

AI-driven forecasting and portfolio optimization under ESG and uncertainty regimes: evidence from global equity indices

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Abstract

Purpose – This study investigates how advanced machine learning (ML) and deep reinforcement learning (DRL) models can enhance forecasting accuracy and portfolio decision-making under environmental, social, and governance (ESG)-driven and uncertainty-sensitive market conditions. The objective is to compare the predictive efficiency of state-of-the-art ML architectures with policy-based portfolio strategies to uncover the role of sustainability indicators in shaping market dynamics.

Design/methodology/approach – We analyze daily data for major ESG and conventional market indices across the USA, Europe, and China, integrating the Standard Statistics Company and Poor's Publishing Company (S&P) Green Bond Index, Geopolitical Risk (GPR), the US Financial Stress Index (FSI), Physical Risk Index (PRI), and Transition Risk Index (TRI). The forecasting stage combines a 20-day long short-term memory (LSTM) temporal representation with Categorical Boosting (CatBoost), Light Gradient Boosting Machine (LightGBM), and Extreme Gradient Boosting (XGBoost) under a strict 70/15/15 chronological train-validation-test design and train-only scaling. The portfolio stage compares Twin Delayed Deep Deterministic Policy Gradient (TD3), Soft Actor-Critic (SAC), and Deep Deterministic Policy Gradient (DDPG) in a weekly self-financing environment with long-only weights, a 40% position cap, and proportional transaction costs. Random-Walk/Ridge/LSTM forecasting benchmarks and Equal-Weight/Minimum-Variance portfolio benchmarks are included, together with multi-seed and transaction-cost robustness checks. Local interpretable model-agnostic explanations (LIME) is retained for local model interpretation.

Findings – Forecasting performance is market-dependent rather than governed by a universally dominant learner. Validation selects LSTM-LightGBM for the China and US ESG indices, LSTM-XGBoost for Europe ESG, and LSTM-CatBoost for the three conventional indices. Multi-seed robustness yields positive average root mean square error (RMSE) gains over the Random Walk in five of six markets, with the strongest stability in China and statistically significant main-seed improvement for US ESG. In portfolio allocation, TD3 on the conventional opportunity set provides the strongest ex-post DRL performance (11.10% annualized return; Sharpe ratio 0.776), while SAC is the strongest ESG DRL strategy. Equal Weight remains a demanding benchmark, particularly for ESG portfolios, and the DDPG policies selected ex ante on validation remain profitable across three seeds and under transaction-cost scenarios up to 25 basis points (bps).

Originality/value – The study extends the emerging literature by integrating explainable hybrid forecasting and continuous-action DRL within a leakage-controlled, benchmark-oriented framework. Its contribution lies in combining ESG-sensitive uncertainty variables, chronological validation, realistic self-financing portfolio constraints, explicit transaction-cost analysis, and reproducibility checks rather than assuming universal AI or ESG superiority.

Keywords ESG stock prices, Financial stress, Geopolitical risk, Green bonds, Physical risk index, Transition risk index

Paper type Research article

1. Introduction

The introduction of climate fund incentives has significantly contributed to reducing greenhouse gas (GHG) emissions, highlighting the long-term environmental benefits of

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transitioning from fossil fuels to renewable energy sources (Carfora and Scandurra, 2019). In fact, there is growing interest among researchers and policymakers in identifying the key drivers that can accelerate the shift toward clean and sustainable energy systems. Alongside this, the growing prominence of environmental, social, and governance (ESG) principles has reshaped investment practices worldwide, encouraging regulators, institutional investors, and policymakers to consider the broader economic and societal outcomes associated with ESG-oriented strategies. Introduced in 2005 through the United Nations Principles for Responsible Investment (PRI), the ESG concept underscores the importance of climate risk, human rights, and corporate governance in shaping economic and financial performance. As a result, evaluating an investment portfolio in modern financial markets requires the integration of ESG considerations alongside traditional financial indicators, an approach increasingly recognized as essential for promoting sustainability within the global financial system (Eskantar *et al.*, 2024; Pandey *et al.*, 2024).

