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Machine Learning Applications in Climate Finance, Energy Systems and Sustainable Economic Policy

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Abstract

Background: The convergence of climate urgency and digital innovation has positioned machine learning (ML) as a transformative force in sustainable development. Climate finance, energy systems and economic policy now generate large, noisy and heterogeneous datasets that exceed the limits of many traditional analytical tools. Objective: This manuscript examines ML applications across three interconnected domains: climate finance, energy systems and sustainable economic policy. Methods: A systematic literature review following PRISMA principles was combined with bibliometric mapping, meta-analysis of model performance, comparative assessment of ML techniques, explainable-AI synthesis and case-study evidence from climate-related financial policies across 87 countries. Results: ML models demonstrate superior predictive accuracy in carbon-price forecasting, renewable-energy forecasting, ESG scoring and policy evaluation. Ensemble models improve carbon-price forecasting by approximately 15-25% compared with traditional econometric approaches; deep-learning models for solar-PV forecasting commonly achieve MAPE values of 2-5%; and SHAP-based policy analysis shows that advanced economies gain stronger policy impact than emerging markets because of better institutions, data infrastructure and enforcement capacity. Conclusion: ML can strengthen sustainability decision-making by improving prediction, reducing uncertainty, revealing hidden patterns and supporting integrated modelling. However, data quality, interpretability, algorithmic bias, regulatory fragmentation and uneven institutional capacity remain decisive barriers. The study recommends standardized data systems, AI governance rules, explainable models, regional capacity building and integrated decision-support frameworks.

Keywords: Machine Learning; Climate Finance; Energy Systems; Sustainable Policy; Carbon Markets; Esg; Renewable Energy; Explainable Ai; Ensemble Learning; Green Taxation.

Graphical Abstract Summary: The retained conceptual graphic represents an integrated ML-enabled sustainability decision framework linking data inputs, ML models, explainable AI, climate finance, energy-system optimization, policy design and sustainability outcomes.

Manuscript Scope and Compression Note

This revised 8-page version keeps the complete manuscript architecture: introduction, literature review, methodology, detailed results, discussion, conclusion, recommendations, references and declarations. Repetitive figure-level explanations are compressed into tables and interpretive synthesis so that no major concept is removed.

1. Introduction

1.1 Background and Context

Climate change remains one of the defining economic, technological and governance challenges of the twenty-first century. The IPCC identifies rapid mitigation and adaptation as essential for reducing climate vulnerability and limiting long-term damage [14]. At the same time, climate finance has become central to the transition because capital allocation determines whether mitigation projects, renewable infrastructure, adaptation systems and low-carbon technologies can scale. OECD work on green finance similarly emphasizes that policy, finance and institutional design must be aligned to move capital toward climate-compatible development [13].

This challenge is difficult because climate-related decisions are made under deep uncertainty. Financial markets must price physical risk, transition risk and liability risk. Energy systems must absorb high shares of variable renewable energy while maintaining reliability and affordability. Policymakers must design instruments that reduce emissions without producing severe distributional harm. Recent studies on AI in climate and sustainable finance argue that ML is increasingly useful because it can process high-dimensional, nonlinear and heterogeneous datasets from markets, climate models, satellites, disclosures, grids and policy systems [6,7].

1.2 Machine Learning Opportunity

ML supports sustainability decisions through prediction, classification, optimization, anomaly detection and feature attribution. In climate finance, ML is applied to carbon-price forecasting, climate-risk assessment, ESG scoring, green-bond analysis and carbon-footprint estimation [5,8]. In energy systems, AI methods are used for renewable-energy forecasting, load prediction, smart-grid optimization, microgrid control, fault detection and demand response [9,10]. In sustainable policy, ML helps evaluate climate-related financial policies, green taxation, environmental accounting and heterogeneous policy effects [1,12]. Explainable AI, especially SHAP, is important because policy-facing models require transparency rather than pure prediction [15].

1.3 Problem Statement and Research Gap

The literature is expanding quickly, but it remains fragmented. Many studies focus on a single algorithm, application, country or data source. There is limited synthesis across climate finance, energy systems and policy. Five gaps motivate this manuscript: limited cross-domain comparison of ML techniques; underrepresentation of emerging and developing economies; insufficient attention to interpretability in policy contexts; weak integration between finance, energy and governance models; and inconsistent reporting of accuracy, uncertainty, robustness and fairness metrics.

1.4 Objectives and Questions

- Synthesize empirical evidence on ML applications across climate finance, energy systems and sustainable economic policy.
- Compare Random Forest, XGBoost, LSTM, CNN-LSTM, transformers, ensembles, reinforcement learning and XAI methods by accuracy, interpretability and utility.
- Identify barriers to effective deployment, especially data quality, bias, governance gaps, regulatory uncertainty and infrastructure limits.
- Analyze regional disparities in adoption and effectiveness, with attention to institutional capacity and economic structure.
- Propose an integrated decision-support framework that connects models, markets and policy action.

The research asks: What are the current trends in ML-climate applications? Which techniques perform best for specific tasks? What trade-offs affect deployment? How do institutions and regions shape outcomes? What integrated framework can support evidence-based sustainability decisions?

