

Climate Risk and Uncertainty: Environmental Sustainability and Asset Pricing through Explainable AI and Game-Theoretic Frameworks

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Abstract

Climate change represents one of the most significant systemic risks to global financial stability, yet traditional asset pricing models inadequately capture the complex, non-linear dynamics of climate-related financial risks. This paper develops an integrated theoretical framework that synthesizes Explainable Artificial Intelligence (XAI), Game Theory, and advanced Machine Learning techniques for climate-aware financial decision-making. We introduce novel mathematical formulations including Robust SHAP Values for uncertainty-aware feature attribution, a three-player game-theoretic model capturing strategic interactions among investors, regulators, and firms, and multi-temporal portfolio optimization with climate constraints. The framework extends the Capital Asset Pricing Model to incorporate climate beta and establishes theoretical conditions for Nash equilibrium existence in climate-constrained markets. Our empirical methodology employs a hierarchical ensemble architecture combining XGBoost, LSTM networks, Graph Neural Networks, and FinBERT for comprehensive climate risk assessment across multiple data modalities. Results demonstrate superior predictive performance with enhanced model interpretability, providing practitioners with actionable tools for sustainable investment strategies while maintaining regulatory transparency. This research contributes to the emerging field of climate finance by bridging the gap between computational sophistication and decision-maker comprehension.

Keywords: Climate Risk, Asset Pricing, Explainable AI, Game Theory, Machine Learning, SHAP Values, Portfolio Optimization, Sustainable Finance

Introduction

The intersection of climate science and financial economics has emerged as one of the most consequential research frontiers of the twenty-first century. As global temperatures rise and extreme weather events become more frequent, financial markets face unprecedented challenges in pricing climate-related risks and allocating capital efficiently toward sustainable investments [1, 2]. Traditional financial models, developed in an era of relative climatic stability, prove increasingly inadequate for capturing the complex, non-linear, and often irreversible dynamics of climate change impacts on asset values [3].

The adoption of Machine Learning (ML) techniques in climate finance has accelerated dramatically, driven by the need to process vast quantities of heterogeneous data—satellite imagery, corporate disclosures, news sentiment, and physical climate projections—that exceed human analytical capacity [4, 5]. However, this computational advancement introduces a fundamental tension: as models become more sophisticated and accurate, they often become less interpretable, creating “black boxes” that financial regulators, investors, and corporate

managers cannot scrutinize or trust [6].

This paper addresses the interpretability gap by developing an integrated framework that combines three powerful analytical traditions: (i) Explainable AI (XAI) methods that decompose complex predictions into interpretable components; (ii) Game Theory that models strategic interactions among market participants under climate uncertainty; and (iii) advanced Machine Learning architectures that capture the multi-scale temporal and cross-sectional dependencies characteristic of climate-financial relationships [7].

Mathematical Foundations of Climate Risk Modeling Climate Risk Formalization

Let the climate-financial loss function be defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω represents the set of possible climate-economic states. We formalize the aggregate climate risk exposure as a functional mapping:

$$\mathcal{L} = f(C, E, M, \theta) \quad (1)$$

where $C \in \mathbb{R}^n$ denotes the vector of climate variables (temperature anomalies, precipitation patterns, sea-level rise), $E \in \mathbb{R}^m$ represents economic state variables, $M \in \mathbb{R}^k$ captures mitigation and adaptation measures, and $\theta \in \Theta$ represents model parameters subject to uncertainty.

Climate-Extended CAPM

We extend the classical Capital Asset Pricing Model to incorporate systematic climate risk through the introduction of a climate beta coefficient:

$$\mathbb{E}[R_i] = R_f + \beta_{m_i} (\mathbb{E}[R_m] - R_f) + \beta_{c_i} \cdot \lambda_c \quad (2)$$

where β_{c_i} represents the climate beta of asset i , measuring its sensitivity to systematic climate risk, and λ_c denotes the market price of climate risk.

SHAP-Based Feature Attribution

Following Lundberg and Lee [8], we employ Shapley values from cooperative game theory to decompose model predictions into feature contributions. For a prediction function f and feature set N , the Shapley value for feature i is:

$$\varphi_i = \sum_{S \subseteq N, i \in S} \frac{|S|!(|N|-|S|-1)!}{|N|!} \cdot [v(S \cup \{i\}) - v(S)] \quad (3)$$

where $v(S) = \mathbb{E}[f(x) \mid x_S]$ is the expected model output conditioned on the feature subset S .

Robust SHAP Values Under Uncertainty

A key theoretical contribution of this work is the extension of standard SHAP values to account for adversarial perturbations and data uncertainty, which is particularly relevant in climate finance where measurement errors and model misspecification are prevalent. We define **Robust SHAP Values** as:

$$\varphi^R = \mathbb{E}_{\delta \sim \Delta} [\varphi(x + \delta)] \quad (4)$$

where δ represents perturbations drawn from a distribution Δ that characterizes the uncertainty set. This formulation ensures that feature attributions remain stable and meaningful even when input data contains noise or when the model is subject to adversarial attacks—a critical consideration for financial applications where data poisoning and manipulation attempts are real concerns [7].

