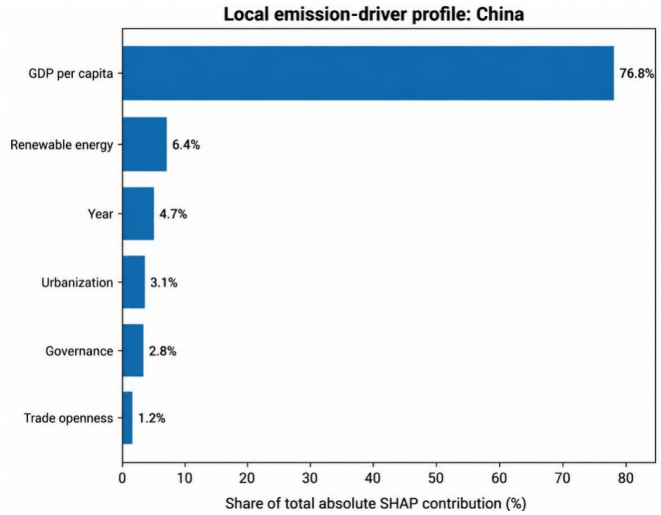


Figure 12. Local emission-driver profile: China.

4.8.3. Germany

Table 9 show principal drivers of Germany test-period predictions.

Germany's local emission driver profile is displayed in Figure 13. Although its negative SHAP effect suggests lower anticipated emissions than other high-income nations, GDP per capita is Germany's primary predictor. Emissions are increased by industrial activity, although this effect is partially counteracted by trade openness, governance, and national characteristics. These results are in favor of policies that favor energy storage, green hydrogen, industrial electrification, renewable energy integration, and ongoing transportation and manufacturing decarbonization.

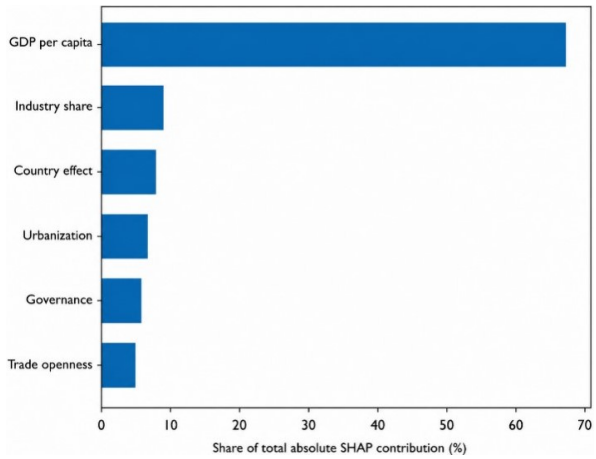


Figure 13. Local emission-driver profile: Germany.

Table 8. Principal drivers of China's test-period predictions.

Predictor	Mean Direction	Share of Local Explanation (%)
GDP per capita	Increases prediction	**77.30**
Renewable-energy share	Reduces prediction	6.95
Year	Increases prediction	4.83
Urbanization	Increases prediction	3.84
Governance	Reduces prediction	3.48
Trade openness	Slightly increases prediction	1.49
Other features (combined)	Not reported	2.11

Table 9. Principal drivers of Germany's test-period predictions.

Predictor	Mean Direction	Share of Local Explanation (%)
GDP per capita	Reduces prediction on average	**64.73**
Industrial share	Increases prediction	7.16
Country effect	Reduces prediction	6.46
Urbanization	Mixed, slightly positive average	5.90
Governance	Reduces prediction	5.08
Trade openness	Reduces prediction	4.09
Other features (combined)	Not reported	6.58

4.8.4. United States

Table 10 summarizes model contributions to United States test-period predictions.

The United States' local emission driver profile is displayed in Figure 14. Trade openness, governance, country-specific characteristics, and industrial structure are the next most important predictors of U.S. emissions after GDP per capita. The positive effect points to other unnoticed factors including energy use, transportation, and consumption habits. These results emphasize the need for vehicle electrification, building efficiency, renewable energy expansion, electricity-grid decarbonization, and improved coordination of climate policies.

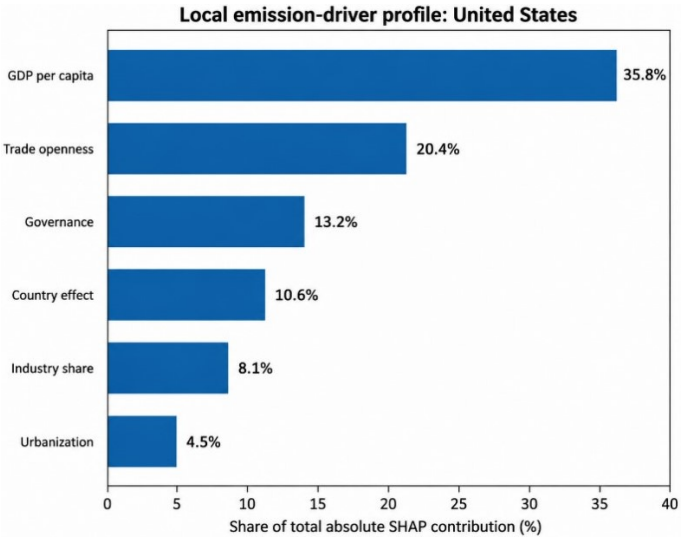


Figure 14. Local emission-predictor profile for the United States.