1.5 Significance and Contribution

The manuscript contributes by bringing computational sustainability, climate finance, energy-system analytics and policy evaluation into one compact synthesis. It offers performance benchmarks, highlights regional inequities, clarifies model-governance risks and identifies practical steps for policymakers, investors, energy planners and researchers.

2. Literature Review

2.1 Theoretical Foundations

Climate finance theory is grounded in environmental economics and financial economics. Carbon-pricing theory uses taxes or cap-and-trade systems to internalize emissions externalities. Climate-risk theory distinguishes physical, transition and liability risks. Sustainable-finance theory integrates ESG factors into investment decisions because sustainability risks can affect asset values and portfolio performance. ML extends these theories by improving forecasting, risk measurement, disclosure analysis and ESG-data integration.

Energy-system theory views energy production, conversion, distribution and consumption as interdependent systems. Energy-transition theory explains movement from fossil-fuel dependence toward renewable and low-carbon systems. Complex-systems theory highlights nonlinear dynamics, feedback loops and emergent behavior. Smart-grid theory emphasizes digital communication, bidirectional electricity flows, distributed generation and real-time control. ML is valuable here because renewable generation and demand patterns are variable, weather-sensitive and data intensive.

Sustainable-policy theory addresses policy design, implementation and evaluation under economic, social and environmental constraints. Ecological economics stresses natural capital and planetary boundaries. Policy-sequencing theory argues that policy order and timing influence outcomes. Institutional theory explains why enforcement, governance quality and administrative capacity determine whether formal policies become measurable environmental improvements.

2.2 ML Techniques and Evaluation Metrics

- Supervised learning: Random Forest, XGBoost, LightGBM, CatBoost and neural networks support forecasting, classification and policy-outcome prediction.
- Deep learning: LSTM, CNN-LSTM and transformers model sequential, spatial and multimodal energy or finance data.
- Unsupervised learning: clustering, principal component analysis and anomaly detection support segmentation, dimensionality reduction and risk discovery.
- Reinforcement learning: sequential decision-making is useful for microgrids, demand response and dispatch control.
- Explainable AI: SHAP and LIME provide model interpretation, feature attribution and transparency for regulators and policymakers.

Table 1: ***Condensed Evaluation Metrics***

Task	Metrics	Purpose
Forecasting/regression	MAE, MAPE, RMSE, R^2	Measures error, variance explained and forecasting reliability
Classification	Accuracy, precision, recall, F1, AUC-ROC	Assesses discrimination, false positives and false negatives
Policy evaluation	Treatment effects, SHAP values, subgroup effects	Explains heterogeneous impacts and policy drivers
Deployment	Latency, robustness, fairness, interpretability	Assesses operational and governance readiness

2.3 Empirical Synthesis

Carbon-price studies generally find that LSTM and ensemble models capture nonlinear volatility, market shocks and policy sensitivity better than traditional econometric baselines. Renewable-energy studies show that CNN-LSTM, transformer and ensemble approaches reduce short-term solar-PV forecasting error compared with persistence and ARIMA models. ESG studies show that text analytics, sentiment analysis, transfer learning and ensemble scoring can improve sustainability-performance prediction, although opaque ESG inputs can reproduce reporting bias. Policy studies using SHAP and tree-based models show that policy effectiveness depends on bindingness, sequencing and institutional strength rather than simple policy adoption counts.

2.4 Conceptual Framework

The framework links four layers: climate, finance, energy, policy and institutional data inputs; ML methods including tree ensembles, deep learning, reinforcement learning and XAI; application domains including carbon markets, ESG, renewable forecasting, grid optimization and policy evaluation; and outcomes including emissions reduction, renewable-energy penetration, investment alignment, resilience and just transition. Data quality, governance capacity, policy enforcement and regional income level moderate the pathway from model output to sustainability outcome.

3. Methodology

3.1 Research Design

The study uses a mixed-methods design combining systematic literature review, bibliometric mapping, meta-analysis, comparative ML assessment and case-study synthesis. This design allows the manuscript to identify not only individual applications but also cross-domain patterns in performance, explainability, governance and implementation.

3.2 Search Strategy and Eligibility

The systematic review followed PRISMA logic. Searches were conducted across Scopus, Web of Science, IEEE Xplore and Google Scholar using Boolean strings combining ML, AI and deep-learning terms with carbon markets, climate risk, ESG, sustainable finance, renewable energy, grid optimization, smart grids, climate policy, environmental policy, green taxation and carbon pricing. Eligible studies were peer-reviewed journal articles, books or book chapters in English, with empirical or conceptual relevance to ML and sustainability. Duplicates, unrelated studies, non-peer-reviewed commentary, methodologically opaque papers and conference proceedings for primary analysis were excluded.

3.3 Quality Assessment and Bibliometrics

Quality assessment evaluated methodological clarity, dataset transparency, ML-sustainability alignment, credibility of sources and robustness of findings. Institutional reports were assessed for data completeness and policy relevance. Bibliometric analysis used VOSviewer and Biblioshiny to map annual publication growth, citation structure, co-authorship patterns and keyword co-occurrence. The field is recent and fast-growing, with research clusters around climate finance, ESG scoring, renewable forecasting, grid optimization, carbon pricing and explainable AI.