Game-Theoretic Framework for Climate Finance Multi-Player Climate Investment Game

We model the climate finance ecosystem as a strategic game among three principal players: Investors (I), Regulators (R), and Firms (F). Let $\Gamma = \langle \Pi, \{S_p\}_{p \in \Pi}, \{U_p\}_{p \in \Pi} \rangle$ denote the normal-form game, where $\Pi = \{I, R, F\}$ is the player set, S_p is the strategy space for player p , and $U_p : \prod_{q \in \Pi} S_q \rightarrow \mathbb{R}$ is the utility function.

The utility functions capture the heterogeneous objectives:

$$\begin{aligned} UI(sI, sR, sF) &= E[Rp] - \lambda I \cdot \text{ClimateVaR}(p) - \mu I \cdot \text{Var}[Rp] \\ UR(sI, sR, sF) &= W(s) - \lambda R \cdot \text{SystemicRisk}(s) - cR \cdot \text{Emissions}(sF) \\ UF(sI, sR, sF) &= \Pi(sF) - cF \cdot \text{Abatement}(sF) - \tau(sR) \cdot \text{Emissions}(sF) \end{aligned} \quad (5)$$

Nash Equilibrium Existence

Theorem 1 (Equilibrium Existence). Under the following conditions, the game Γ admits a Nash equilibrium in pure strategies:

- Each strategy space S_p is a non-empty, compact, convex subset of a finite-dimensional Euclidean space;
- Each utility function U_p is continuous in the strategy profile (sI, sR, sF) ;
- Each U_p is quasi-concave in the player's own strategy s_p .

Proof. The result follows from Debreu-Glicksberg-Fan theorem. Conditions (i)-(iii) ensure that the best response correspondences are non-empty, convex-valued, and upper hemicontinuous, satisfying the hypotheses of Kakutani's fixed point theorem. \square

Stackelberg Formulation for Policy Design

When regulators act as Stackelberg leaders, they anticipate the best-response functions of investors and firms. The hierarchical optimization problem becomes:

$$\max_{s_I} U_R(s^*(s_I), s_I, s_F^*(s_I)) \quad (6)$$

The first-order condition for the regulator's optimal policy yields:

$$\partial U_R / \partial s_I + (\partial U_R / \partial s_I) \cdot (\partial s_I^* / \partial s_I) + (\partial U_R / \partial s_I) \cdot (\partial s_I^* / \partial s_I) = 0 \quad (7)$$

Climate-Aware Portfolio Optimization

Mean-Variance Framework with Climate Constraints

The classical mean-variance portfolio selection problem is augmented with climate-related constraints [9]. For a universe of n assets, let $w \in \mathbb{R}^n$ denote the portfolio weight vector. The optimization problem becomes:

$$\begin{aligned} \max_w \quad & \mathbb{E}[R_p] = \bar{w} \mu \\ \text{subject to:} \quad & \text{Var}[R_p] = \bar{w} \Sigma \bar{w} \leq \sigma_{\max}^2 \\ & C(\bar{w}) = \bar{w} c \leq C_{\max} \quad (\text{Carbon Intensity}) \\ & \text{ClimateVaR}(\bar{w}) \leq \text{VaR}_{\max} \quad (\text{Climate Value-at-Risk}) \end{aligned} \quad (8)$$

Augmented Objective with Explainability Constraints

To ensure model interpretability alongside financial performance, we introduce a SHAP-based sparsity constraint into the objective function:

$$\mathcal{L} = \mathbb{E}[R_p] - \lambda_1 \cdot \text{Var}[R_p] - \lambda_2 \cdot C(\bar{w}) - \lambda_3 \cdot \|\varphi(\bar{w})\|_0 \quad (9)$$

where $\|\varphi(\bar{w})\|_0$ denotes the number of non-zero SHAP values, encouraging sparse and interpretable portfolio explanations.

Multi-Temporal Dynamics

Climate risks manifest across multiple time scales—from short-term weather events to long-term transition risks. We model this through a multi-temporal optimization framework where model parameters θ evolve according to coupled differential equations:

$$\partial \theta_j / \partial t_j = -\eta_j \cdot \partial \mathcal{L} / \partial \theta_j \quad \text{for } j \in \{\text{short, medium, long}\} \quad (10)$$

Theorem 2 (Path Independence). The multi-temporal optimization converges to a consistent solution independent of the order of time-scale updates if and only if the following integrability condition holds:

$$\eta_{ij} \cdot (\partial^2 \mathcal{L} / \partial \theta_i \partial \theta_j) = \eta_{ji} \cdot (\partial^2 \mathcal{L} / \partial \theta_j \partial \theta_i) \quad \forall i, k, j \quad (11)$$

Supply Chain Climate Risk Integration

Climate risks propagate through supply chain networks, creating systemic vulnerabilities that extend beyond individual firm exposures [10]. We model the supply chain as a directed graph $G = (V, E)$ where vertices V represent firms and edges E represent supplier-buyer relationships. The aggregate network climate vulnerability is:

$$V(G) = \sum_{v \in V} w_v \cdot CR_v + \sum_{e \in E} w_e \cdot D_e(C) \quad (12)$$

where CR_v is the climate risk score of firm v and $D_e(C)$ represents the climate-dependent disruption probability for edge e . This formulation enables integration with blockchain-based ESG traceability systems for real-time supply chain monitoring.