4.9. Cluster Analysis

The manuscript reports K-means grouping of country-level indicator averages into four clusters. The choice of K-means, $k = 4$, feature scaling, random initialization, and cluster stability are not documented. Results should be considered exploratory until the authors report standardized inputs, candidate-k diagnostics (such as silhouette scores), random seeds, and assignment stability across reruns. Principal-component analysis (PCA) is a visualization or dimension-reduction step, not independent confirmation of cluster validity. PCA is a variance-preserving projection rather than a clustering validation test [33]. Silhouette analysis can assess cluster cohesion and separation [34], while k-means++ provides a documented seeding approach that could be considered in a reproducible rerun [35]; neither procedure is claimed to have been implemented in the reported analysis.

Figure 15 is a descriptive projection. Apparent separation in two principal components does not validate the number of clusters. The explained variance and assignments must agree with Figure 16 and Table 11 before substantive interpretation.

Figures 15 and 16 should show the same final four-cluster solution, PCA variance, and memberships as Table 11. Conflicting plotted labels cannot be resolved without the PCA and K-means outputs.

Table 11 reports mean CO_2 of 1.117 in the 36-country high-emitter group and 1.006 in the 29-country established-emitter group. The 23-country group called "emerging economies" has a lower reported mean (0.625) than the 30-country "lower-emission transition" group (0.667). These labels are descriptive and potentially misleading; the assignments and definitions should be verified against the source data before giving the groups substantive names.

4.10. Exploratory Cluster Profiles and Policy Questions

Table 12 presents illustrative policy questions by cluster. These topics were not estimated as intervention effects.

The reported groups are descriptive. Policy suggestions reflect interpretation and external policy reasoning rather than a documented mapping from a SHAP value or K-means label to an optimal action. The current results cannot rank the expected benefits of the interventions.

Table 10. Principal drivers of United States test-period predictions.

Predictor	Mean Direction	Share of Local Explanation (%)
GDP per capita	Increases prediction	**36.12**
Trade openness	Increases prediction	21.27
Governance	Mixed, positive average	13.66
Country effect	Increases prediction	10.92
Industrial share	Increases prediction	8.83
Urbanization	Increases prediction	3.50
Other features (combined)	Not reported	5.70