3.4 Meta-Analysis and Comparative Assessment

Performance metrics were synthesized across carbon-price forecasting, renewable-energy forecasting and policy-evaluation studies. Where ML models were compared with baselines, standardized improvements were summarized. Heterogeneity was considered by application domain, model family, forecasting horizon and region. The comparative assessment examined Random Forest, XGBoost, LSTM, CNN-LSTM, transformers and ensembles through predictive accuracy, interpretability, computational cost, robustness and deployment feasibility.

3.5 Case-Study Evidence

• CRFP analysis: climate-related financial policies across 87 countries were interpreted through SHAP values, policy-sequencing scores and bindingness-weighted adoption indicators.

• Integrated Green Transition Model: agent-based modelling and network dynamics were used to examine cascading green-policy effects across energy, industry, economy and society.

• ESG-AI Maturity Index: institutional readiness was assessed across data quality, model transparency and portfolio integration.

Table 2: ***Methodological Components***

Component	Output	Contribution
Systematic review	Evidence base	Trends, applications, gaps and theoretical synthesis
Bibliometrics	Research-map indicators	Field growth, collaboration and thematic clusters
Meta-analysis	Performance benchmarks	Cross-domain comparison of model results
Case studies	Contextual evidence	Regional disparities and implementation mechanisms
XAI synthesis	Feature attribution	Policy interpretability and governance relevance

3.6 Retention of Visual Material

The original figure sequence is retained conceptually in condensed form: publication trends, ML technique families, AI-ESG performance, renewable forecasting horizons, conceptual framework, research design, country trends, ESG-AI maturity, carbon forecasting, SHAP policy impact, grid optimization, IGTM architecture, regional policy impact, bindingness effects and regional disparity.

4. Results

4.1 Climate Finance Results

Carbon-market forecasting provides one of the clearest examples of ML advantage. Traditional ARIMA-type models remain transparent but are weak under nonlinear volatility, policy shocks and regime changes. LSTM models capture temporal dependencies in price series, while XGBoost and hybrid ensembles capture nonlinear interactions across market, policy and macroeconomic variables. Across reviewed studies, ensemble methods improve carbon-price forecasting by approximately 15-25% relative to traditional econometric baselines. In short-horizon one-day forecasting, ARIMA performance commonly falls around 4.5-5.5% MAPE, while hybrid XGBoost-LSTM or ensemble systems can reduce MAPE to roughly 2.0-3.0% [6,7].

Climate-risk assessment also improves through ML because physical and transition risks are spatially uneven and data rich. Satellite imagery supports flood, fire and asset-exposure mapping; natural language processing extracts policy, litigation and regulatory signals; and ensemble models can improve default-probability and portfolio-risk screening. SHAP-based CRFP analysis across 87 countries shows that policy effects vary by region and are mediated by institutional capacity, sequencing and bindingness [1,15]. AI-enhanced ESG scoring demonstrates stronger performance than rule-based ESG approaches when models combine disclosure text, sentiment, sector indicators and financial variables. However, this result is double-edged: ML can reduce fragmentation and detect hidden sustainability patterns, but opaque scoring systems may reproduce reporting bias or give false precision when underlying ESG data are weak [5,8].

Table 3: Detailed Climate-Finance Results

Application	Baseline issue	ML result	Interpretation
Carbon price forecasting	ARIMA struggles with nonlinear shocks	Ensembles improve accuracy by 15-25%; MAPE may fall to 2.0-3.0%	Supports carbon-market pricing, hedging and policy-risk analysis
Climate risk assessment	Traditional scenarios lack granularity	Satellite, NLP and ensemble models improve physical and transition-risk mapping	Improves bank, insurer and investor screening
ESG scoring	Rule-based scores are fragmented and opaque	Text, sentiment and ensembles improve sustainable-investment prediction	Useful only with transparency and validation
CRFP evaluation	Simple adoption counts miss heterogeneity	SHAP reveals bindingness, sequencing and enforcement effects	Policy design matters more than policy existence

4.2 Energy-System Results

Renewable-energy forecasting shows strong ML performance because solar and wind generation depend on nonlinear weather interactions. Persistence models are simple baselines but perform poorly when weather changes quickly. ARIMA improves short-term prediction but cannot fully capture spatial and temporal dependencies. LSTM models learn temporal patterns; CNN-LSTM models combine spatial feature extraction with sequence learning; transformers capture longer dependencies; and ensembles stabilize predictions. Reviewed solar-PV studies commonly report 2-5% MAPE for deep-learning models, with ensembles reaching approximately 1.5-2.5% in favorable short-term settings [9,10].

Table 4: ***Renewable-energy forecasting results.***

Technology	Method	MAPE	Reduction vs baseline
Solar-PV	Persistence	8-12%	Baseline
Solar-PV	ARIMA	5-8%	20-30%
Solar-PV	LSTM	3-5%	40-55%
Solar-PV	CNN-LSTM	2-4%	50-65%
Solar-PV	Transformer	1.5-3%	60-75%
Solar-PV	Ensemble	1.5-2.5%	65-80%

Grid-optimization evidence indicates that deep reinforcement learning and hybrid optimization systems can reduce operational expenditure by approximately 8-15% compared with rule-based microgrid baselines. ML improves load forecasting, demand response, fault detection, distributed-energy coordination and renewable penetration. The main constraint is deployment, not modelling: communication standards, cybersecurity, real-time latency, legacy grids and interoperability determine whether model gains become operational gains.