More precisely, ESG investment refers to an investment approach that integrates environmental, social, and governance indicators with the aim of achieving competitive financial returns while generating long-term social benefits (Tabassum *et al.*, 2026). With growing global awareness of sustainability challenges, opportunities aligned with ESG strategies have attracted considerable attention and are expected to continue expanding. Investors can further align profit-oriented objectives with environmental priorities by allocating capital to renewable energy sectors (Farid *et al.*, 2023). This increasing awareness has prompted nations to reassess their development strategies through the lens of sustainability, fostering greater interest in ESG-aligned investments as a means of promoting sustainable development (Yu *et al.*, 2024). Empirical evidence supports this trend: firms with higher ESG scores tend to exhibit superior stock returns and lower risk in the U.S. (Ding *et al.*, 2021), while in China, strong ESG performance is associated with reduced financial risk (Broadstock *et al.*, 2021). ESG performance also plays a key role in mitigating financial risk during periods of instability, its effects becoming particularly notable during crises, while less pronounced in stable periods (Broadstock *et al.*, 2021). These dynamics underscore the growing recognition among investors, firms, and policymakers of the need to integrate ESG factors into decision-making processes, particularly as a protective measure during turbulent market conditions (Liu *et al.*, 2023). Recently, financial markets have been transformed by advancements in artificial intelligence (AI) and computational finance, which have introduced new methods for forecasting and portfolio optimization. Therefore, portfolio managers increasingly rely on these advanced tools to manage risk and enhance returns. Among these approaches, deep reinforcement learning (DRL) has emerged as a promising technique, enabling agents to learn optimal allocation strategies through sequential decision-making in response to evolving market conditions. DRL algorithms have been successfully applied to portfolio management, demonstrating strong potential for improving investment performance.

To predict ESG and conventional MSCI stock prices, we develop a forecasting support tool that evaluates the contribution of financial uncertainty (FSI and GPR), climate uncertainty (PRI and TRI), and the S&P Green Bond Index within three LSTM-boosting architectures. We then compare DDPG, SAC, and TD3 for dynamic asset allocation. The contribution is not to assume that ESG or one AI model is universally superior, but to test whether predictive and allocation gains survive chronological validation, benchmark comparisons, multi-seed analysis, and realistic trading frictions across China, Europe, and the U.S.

The primary motivation of this research stems from the recognition that, as ESG investments become a central asset class, accurate and robust forecasting can support informed investment decisions. This context raises three questions: Which hybrid forecasting methods provide the most reliable out-of-sample predictions? Which uncertainty and sustainability factors contribute most strongly to model outputs? And to what extent can DRL-based allocation add value relative to simple portfolio benchmarks after trading constraints are imposed? Rather than claiming a first-of-its-kind framework, the study extends an emerging

strand of research by jointly evaluating hybrid forecasting, explainability, and continuous-DRL across ESG and conventional regional indices.

The remainder of this paper is organized as follows. [Section 2](#) presents the literature review. [Section 3](#) outlines the methodological framework. [Section 4](#) describes the data sources and variables. [Section 5](#) presents the empirical results and robustness checks. [Section 6](#) discusses theoretical, managerial, and policy implications, and [Section 7](#) concludes the paper.

2. Literature review

The academic literature on green and sustainable finance has expanded rapidly over the last decade, reflecting the growing importance of environmental, social, and governance (ESG) considerations in global capital markets. As financial ecosystems become increasingly shaped by climate risk, geopolitical uncertainty, and structural market stress, investors and policymakers are exploring new analytical tools to better understand and forecast asset price dynamics. In this regard, ESG (environmental, social, and governance) investing has attracted considerable interest among asset managers. Moreover, integrating ESG indices alongside traditional financial assets has emerged as a cornerstone of modern investment strategies. Portfolio managers are progressively reallocating capital toward assets with stronger ESG profiles, while researchers emphasize the need to identify the most influential factors driving price formation and forecasting accuracy. More recently, [Broadstock et al. \(2021\)](#) illustrated that, stocks with high ESG performance exhibit greater resilience during periods of market-wide financial crisis. This evolving nexus between sustainability, uncertainty, and financial performance forms a multi-dimensional framework that affects economic, environmental, and geopolitical policies worldwide.

2.1 Sustainable assets and ESG investments

Environmental, social, and governance (ESG) considerations have become central to both academic research and investment practice ([Bénabou and Tirole, 2010](#); [Gibson Brandon et al., 2021](#)). ESG indicators are now widely adopted as decision-making criteria, enabling investors to incorporate non-financial risks such as carbon intensity, social inequality, and governance quality into their asset allocation strategies. In fact, ESG investing aligns financial goals with sustainability priorities and increasingly influences objectives capital flows ([Silva and Cortez, 2016](#); [Bodhanwala and Bodhanwala, 2019](#)).