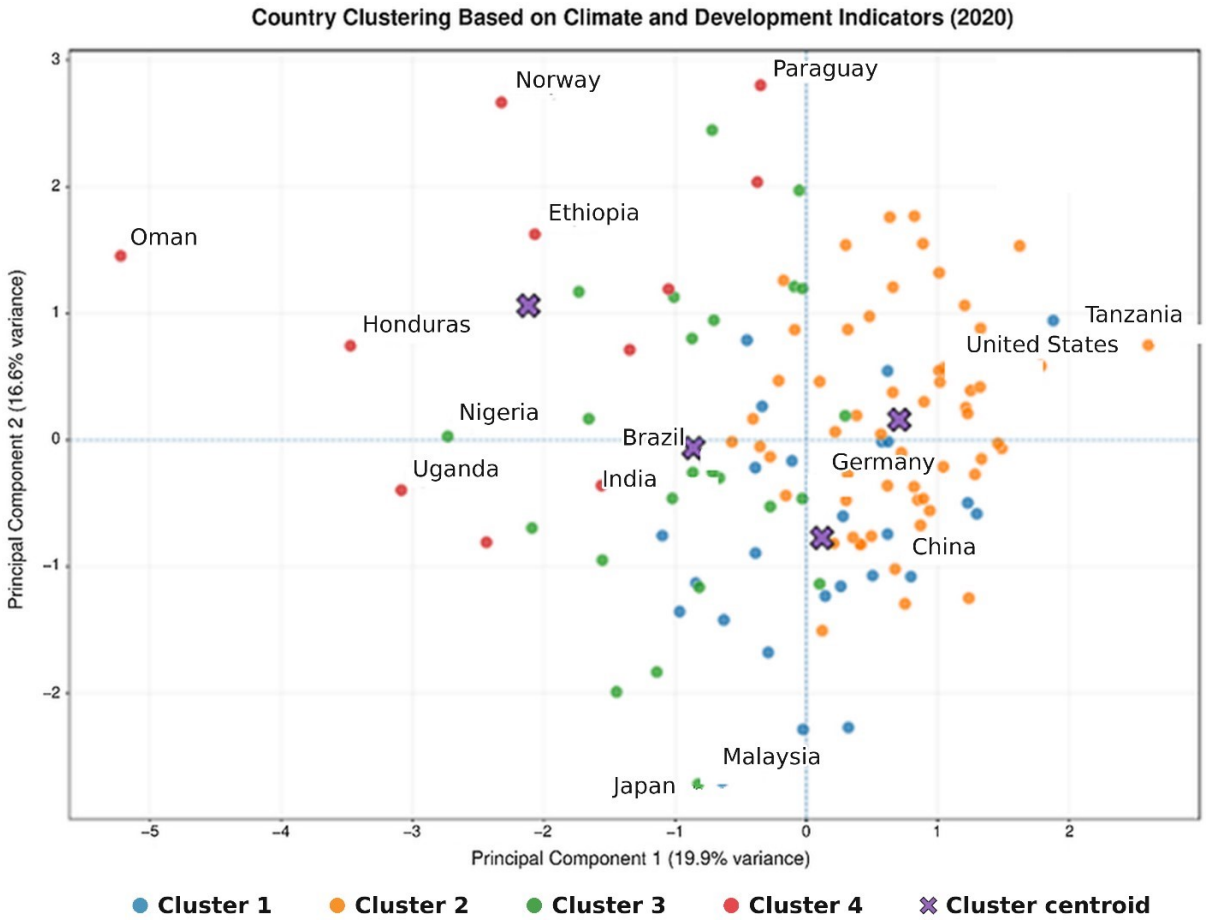


Figure 15. PCA-based clustering of 118 countries according to climate and development indicators. Note: This PCA visualization is descriptive.

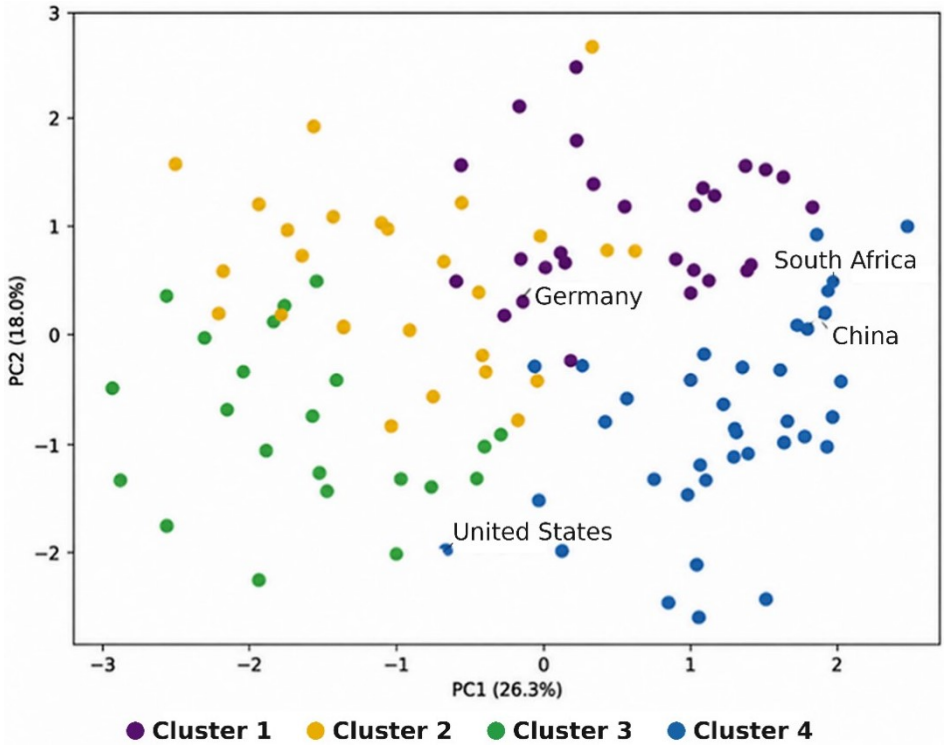


Figure 16. Country clusters in principal-component space.

Table 11. Characteristics of the four country clusters.

Cluster	Countries	Mean CO_2	Mean GDP per Capita	Renewable Energy (%)	Industry (%)	Urbanization (%)	Trade (%)	Governance
High emitters	36	1.117	49,940.50	20.60	29.96	60.34	71.52	−0.166
Established emitters	29	1.006	38,528.92	20.18	31.01	57.12	66.59	0.206
Emerging economies	23	0.625	14,675.01	19.14	31.97	63.91	68.84	−0.017
transition economies	30	0.667	16,520.90	19.80	29.13	58.31	72.25	0.057