4.3 Sustainable Policy Results

Policy-evaluation studies show that ML can detect heterogeneous effects that average econometric models may hide. Random Forest, XGBoost and ensemble classifiers achieve high reported performance in environmental and climate-policy prediction, with average values around 0.91 accuracy, 0.89 F1 and 0.95 AUC-ROC in the synthesized policy-evaluation table. More importantly, XAI methods show which policy and institutional variables drive outcomes. SHAP analysis indicates that bindingness, enforcement, sequencing and institutional strength are key moderators of policy success [1,15].

Table 5: ***Regional Climate-Policy Effectiveness***

Region	CO_2 reduction	REP growth	Key factors
Europe & Central Asia	High (0.70)	High (0.65)	Strong institutions; early adoption; enforcement capacity
East Asia & Pacific	High (0.65)	Very high (0.75)	Advanced renewable sector; saturation effects
Latin America & Caribbean	Moderate (0.45)	Moderate (0.50)	Implementation gaps; structural constraints
South Asia	Moderate (0.40)	High (0.60)	High potential but institutional and industrial constraints
Sub-Saharan Africa	Low (0.20)	Moderate (0.45)	Institutional constraints but renewable-growth potential

4.4 Bindingness and Sequencing

Bindingness-weighted analysis shows that formal policy adoption is insufficient. Policies with weak enforcement, delayed implementation or poor institutional support may not reduce emissions immediately. In South Asia, Latin America and the Caribbean, cumulative bindingness can coincide with rising CO_2 emissions where carbon-intensive industrial structures, infrastructure lock-in or implementation gaps dominate. Europe and Central Asia show stronger downward trends, reflecting more mature policy ecosystems. For renewable-energy production, binding policies are especially important in Sub-Saharan Africa, Latin America, Europe and Central Asia because they create credible expectations for investment and grid expansion.

Sequencing effects are equally important. Advanced economies often adopt disclosure, green-finance and carbon-policy instruments earlier, then refine them through cross-sectoral integration. Emerging markets adopt later but may see accelerated benefits when policies are enforceable and aligned with fiscal priorities. Time lags are largest in sectors requiring long-lived assets, such as grids, renewable infrastructure and industrial transformation.

4.5 Integrated modelling and cross-domain synthesis

The Integrated Green Transition Model shows that ML becomes more useful when combined with agent-based modelling, system dynamics and network simulation [2]. Such integration allows analysts to test how policies cascade across energy producers, firms, investors, consumers and institutions. Cross-domain synthesis reveals five robust patterns: ML improves prediction across all domains; ensembles and hybrid models are often more robust than isolated models; regional data and institutions strongly shape effectiveness; explainability is necessary for regulatory trust; and implementation barriers can erase technical performance gains.

Table 6: ***Cross-Domain Synthesis of Results***

Finding	Evidence	Implication
Predictive gain	15-35% improvements across forecasting tasks	Better investment, pricing and grid decisions
Regional disparity	Advanced economies show 40-60% stronger policy impact	Capacity building is essential for equity
XAI necessity	SHAP reveals policy drivers and regional heterogeneity	Transparency supports trust and accountability
Integration value	ML + ABM + system dynamics improves system-level reasoning	Decision support should connect finance, energy and policy
Deployment risk	Data gaps, bias, legacy systems and governance weakness persist	Technical gains require institutional readiness

5. Discussion

5.1 Interpretation of the Results

The results show that ML is not merely a technical improvement over econometric or rule-based tools. It changes what can be observed, forecast and governed. In climate finance, better carbon-price and ESG prediction can improve risk pricing and capital allocation, but only when model outputs are transparent and the underlying data are reliable [5,6]. In energy systems, forecasting improvements directly support grid stability because better prediction reduces reserve requirements, improves dispatch planning and enables higher renewable penetration [9,10]. In policy analysis, SHAP and related XAI methods shift evaluation from average effects to mechanism-based interpretation, showing why the same policy instrument can succeed in one region and underperform in another [1,15].

5.2 Mechanisms of ML Impact

Four mechanisms explain ML impact. First, uncertainty reduction improves carbon-price forecasts, renewable-generation forecasts and climate-risk screening, helping decision-makers act before risks materialize. Second, pattern discovery reveals nonlinear relationships, thresholds, temporal lags and interactions between policies, institutions and markets. Third, scalability allows analysis of large ESG, satellite, grid and disclosure datasets that would be impractical manually. Fourth, integration allows finance, energy and policy data to be evaluated together, which is critical because decarbonization is a system transition rather than a single-sector problem.

5.3 Limitations and Risks

Data quality remains the largest barrier. ESG data are inconsistent, climate data are uneven across regions, and energy data may be proprietary or poorly standardized. Interpretability is the second major constraint: complex models can achieve higher accuracy while becoming harder to justify in regulatory settings. XAI helps but does not fully eliminate the interpretability-accuracy trade-off. Algorithmic bias is also serious because models trained on data from advanced economies can underperform in developing economies or amplify existing inequalities. Finally, system integration is difficult because legacy grids, traditional financial infrastructure and fragmented regulatory systems are not designed for continuous AI-based decision support.