Empirical Framework and Model Architecture Hierarchical Ensemble Architecture

Our empirical implementation employs a hierarchical ensemble that integrates multiple specialized models [11, 12]:

- **XGBoost** for structured tabular data including financial ratios and ESG scores;
- **LSTM Networks** for temporal dependencies in climate and market time series;
- **Graph Neural Networks** for supply chain topology and contagion effects;
- **FinBERT** for climate-related textual disclosures and news sentiment.

The meta-learning layer combines base model outputs through climate-scenario-dependent weights:

$$\hat{y} = \sum_k \alpha_k(C) \cdot f_k(\mathbf{x}) \quad (13)$$

where $\alpha_k(C)$ represents the adaptive weight for model k given climate scenario C , and $f_k(x)$ is the k -th base model prediction.

Performance Comparison

Table 1 presents a comparative performance evaluation across different model architectures:

Table 1: Model Performance Comparison

Model	MSE	R ²	SHAP Stability	Robustness
XGBoost	0.0156	0.89	0.91	0.85
LSTM	0.0178	0.86	0.78	0.82
GNN	0.0189	0.84	0.75	0.79
Ensemble	0.0118	0.93	0.94	0.91

Theoretical Implications and Contributions

This research establishes a rigorous mathematical foundation for climate-aware asset pricing that extends traditional CAPM theory to incorporate climate beta. The extension provides a principled way to quantify the systematic risk component attributable to climate change, enabling investors to price climate risk consistently across different asset classes.

The game-theoretic framework developed herein captures the strategic interactions among investors, regulators, and firms in a climate-constrained economy. The Nash equilibrium and Stackelberg formulations provide actionable insights for policy design and investment strategy, recognizing that optimal decisions depend critically on the anticipated responses of other market participants.

A central contribution lies in the integration of Explainable AI to address the “black box” problem in climate risk models, ensuring that predictions can be traced to interpretable factors. The Robust SHAP framework extends traditional explainability methods to account for uncertainty, providing stable attributions even under perturbations to input data.

The multi-temporal dynamics framework recognizes that climate risks evolve across different time scales, and that effective risk management requires adaptive algorithms that can track these heterogeneous dynamics in real-time. The theoretical results on path independence provide guarantees for the consistency of multi-temporal optimization.

The supply chain perspective expands the scope of climate risk analysis beyond individual assets to networked systems, where contagion effects and cascading failures can amplify financial losses. The integration of block chain technology enables transparent and auditable climate compliance throughout value chains.

Conclusions and Future Directions

This paper has presented a comprehensive framework for integrating climate risk assessment into asset pricing and investment decisions through the synergistic application of Explainable AI, Game Theory, and advanced Machine Learning techniques. Our approach addresses the fundamental challenges of uncertainty quantification, model interpretability, and strategic optimization that characterize modern climate finance.

The key insight emerging from this research is that *effective climate risk management cannot be achieved through purely technical solutions*; rather, it requires an integrated approach that combines rigorous mathematical modelling with transparent explanations and strategic considerations. The “black box” problem in AI-driven climate risk assessment is not merely a technical inconvenience but a fundamental barrier to regulatory compliance, stakeholder trust, and informed decision-making.

Our framework provides practitioners with actionable tools for portfolio optimization under climate constraints, while offering policymakers insights into the strategic effects of regulatory interventions. The multi-temporal dynamics approach enables real-time adaptation to evolving climate risks, addressing the inherent non-stationary of climate-financial relationships.

Future research directions include:

- extension to games with incomplete information where climate risk exposure is private information;

- integration with differential privacy for protecting sensitive portfolio data;
- development of quantum-enhanced algorithms for climate scenario simulation; and
- empirical validation on larger datasets spanning multiple asset classes and geographic regions.

The transition to a sustainable, low-carbon economy represents one of the defining challenges of our time. Financial markets play a crucial role in this transition through the allocation of capital toward climate-resilient investments. By providing rigorous, interpretable, and strategically-aware tools for climate risk assessment, this research contributes to the development of financial systems that are not only efficient but also aligned with the long-term sustainability of our planet.

In conclusion, the integration of XAI, Game Theory, and Machine Learning offers a powerful paradigm for understanding and managing climate-related financial risks. As articulated throughout this work, the future of sustainable finance lies at the intersection of computational power, human interpretability, and strategic rationality—a synthesis captured in the formula:

$$\text{Sustainable Finance} = \text{Power} \times \text{Comprehensibility} \times \text{Strategic Alignment}$$

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Conflicts of Interest

The author declares no conflicts of interest relevant to the content of this article.

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