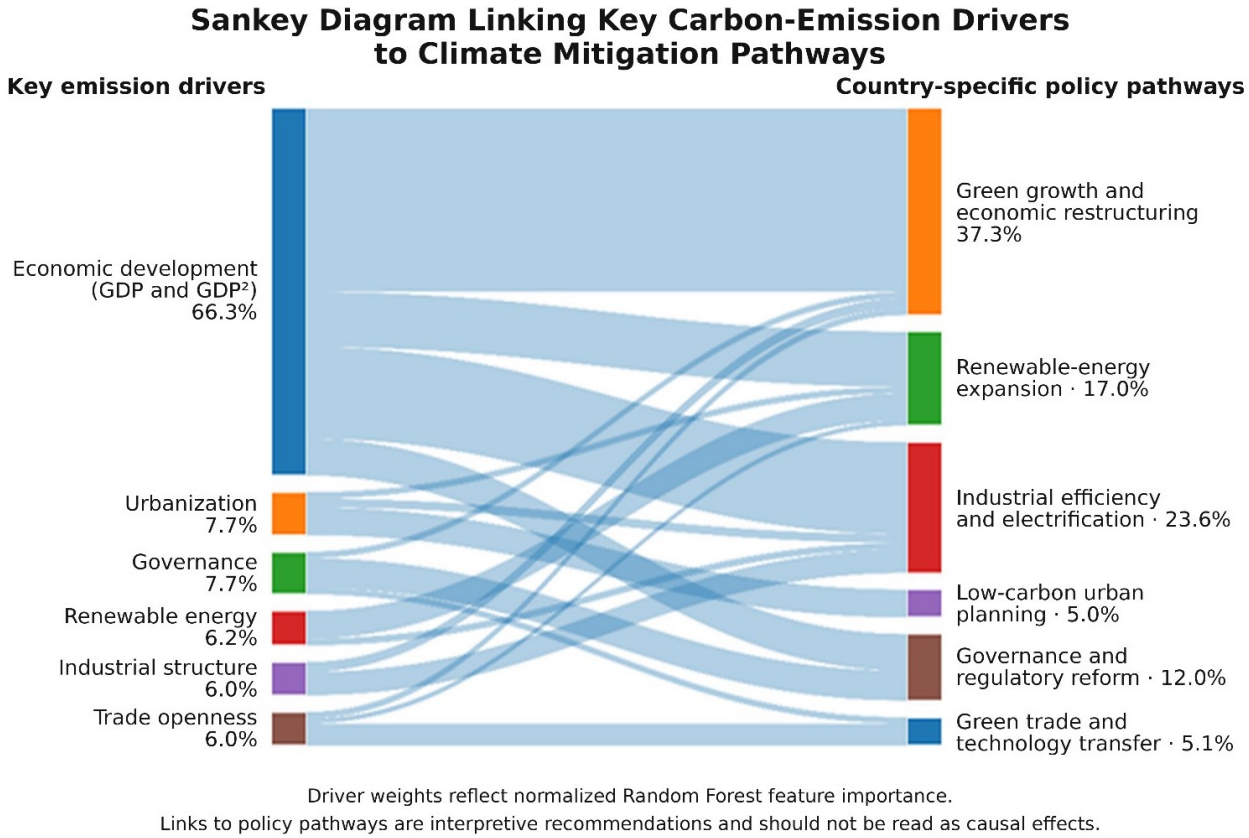


Figure 17. Conceptual mapping from model inputs to possible climate-policy questions. Note: This conceptual mapping links model predictors to literature-informed policy topics; flow widths should not be presented as estimated policy effects. The reported global importance analysis uses XGBoost SHAP, not Random Forest importance. The manuscript does not document a numerical rule for Sankey widths.

Figure 17 presents an author-proposed mapping between model inputs and policy topics. These links are conceptual and do not represent measured intervention effects, causal links, or calibrated priority weights.

Figure 18 illustrates proposed country-specific discussion topics. The current materials do not establish how each country was assigned a dominant category; no geographic pattern in the map should be presented as a validated model output until its assignment rule and country labels are audited.

4.11. Robustness and Limitations of the Results

The test R^2 of 0.324 indicates substantial unexplained variation. SHAP values describe predictions, not intervention effects or physical shares of emissions. Country identity may capture unmeasured factors, and the original code is needed to confirm its encoding, missing-data handling, tuning, target units, plot values, and cluster assignments. Energy mix, transport, carbon pricing, and related policy variables are not model inputs. Accordingly, the profiles and suggested policies are hypotheses for further assessment rather than evaluated mitigation pathways.

Table 12. Illustrative "Recommended climate pathways by country cluster by reported cluster".

Cluster	Principal Challenge	Recommended Climate Pathway
High emitters	High income, consumption, and emission levels	Rapid fossil fuel retirement, renewable-energy expansion, carbon pricing, transport electrification, and industrial decarbonization
Established emitters	Stronger governance but persistent emissions	Strengthen policy implementation, phase out fossil-fuel subsidies, improve building efficiency, and accelerate clean innovation
Emerging economies	Risk of industrial and urban carbon lock-in	Finance clean electricity, sustainable cities, public transport, efficient industry, and resilient infrastructure
Lower-emission transition economies	Maintaining lower emissions during development	Expand decentralized renewables, energy access, green investment, efficient infrastructure, and climate resilience