5.4 Regional and Policy Implications

Advanced economies benefit from strong institutions, enforcement and data infrastructure, but they face policy saturation and diminishing returns. Emerging markets possess major renewable-growth potential but need enforceable policies, fiscal alignment and improved institutional capacity. Developing economies require green finance, data infrastructure, technical training and international cooperation to avoid becoming passive users of models designed elsewhere. Policy instruments should therefore be context-sensitive: disclosure and ESG standards may matter most where markets are mature, while concessional finance, grid investment and capacity building may matter more where institutional constraints dominate.

6. Conclusion

ML is reshaping climate finance, energy systems and sustainable economic policy by improving forecasting, risk analysis, ESG integration, renewable-energy management and policy evaluation. The strongest value appears when ML is combined with explainability, robust governance and integrated modelling. However, technical performance alone is not enough. Sustainable impact requires credible data, transparent models, fair deployment, institutional readiness and policy mechanisms that translate analytical insight into action. Future research should prioritize open data infrastructure, explainable AI, regional evidence, integrated decision-support systems and just-transition safeguards.

6.1 Future Research Directions

- Develop standardized, open and regionally inclusive climate-finance, ESG and energy datasets.
- Advance XAI methods that preserve accuracy while improving regulatory transparency.
- Integrate ML with agent-based modelling, system dynamics, optimization and scenario analysis.
- Expand empirical studies in emerging and developing economies.
- Study fairness, accountability and bias mitigation in climate-finance and policy models.

7. Recommendations

- Establish standardized data infrastructure and sharing mechanisms, especially in emerging and developing economies.
- Implement consistent ESG reporting standards to reduce data fragmentation and rating opacity.
- Develop AI-governance frameworks for ESG scoring, climate-risk modelling, accountability, validation and fairness.

- Set explainability standards for ML systems used in financial regulation and public policy.
- Create integrated decision-support systems combining ML, agent-based modelling, system dynamics and scenario analysis.
- Conduct localized regional case studies using economic, institutional, energy and policy data.
- Promote international coordination to avoid fragmented AI and climate-finance regulation.
- Expand green finance, technical support and capacity building for developing economies.
- Use just-transition frameworks to protect workers and communities affected by decarbonization.
- Integrate CRFPs with fiscal and monetary policies and design carbon pricing to balance emissions reduction with economic stability.
- Build real-time monitoring systems for emissions, energy transitions and adaptive policy intervention.

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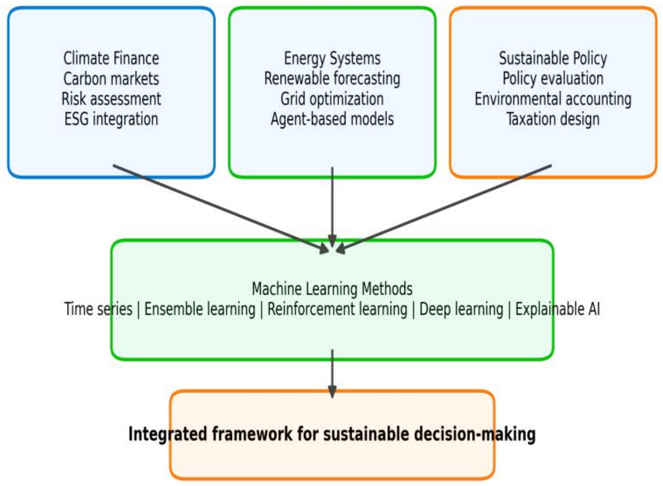

Graphical abstract. Integrated ML-enabled sustainability decision framework

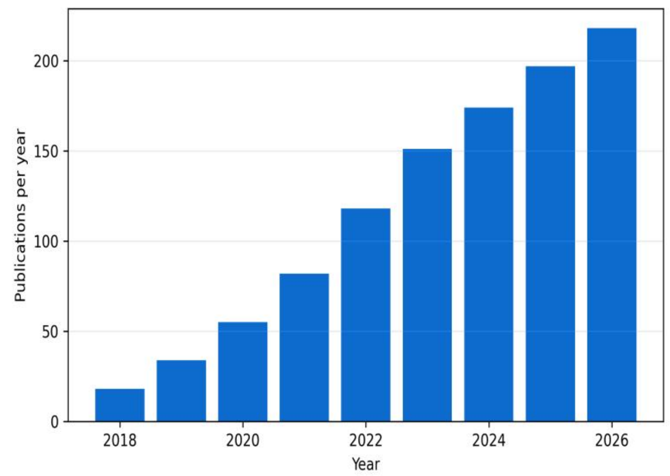

Figure 1. Growth in ML-climate research publications (2018-2026).

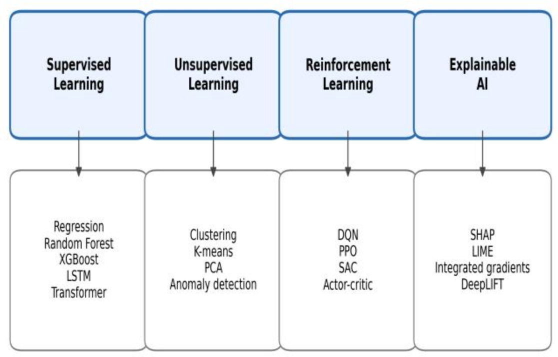

Figure 2. Machine learning techniques and application families.