In investment practice, ESG assets are often combined with traditional financial instruments, as investors seek to enhance both financial performance and risk management. A growing body of empirical evidence supports this trend. [Broadstock et al. \(2021\)](#) show that high-ESG portfolios outperform low-ESG portfolios, particularly during financial crises, highlighting the role of ESG performance as a stabilizing factor in turbulent markets. Similarly, [Hoepner et al. \(2024\)](#) document that active ESG engagement mitigates downside risk, reinforcing the strategic importance of sustainability in portfolio design. [Cornell \(2021\)](#) notes that ESG scores do not systematically generate excess returns. However, their importance as diversification instruments continues to grow, particularly during periods of heightened climate concern, as highlighted by [Bolton and Kacperczyk \(2021\)](#). Overall, the literature strongly suggests that ESG investments enhance portfolio resilience by improving risk-adjusted returns and reducing exposure to long-term sustainability shocks.

2.2 Climate change, financial uncertainty, and key development factors

The increasing prominence of climate change has expanded the domain of green and climate finance, giving rise to a dual classification of climate risk: physical risks, stemming from extreme weather events, natural disasters, and climatic stress, and transition risks, associated with policy shifts toward low-carbon economies ([Breitenstein et al., 2021](#); [Venturini, 2022](#)). Physical risks include meteorological, hydrological, climatological, and geophysical events

that can severely damage physical assets and disrupt corporate operations (Doktycz and Abkowitz, 2019). Transition risks arise from regulatory pressures and environmental policies, including carbon taxation, emission-reduction mandates, and sustainability frameworks such as the Greenhouse Gas Protocol. These risks significantly influence corporate investment strategies and are strongly reflected in market valuations (Engle *et al.*, 2020). Recent literature also highlights that transition risks often outweigh direct climate impacts in determining stock performance, particularly in heavily regulated markets (Faccini *et al.*, 2021). Climate concerns similarly influence the performance of sustainability indices (Ren and Ren, 2024), reinforcing their role as indicators of environmental transition.

Uncertainty factors play a complementary role. Financial stress, volatility indices, and policy uncertainty significantly affect returns in green and clean-energy markets (Lundgren *et al.*, 2018; Zhao, 2020). Clean energy equities often exhibit defensive traits during crises (Chakrabarti and Sen, 2021), making them attractive to risk-averse investors. Moreover, Soltani *et al.* (2024) demonstrate that uncertainty indicators such as the Financial Stress Index enhance price forecasting accuracy when integrated into advanced machine learning frameworks. Geopolitical tensions further complicate this landscape. Uncertainty driven by geopolitical shocks affects financial markets broadly (Balcilar *et al.*, 2018; Bouri *et al.*, 2019; Caldara and Iacoviello, 2022). ESG initiatives may mitigate part of these shocks, as argued by Yang *et al.* (2024), underscoring the resilience of sustainable investments. Yet geopolitical instability can also undermine ESG performance across environmental (King and Shaver, 2001), social (Bapuji and Neville, 2015), and governance (Aguilera *et al.*, 2007) dimensions. Cheng *et al.* (2025) further show that geopolitical risk (GPR) constitutes a barrier to achieving strong ESG outcomes. Consistent with this multidimensional view, Drira *et al.* (2025) show that combining geopolitical risk, financial stress, green-market indicators, and behavioral information within deep-learning forecasting can improve the representation of uncertainty-sensitive price dynamics, supporting the use of a joint risk-information set rather than isolated predictors.

Finally, the emergence of green bonds represents one of the most important innovations in sustainable finance. Designed to fund climate-mitigation projects, green bonds support portfolio diversification and improved risk management (Huynh, 2022; Gupta *et al.*, 2025). Taken together, these studies confirm the critical importance of integrating climate, financial, and geopolitical uncertainties into asset-pricing models and forecasting frameworks.

2.3 Growth of sustainable finance, forecasting analysis and portfolio optimization

As ESG considerations continue to shape global financial markets, their integration into forecasting models and portfolio optimization strategies has become essential. Investors increasingly prioritize ESG factors to align financial objectives with global sustainability goals and regulatory frameworks. Regions such as the European Union, China, and the United States, characterized by advanced markets, strong institutions, and high capital flows, play a pivotal role in setting ESG and sustainability standards (He *et al.*, 2023; Naqvi *et al.*, 2023). Recent empirical findings sustain the view that incorporating ESG metrics enhances portfolio diversification and return stability. Liu *et al.* (2022) show that ESG integration improves diversification benefits, while Huang *et al.* (2024) find that consistent ESG practices reduce volatility and agency problems, particularly during downturns. Accordingly, ESG strategies increasingly serve not only ethical purposes but also pragmatic financial goals.