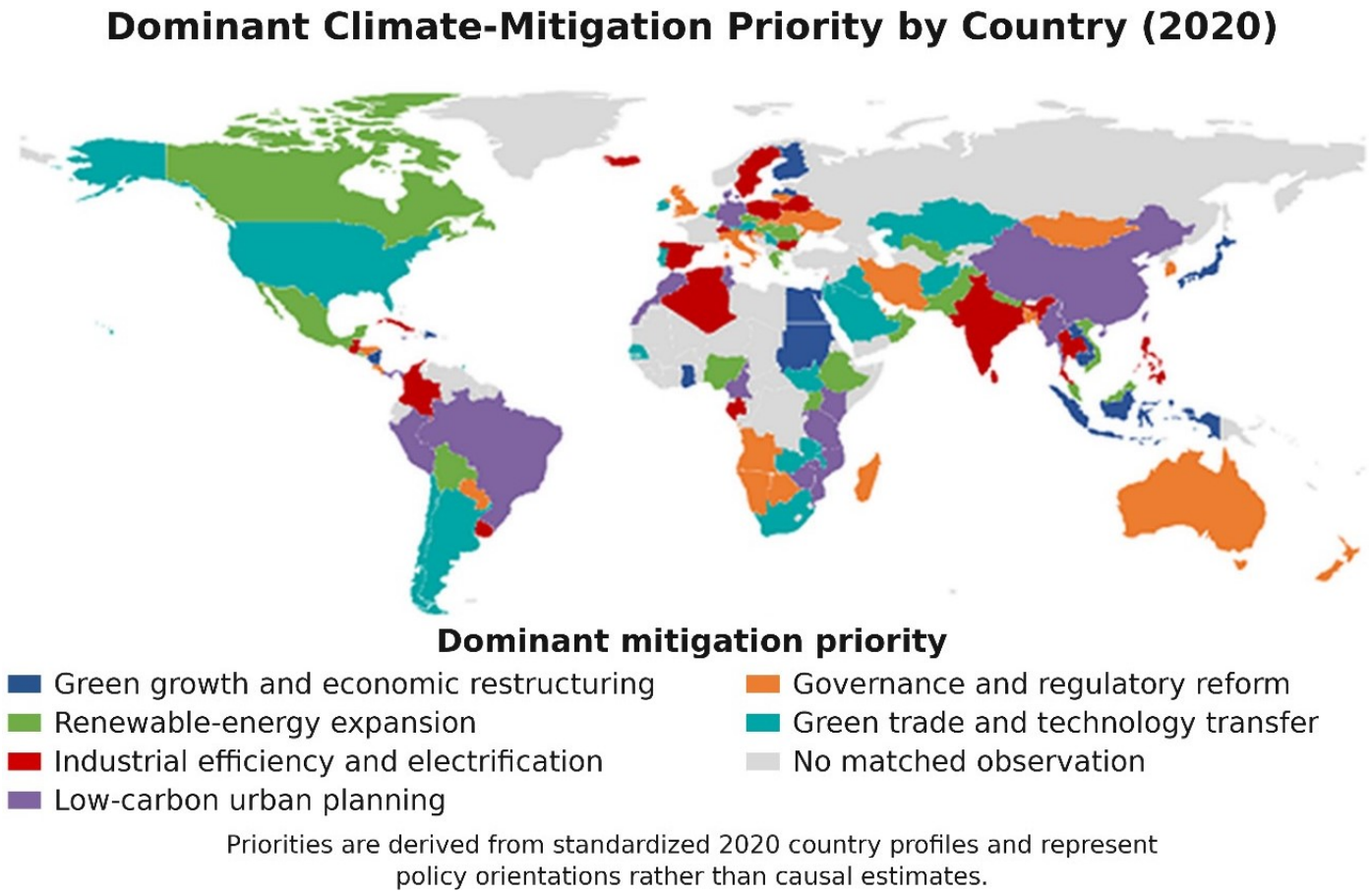


Figure 18. Global distribution of dominant climate-mitigation priorities across 118 countries. Note: This map displays proposed priorities, not measured intervention effects. A reproducible per-country assignment would require a stated rule mapping the largest relevant absolute local XGBoost SHAP contribution to one of the displayed policy categories, including tie handling and variables with no direct policy equivalent. That rule and the underlying country-level assignments are not provided in the manuscript and must be verified before treating the map as a computed result.

5. Discussion

This study developed an integrated machine-learning and explainable AI framework to predict the reported CO_2 emissions target across 118 countries between 2000 and 2020. XGBoost achieved the highest predictive performance among the evaluated models. Global SHAP anal-

ysis summarized the contributions of GDP per capita, governance, renewable-energy share, urbanization, trade openness, industrial share, country effects, and Year, with their relative importance reported in Table 6. These contributions describe model predictions rather than causal effects. The observed cross-country variation suggests that mitigation priorities should be assessed in their national contexts.

5.1. Why Countries Differ in Their Emission Pathways

The findings show significant cross-national variation in the factors influencing carbon emissions. Despite being the most important global predictor, GDP per capita has different regional contributions. Due to limited industrialization and energy access, lower GDP is linked to lower anticipated emissions in Africa. Economic expansion continues to be China's primary engine, with emissions partially countered by governance and renewable energy. While the United States shows additional nation-specific variables relating to energy use and consumption patterns, Germany benefits from governance and structural factors that limit industrial emissions. The need for distinct, as opposed to homogeneous, climate mitigation methods is further supported by cluster analysis.

5.2. Policy Implications

These model profiles can help organize country-level policy discussions, subject to the modest test fit. Suggestions concerning carbon pricing, finance, storage, and sector-specific technologies come from broader policy literature and require independent evaluation; they are not effects estimated by this model [16, 20, 21].