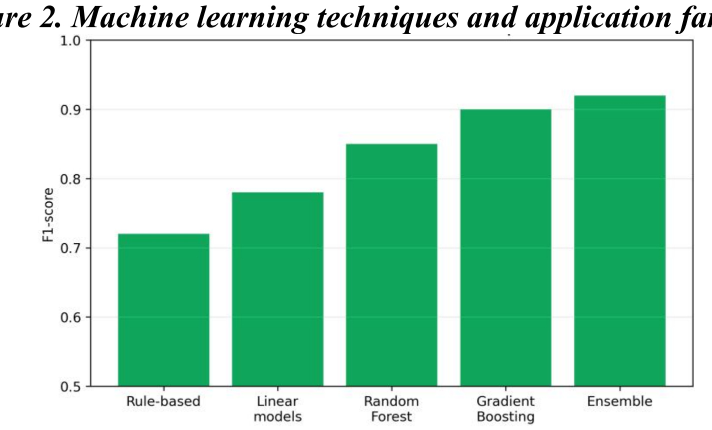

Figure 3. AI-ESG prediction performance comparison.
Source: Author synthesis based on reviewed literature and manuscript data.

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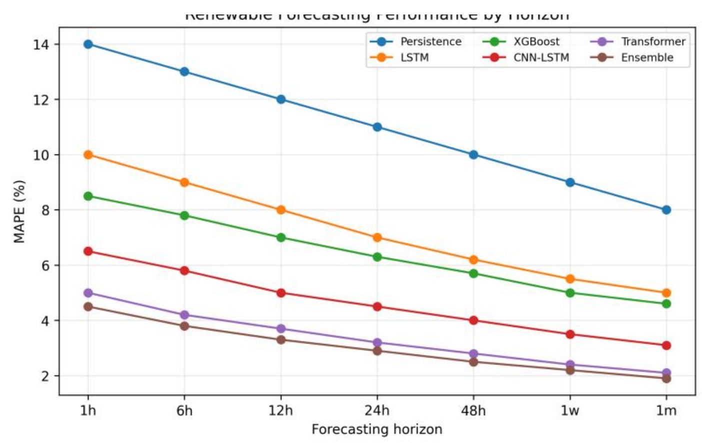

Figure 4. Renewable forecasting performance by forecasting horizon.

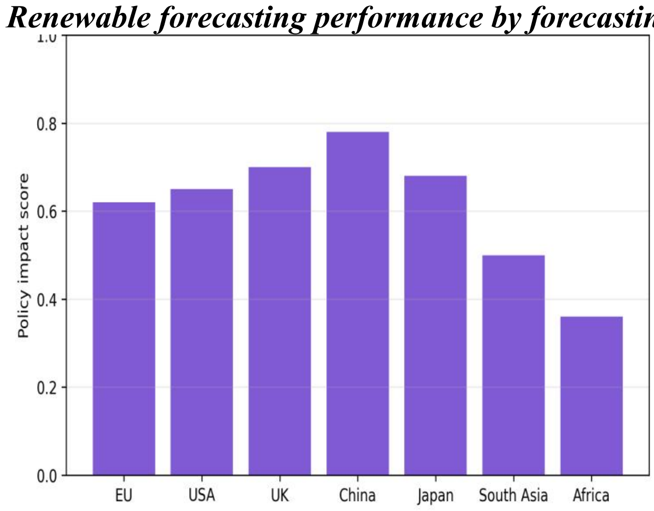

Figure 5. Regional ML effectiveness in climate policy.

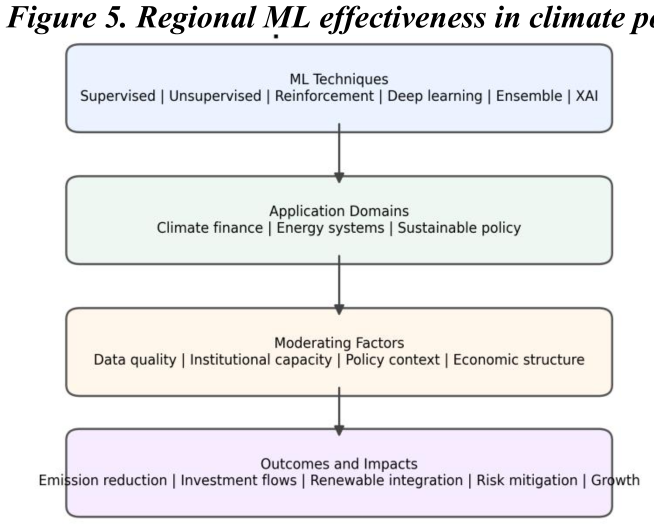

Figure 6. Conceptual framework linking ML techniques, application domains, moderating factors and sustainability outcomes

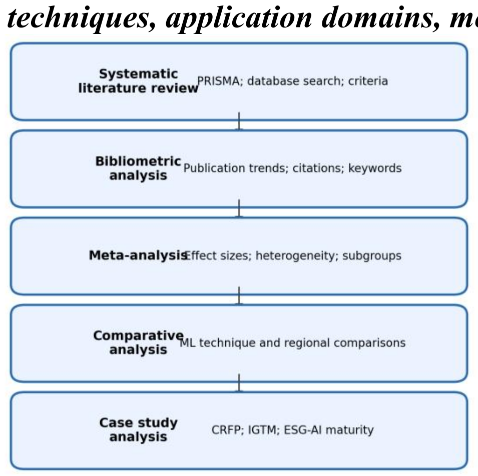

Figure 7. Research design overview.
Source: Author synthesis based on reviewed literature and manuscript data