Existing research has largely focused either on the relationship between ESG performance, asset returns, and risk exposure (Friede *et al.*, 2015; Albuquerque *et al.*, 2020; Broadstock *et al.*, 2021; Elbayer *et al.*, 2026), or on the application of conventional machine learning techniques to financial prediction and asset allocation tasks (Gu *et al.*, 2020; Fischer and Krauss, 2018; Heaton *et al.*, 2017; Ben Hamadou and Boujelbène Abbes, 2025).

Recent research has substantially advanced the use of machine learning in sustainable finance, including interpretable ESG price forecasting under climate risk (Awijen *et al.*, 2024),

LightGBM-based ESG portfolio analysis (Gong *et al.*, 2024), and uncertainty-sensitive forecasting of green and sustainable assets (Soltani *et al.*, 2024). However, forecasting, explainability, and dynamic allocation are still frequently evaluated as separate tasks and often under different validation assumptions. The present study therefore does not claim an absence of prior ML or DRL applications; instead, it extends this emerging literature by evaluating the three components within a common information environment and by imposing benchmark-oriented out-of-sample validation at both the forecasting and portfolio stages.

Recent evidence also strengthens the portfolio and regime-dependence dimensions of this literature. Drira *et al.* (2026a) apply TD3, DDPG, and SAC to dynamic portfolio allocation under uncertainty while explicitly incorporating transaction costs and risk constraints, demonstrating the relevance of continuous-action DRL when trading frictions are recognized. Complementarily, Drira *et al.* (2026b) show that predictive and portfolio performance can vary across calm and stress regimes when climate and geopolitical shocks interact. These findings motivate the present study to test, rather than assume, whether hybrid forecasting and DRL gains generalize to ESG and conventional equity opportunity sets across China, Europe, and the United States under a common out-of-sample design.

2.4 Theoretical foundations and conceptual contribution

The theoretical underpinnings of this study build upon three complementary perspectives from financial economics and sustainable investment theory. First, adaptive learning and informational efficiency theory (Fama, 1970; Barberis *et al.*, 2005) suggests that financial markets incorporate information in a gradual, non-linear manner. This aligns with machine learning algorithms such as LSTM, XGBoost, CatBoost, and LightGBM, which are designed to capture structural breaks, non-linear dependencies, and long-memory patterns in financial time series, features that are amplified in ESG-sensitive markets subject to policy transitions and climate-related shocks. Second, the risk-pricing channel of sustainability posits that ESG performance lowers firms' exposure to environmental, regulatory, and reputational risks, thereby reducing required risk premiums. Studies show that ESG performance enhances portfolio resilience during crises (Broadstock *et al.*, 2021; Hoepner *et al.*, 2024), reinforcing its role as a risk-mitigation mechanism. Integrating uncertainty indicators such as GPR, FSI, and transition-risk indices thus reflects the theoretical premise that risk transmission intensifies under sustainability shocks. Third, reinforcement-learning theory provides a dynamic framework for portfolio construction in environments characterized by structural uncertainty. Deep reinforcement learning (DRL) algorithms such as TD3, SAC, and DDPG learn continuous allocation policies by interacting with evolving market conditions. This dynamic adjustment capability provides a flexible alternative to static portfolio rules, but whether it improves performance remains an empirical question once transaction costs and benchmark portfolios are imposed.

This theoretical framework supports our empirical approach by linking AI-driven forecasting, ESG-risk transmission, and dynamic portfolio optimization within a unified analytical structure.

3. Methodological framework

This section outlines the hybrid machine learning models applied to forecast ESG and conventional MSCI indices and the reinforcement-learning algorithms used for portfolio optimization. In response to concerns about methodological transparency, the revised design explicitly reports chronological data partitioning, train-only preprocessing, principal hyperparameters, validation-based model selection, benchmark models, multi-seed checks, and transaction-cost robustness.

The methodological framework consists of three steps:

- (1) Temporal feature extraction using LSTM,

- (2) Supervised learning using CatBoost, LightGBM, or XGBoost, and
- (3) Portfolio optimization through advanced DRL algorithms under realistic trading constraints.