5.3. Explainable AI versus Black-Box AI

SHAP makes model predictions more interpretable by attributing predictions to inputs under the fitted model [8, 23]. These contributions are associations and can reflect correlated predictors; they do not identify causal emission drivers or intervention effects [24, 25].

5.4. Alignment with the Sustainable Development Goals

The proposed framework can inform country-specific mitigation planning relevant to SDG 13 (Climate Action). Its analysis of renewable energy, industrial structure, urbanization, governance, and trade also has potential relevance to SDGs 7, 9, 11, 12, 16, and 17. These connections indicate areas where the findings may inform policy discussion; they do not demonstrate that the framework delivers measurable progress toward these goals.

5.5. Comparison with Previous Studies

Previous studies address related questions using different outcomes and designs. Costantini et al. examined national CO_2 forecasting [12], while Butt et al. combined econometrics and machine learning for total emissions in three large economies [13]. Their Belt and Road study examined heterogeneity across the per-capita emissions distribution [18], and their China study considered ecological footprint rather than CO_2 [19]. Wang et al. studied investment and emissions in China [15], and Li et al. examined governance, finance, and mitigation technologies in European industrial economies [16]. These studies motivate attention to energy systems, trade, institutions, and national context, but differences in outcomes, samples, and validation prevent direct performance comparisons. The present SHAP patterns describe fitted predictions and do not confirm causal mechanisms or intervention effects estimated or discussed elsewhere.

5.6. Contribution of the Study

By comparing several machine-learning models, using SHAP to explain national and global emission causes, combining country-level profile with cluster analysis, and highlighting the necessity of development-sensitive mitigation methods, this study makes a significant contribution. The suggested framework offers a clear decision-support tool for sustainable development and climate policy.

5.7. Future Research

Future work should document and rerun preprocessing and tuning, validate target units and figure values, compare country-cluster stability, and test policy hypotheses using suitable sectoral and causal evidence. Additional inputs could include energy mix, transport, carbon pricing, and technological innovation.

6. Policy Implications

The descriptive profiles suggest topics for country-specific policy assessment. Because the model explains only part of held-out variation and does not estimate interventions, the recommendations below draw on broader climate-policy reasoning; they should be assessed against local sectoral evidence before implementation [2, 21].

6.1. Renewable-Energy Investment Priorities

Climate policy may prioritize renewable energy in light of national energy systems and independent evidence [14, 20]. Electricity access, grid capacity, fossil-fuel displacement, and equity should be evaluated locally. The fitted renewable-energy association is heterogeneous and cannot establish the effect of a renewable investment.

6.2. Carbon Pricing

The institutional and economic circumstances of the country should be considered when setting carbon prices. While emerging economies can take incremental, sector-specific measures, high-income economies should bolster carbon levies or emissions-trading schemes. Carbon pricing should be paired with fossil fuel subsidy reform, assistance for disadvantaged populations, investment in clean technologies, and open reinvestment of earnings in renewable energy, public transportation, industrial modern-

ization, and climate adaptation to guarantee efficacy and public acceptance [21].

6.3. Green Finance

To prevent carbon-intensive development, emerging economies need green finance. Green bonds, concessional financing, blended financing, and climate risk disclosure should all be increased by governments. While China, Germany, and the US should employ green finance to speed up industrial decarbonization, renewable energy, and low-carbon infrastructure, lower-income nations, especially those in Africa, need affordable funding. To avoid greenwashing, transparent green-finance norms are also required [16, 21].

6.4. Energy Transition

Decoupling economic growth from the use of fossil fuels through low-carbon technology, electrification, energy efficiency, renewable energy, and grid modernization should be the main goals of energy transition strategies. To prevent carbon lock-in, emerging economies should give priority to clean infrastructure. They should also ensure a fair transition by supporting workers and improving energy security with a variety of renewable energy sources [20, 21].

6.5. Climate Adaptation

Since many nations are more at risk from heatwaves, droughts, floods, and water stress, climate adaptation should be used in conjunction with mitigation. Climate-resilient agriculture, water management, resilient infrastructure, sustainable urban design, and localized risk assessments are among the top priorities. Long-term sustainable development can be supported and resilience strengthened by integrating adaptation with public infrastructure and renewable energy [2].

6.6. Governance Reforms

The impact of governance varied between each nation, making it a significant secondary predictor. Therefore, stronger institutions, efficient implementation, transparent climate finance, and strict environmental legislation should be the top prioritize for climate policy. International technical and financial help should be provided for governance changes in lower-income economies. By offering clear, nation-specific insights to support policy review, explainable AI can further improve decision-making.

6.7. Region- and Country-Specific Priorities

Table 13 shows the Priority policy actions for selected regions and countries.

The policy packages should not be interpreted as mutually exclusive. Rather, they identify areas that deserve relatively greater attention based on the observed regional and national profiles.

6.8. Alignment with Sustainable Development

Beyond reducing emissions, climate policies should help other SDGs. SDGs 7, 9, 11, 12, 13, 16, and 17 are influenced by renewable energy, green industrialization, sustainable cities, governance change, and international cooperation. An integrated strategy should manage any trade-offs while striking a balance between institutional responsibility, social justice, economic viability, and environmental efficacy [2, 21].