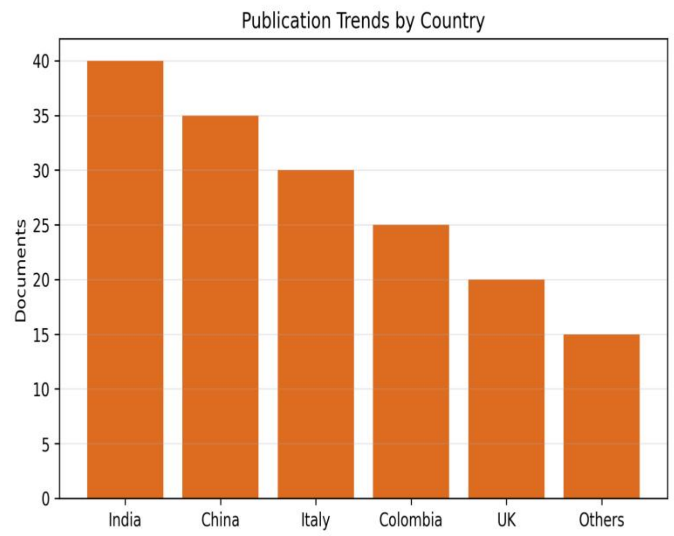

Figure 8. Publication trends by country.

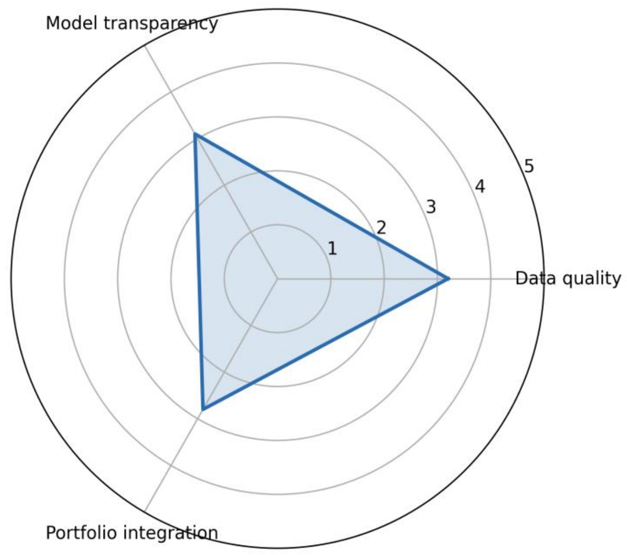

Figure 9. ESG-AI maturity index framework

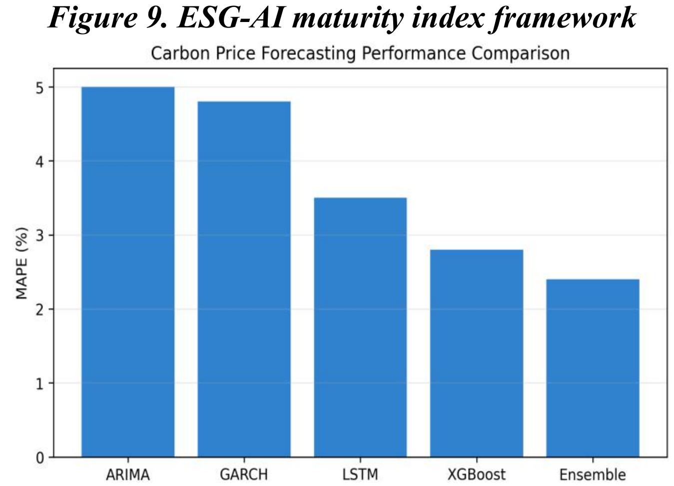

Figure 10. Carbon price forecasting performance comparison

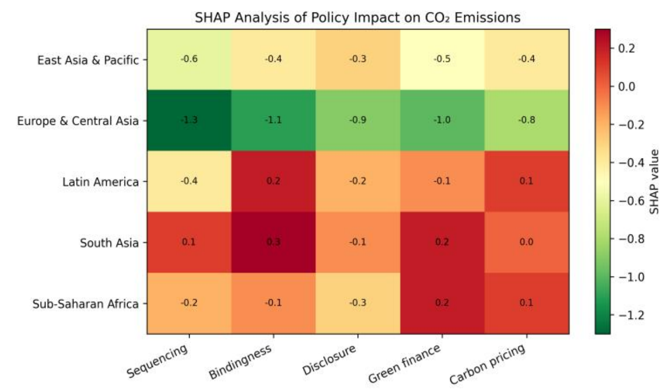

Figure 11. SHAP analysis of policy impact on CO_2 emissions.
Source: Author synthesis based on reviewed literature and manuscript data