The choice of this hybrid methodological framework is motivated by the specific characteristics of ESG-sensitive financial series, which are typically marked by nonlinear dependencies, structural changes, volatility clustering, and sensitivity to uncertainty shocks. In such environments, conventional linear models may fail to adequately capture both temporal persistence and complex cross-variable interactions. Recent studies therefore advocate the use of hybrid machine learning architectures that combine sequential deep learning and boosting-based supervised learning to improve forecasting accuracy in financial and sustainability-related applications. In this study, LSTM is used to extract temporal patterns and long-memory effects from uncertainty-related inputs, while CatBoost, LightGBM, and XGBoost are employed as flexible nonlinear predictors that can effectively model heterogeneous interactions across explanatory variables. Figure 1 presents the overall workflow of the hybrid forecasting framework, from uncertainty-related inputs and sequence construction to LSTM-based feature extraction, boosting prediction, and model evaluation.

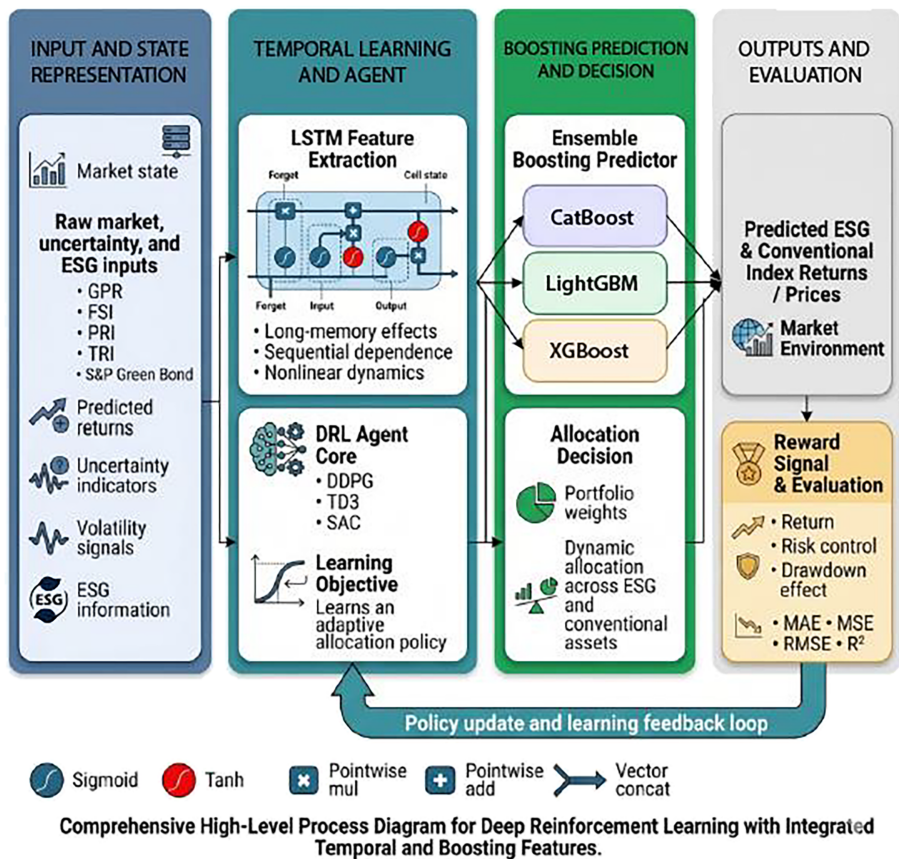


Figure 1. Workflow of the hybrid forecasting framework. Note: The hybrid framework first extracts temporal information from uncertainty indicators using LSTM, then feeds the learned features into CatBoost, LightGBM, or XGBoost to predict ESG and conventional index dynamics. Source: Authors’ elaboration

3.1 Hybrid machine learning models

Hybrid machine learning combines the strengths of sequential deep learning architectures and efficient tree-based boosting algorithms, producing a flexible and accurate forecasting framework. The three hybrid models evaluated (LSTM + CatBoost, LSTM + LightGBM, and LSTM + XGBoost) are summarized in Table 1. This modelling choice is further supported by recent evidence showing that hybrid and ensemble-based machine learning methods perform particularly well in forecasting tasks involving ESG assets, green finance variables, and uncertainty-sensitive market indicators, as they can jointly capture dynamic persistence and nonlinear predictor-response relationships.

The five core exogenous uncertainty indicators are GPR, S&P_GB, PRI, TRI, and the U.S. Financial Stress Index (FSI). The revised forecasting implementation also uses lagged target returns and short-to medium-horizon momentum and volatility features, all constructed from information available no later than $t-1$.