6.9. Role of Explainable AI in Policymaking

Explainable AI can help prioritize questions for further policy evaluation by displaying which inputs influence a fitted prediction. Policy choices about renewable energy, carbon pricing, green finance, adaptation, and governance require independent evidence and local feasibility assessment. The present analysis does not test their impacts [8, 25].

Table 13. Priority policy actions for selected regions and countries.

Region or Country	Main Challenge Identified	Priority Policy Actions
Africa	Development needs and risk of future carbon lock-in	Decentralized renewables, energy access, green industrialization, adaptation finance, resilient infrastructure, and governance capacity
China	Emission pressure associated with economic and urban expansion	Renewable substitution, coal reduction, industrial efficiency, storage, grid modernization, and low-carbon cities
Germany	Remaining industrial and infrastructure emissions	Industrial electrification, building renovation, energy storage, green hydrogen, and stronger sectoral implementation
United States	High-income, infrastructure, trade, and country-specific emission pressures	Grid decarbonization, electric mobility, building efficiency, renewable transmission, carbon pricing, and federal–state coordination

7. Conclusions

Across 118 countries over 2000–2020, XGBoost had the best reported test performance among six models (RMSE 0.475; R^2 0.324). GDP per capita was the largest global XGBoost SHAP predictor. Other contributions, including renewable energy, differed across observations. Country and four-cluster profiles can guide further investigation, but incomplete explained variation and the observational design preclude causal policy conclusions. Future work should incorporate additional energy and policy inputs and evaluate proposed interventions with designs suited to causal questions.

Author Contributions

S.S.: conceptualization, methodology, formal analysis, and writing—original draft preparation; H.M.M.B.: methodology, software, validation, and writing—review and editing; S.K.D.: data curation, investigation, visualization, and writing—review and editing; J.G.: supervision, interpretation of results, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

The datasets used and analyzed during this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no competing interests.

Declaration of Originality

This manuscript has not been submitted to, and is not under consideration by, another journal or publication venue.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Masson-Delmotte, V., Zhai, P., Pirani, A., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2021; 2391 pp. https://doi.org/10.1017/9781009157896.
2. Intergovernmental Panel on Climate Change. Summary for Policymakers. In *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Core Writing Team; Lee, H., Romero, J., Eds.; IPCC: Geneva, Switzerland, 2023; pp. 1–34. https://doi.org/10.59327/IPCC/AR6-9789291691647.001.
3. United Nations Environment Programme. *Emissions Gap Report 2024: No More Hot Air . . . Please! With a Massive Gap between Rhetoric and Reality, Countries Draft New Climate Commitments*; United Nations Environment Programme: Nairobi, Kenya, 2024. https://doi.org/10.59117/20.500.11822/46404.
4. International Energy Agency. *CO_2 Emissions in 2023*; IEA: Paris, France, 2024. Available online: https://www.iea.org/reports/co2-emissions-in-2023 (accessed on 5 November 2024).
5. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. https://doi.org/10.1023/A:1010933404324
6. Chen, T.; Guestrin, C. XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*; Association for Computing Machinery: New York, NY, USA, 2016; pp. 785–794. https://doi.org/10.1145/2939672.2939785
7. Prokhorenkova, L.; Gusev, G.; Vorobev, A.; et al. CatBoost: Unbiased boosting with categorical features. In *Advances in Neural Information Processing Systems 31*; Bengio, S., Wallach, H., Larochelle, H., et al., Eds.; Curran Associates: Red Hook, NY, USA, 2018; pp. 6638–6648.
8. Lundberg, S.M.; Lee, S.-I. A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems 30*; Guyon, I., von Luxburg, U., Bengio, S., et al., Eds.; Curran Associates: Red Hook, NY, USA, 2017; pp. 4765–4774.
9. Barredo Arrieta, A.; Díaz-Rodríguez, N.; Del Ser, J.; et al. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion* **2020**, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
10. Dogan, E.; Turkekul, B. CO_2 emissions, real output, energy consumption, trade, urbanization and financial development: Testing the EKC hypothesis for the USA. *Environ. Sci. Pollut. Res.* **2016**, *23*, 1203–1213. https://doi.org/10.1007/s11356-015-5323-8
11. Stern, D.I. The rise and fall of the environmental Kuznets curve. *World Dev.* **2004**, *32*, 1419–1439. https://doi.org/10.1016/j.worlddev.2004.03.004
12. Costantini, L.; Laio, F.; Mariani, M.S.; et al. Forecasting national CO_2 emissions worldwide. *Sci. Rep.* **2024**, *14*, 22438. https://doi.org/10.1038/s41598-024-73060-0
13. Butt, H.M.M.; Shehzadi, S.; Guo, J. Natural resource depletion, trade flows, and CO_2 emissions: A panel data econometrics and machine learning analysis of the top three economies. *Environ. Qual. Manag.* **2026**, *36*, e70396. https://doi.org/10.1002/tqem.70396
14. Yang, Y.; Lo, K. China's renewable energy and energy efficiency policies toward carbon neutrality: A systematic cross-sectoral review. *Energy Environ.* **2024**, *35*, 491–509. https://doi.org/10.1177/0958305X231167472
15. Wang, Y.; Shinwari, R.; Payab, A.H.; et al. Harmonizing sustainability: Unveiling the nexus of public private investment, natural resources, and environmental dynamics by applying ARDL and machine learning approach. *Ecol. Indic.* **2024**, *161*, 111931. https://doi.org/10.1016/j.ecolind.2024.111931
16. Li, B.; Wang, X.; Khurshid, A.; et al. Environmental governance, green finance, and mitigation technologies: Pathways to carbon neutrality in European industrial economies. *Int. J. Environ. Sci. Technol.* **2025**, *22*, 14899–14912. https://doi.org/10.1007/s13762-025-06608-w
17. Zhou, N.; Fridley, D.; McNeil, M.A.; et al. *China's Energy and Carbon Emissions Outlook to 2050*; Lawrence Berke-