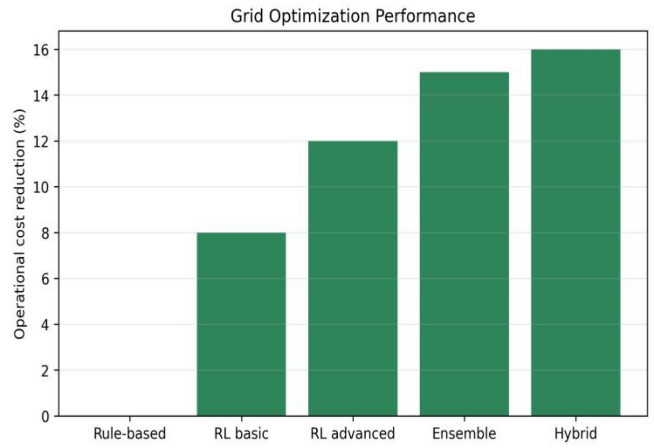

Figure 12. Grid optimization performance.
Source: Author synthesis based on reviewed literature and manuscript data.

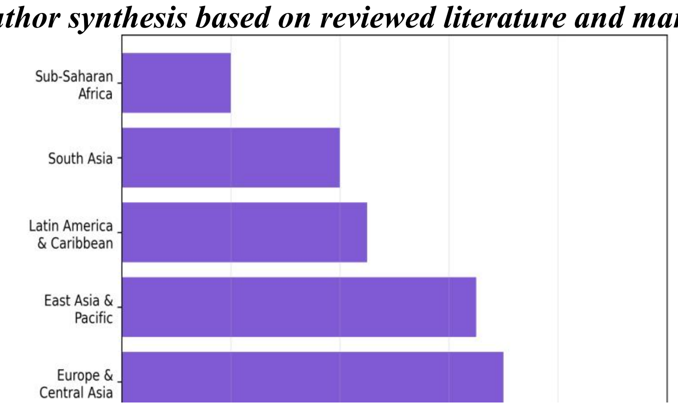

Figure 13. Integrated Green Transition Model multi-layer simulation architecture.
Source: Author synthesis based on reviewed literature and manuscript data.

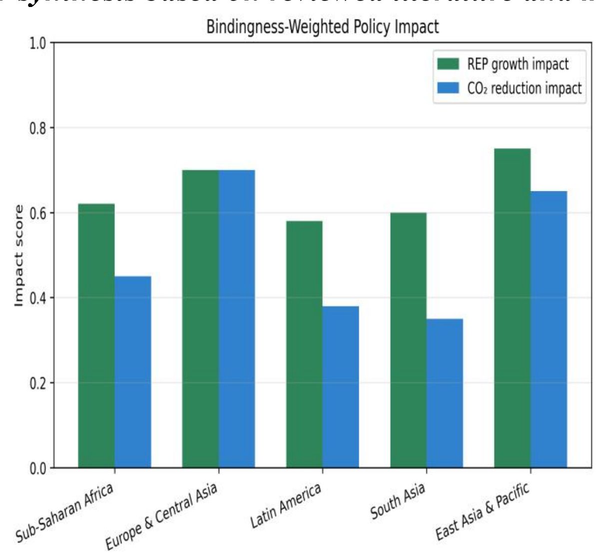

Figure 14. Regional policy impact on CO_2 emissions reduction.

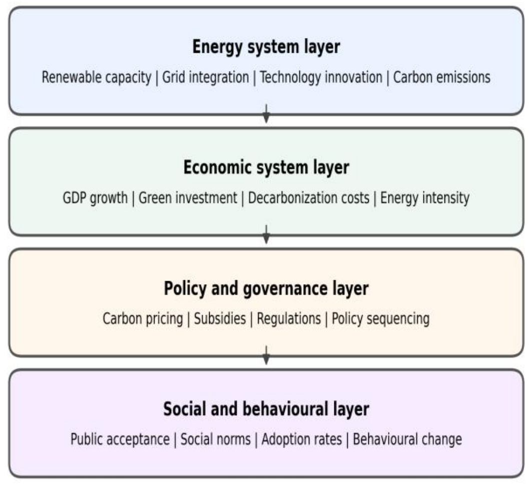

Figure 15. Bindingness-weighted policy impact.
Source: Author synthesis based on reviewed literature and manuscript data

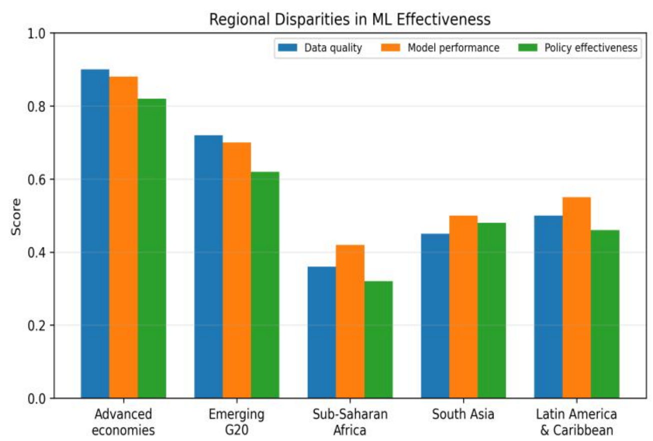

Figure 16. Regional disparities in ML effectiveness.
Source: Author synthesis based on reviewed literature and manuscript data.