ley National Laboratory: Berkeley, CA, USA, 2011. Available online: https://bies.lbl.gov/publications/china-s-energy-and-carbon-emissions (accessed on 28 October 2026).

18. Butt, H.M.M.; Khan, P.N.; Naseem, M.H.; et al. How do trade openness, energy intensity, technology innovation, and economic growth shape carbon emissions in Belt and Road Initiative countries? *CLEAN–Soil Air Water* **2025**, *53*, e70082. https://doi.org/10.1002/clen.70082
19. Butt, H.M.M.; Khan, I.; Durrani, S.K.; et al. China's environmental challenges: The role of energy supply and trade. *Process Integr. Optim. Sustain.* **2026**, *10*, 3461–3470. https://doi.org/ 10.1007/s41660-026-00715-y
20. Gielen, D.; Boshell, F.; Saygin, D.; et al. The role of renewable energy in the global energy transformation. *Energy Strategy Rev.* **2019**, *24*, 38–50. https://doi.org/10.1016/j.esr.2019.01.006
21. Intergovernmental Panel on Climate Change. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, and New York, NY, USA, 2022. https://doi.org/10.1017/9781009157926
22. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. https://doi.org/10.1214/aos/1013203451
23. Lundberg, S.M.; Erion, G.; Chen, H.; et al. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2020**, *2*, 56–67. https://doi.org/10.1038/s42256-019-0138-9
24. Aas, K.; Jullum, M.; Løland, A. Explaining individual predictions when features are dependent: More accurate approximations to Shapley values. *Artif. Intell.* **2021**, *298*, 103502. https://doi.org/10.1016/j.artint.2021.103502
25. Janzing, D.; Minorics, L.; Blöbaum, P. Feature relevance quantification in explainable AI: A causal problem. In *Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics*; Chiappa, S., Calandra, R., Eds.; Proceedings of Machine Learning Research (PMLR): Cambridge, MA, USA, 2020; Volume 108, pp. 2907–2916. Available online: https://proceedings.mlr.press/v108/janzing20a.html
26. Hamad, O.A.M.; Baysen, E.; Usman, A.G. Environmental education as a means of combating growing environmental pollution: An optimized-explainable artificial intelligence (XAI) approach. *Sci. Rep.* **2026**, *16*, 12647. https://doi.org/10.1038/s41598-026-42335-z
27. Roberts, D.R.; Bahn, V.; Ciuti, S.; et al. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* **2017**, *40*, 913–929. https://doi.org/10.1111/ecog.02881
28. Ke, G.; Meng, Q.; Finley, T.; et al. LightGBM: A highly efficient gradient boosting decision tree. In *Advances in Neural Information Processing Systems 30*; Guyon, I., von Luxburg, U., Bengio, S., et al., Eds.; Curran Associates: Red Hook, NY, USA, 2017; pp. 3146–3154.
29. Zou, H.; Hastie, T. Regularization and variable selection via the elastic net. *J. R. Stat. Soc. Ser. B Stat. Methodol.* **2005**, *67*, 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x
30. Bishop, C.M. *Neural Networks for Pattern Recognition*; Oxford University Press: Oxford, UK, 1995. https://doi.org/10.1093/oso/9780198538493.001.0001
31. Bergmeir, C.; Hyndman, R.J.; Koo, B. A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Comput. Stat. Data Anal.* **2018**, *120*, 70–83. https://doi.org/10.1016/j.csda.2017.11.003
32. Hyndman, R.J.; Koehler, A.B. Another look at measures of forecast accuracy. *Int. J. Forecast.* **2006**, *22*, 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001
33. Jolliffe, I.T.; Cadima, J. Principal component analysis: A review and recent developments. *Philos. Trans. R. Soc. A* **2016**, *374*, 20150202. https://doi.org/10.1098/rsta.2015.0202
34. Rousseeuw, P.J. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **1987**, *20*, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7
35. Arthur, D.; Vassilvitskii, S. k-means++: The advantages of careful seeding. In Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms, New Orleans, LA, USA, 7–9 January 2007; Society for Industrial and Applied Mathematics: Philadelphia, PA, USA, 2007; pp. 1027–1035.