3.1.1 LSTM + CatBoost model. Long Short-Term Memory (LSTM) networks are widely adopted in forecasting financial, climate-linked, and ESG-related time series because they can represent sequential dependence (Zhang *et al.*, 2019; Wang *et al.*, 2020; Xia *et al.*, 2022). In the revised implementation, the LSTM receives a 20-day sequence containing lagged target returns and the uncertainty-related inputs, and its learned temporal representation is then supplied to the boosting learner.

The hybrid model proceeds in two phases:

Phase 1 – temporal feature extraction.

$$Z = \text{LSTM}(X) \quad (1)$$

- Z : LSTM temporal representation summarizing lagged market returns and the dynamics of GPR, S&P_GB, PRI, TRI, and U.S_FSI
- X : 20-day historical sequences using information available through $t-1$

Phase 2 – price prediction.

$$\hat{y} = \text{CatBoost}(Z) \quad (2)$$

- $\hat{y}$: predicted ESG and MSCI prices for the three regions

This architecture combines LSTM's sequential learning capability with CatBoost's efficiency on structured data, enhancing predictive accuracy for ESG-related assets.

3.1.2 LSTM + LightGBM model. Light Gradient Boosting Machine (LightGBM) is a gradient boosting framework that efficiently handles large-scale, complex datasets through

Table 1. A comparative evaluation of hybrid machine learning models

Hybrid model	Advantages	Limitations
LSTM + CatBoost	Effective with categorical data	Slower with large datasets
LSTM + LightGBM	Very fast and efficient for large datasets	May overfit if not properly tuned
LSTM + XGBoost	High accuracy with good regularization	Higher computational cost

Note(s): This table provides a summary of the main characteristics of the hybrid machine learning models employed in the forecasting framework. It highlights their respective advantages and limitations in terms of predictive performance, computational efficiency, and suitability for financial time-series modeling

Source(s): Created by the authors

leaf-wise tree growth (Ke et al., 2017). Studies such as Awijen et al. (2024) and Gong et al. (2024) confirm its success in forecasting ESG prices under multiple uncertainty drivers.

Phase 1 – temporal learning.

$$Z = \text{LSTM}(X) \tag{3}$$

Phase 2 – supervised forecasting.

$$\hat{y} = \text{LightGBM}(Z) \tag{4}$$

This hybrid structure leverages LSTM’s understanding of sequential uncertainty dynamics and LightGBM’s supervised learning strengths to model complex non-linearities in financial markets.

3.1.3 LSTM + XGBoost model. Extreme Gradient Boosting (XGBoost), introduced by Chen and Guestrin (2016), incorporates regularization, shrinkage and parallelization, making it highly effective in forecasting ESG and MSCI conventional indices (Lin and Hsu, 2023; Su et al., 2024).

Phase 1 – temporal feature extraction.

$$Z = \text{LSTM}(X) \tag{5}$$

Phase 2 – price prediction.

$$\hat{y} = \text{XGBoost}(Z) \tag{6}$$

This hybrid model is particularly suited for capturing complex price dynamics driven by environmental, geopolitical, and financial uncertainty.

3.2 Model performance metrics

Model accuracy is evaluated using standard statistical measures: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). These metrics quantify forecasting precision and enable consistent comparison across the hybrid models. Table 2 reports these metrics along with their definitions and mathematical expressions to facilitate the interpretation of forecasting accuracy.

3.2.1 Validation, hyperparameters, and forecasting robustness. The forecasting sample is divided chronologically into 70% training, 15% validation, and 15% test observations. All scalars are fitted exclusively on the training information set. The LSTM uses a 20-day lookback, 64 hidden units, one recurrent layer, batch size 64, Adam learning rate 0.001, a maximum of 40 epochs, and early stopping with patience 8. CatBoost uses depth 8, learning rate 0.02, and up to 1,000 iterations; XGBoost uses maximum depth 7, learning rate 0.02, and up to 1,000 estimators; LightGBM uses learning rate 0.03 with validation-selected leaf/estimator settings. These settings are selected or fixed using training/validation information only.

To prevent aggressive return forecasts when validation evidence is weak, a shrinkage coefficient alpha in [0,1] is selected on the validation set and scales the predicted return toward the Random-Walk forecast of zero return. Robustness is assessed against Random Walk, standalone LSTM, and Ridge benchmarks, with Diebold-Mariano tests for squared forecast losses. The validation-selected final model is additionally repeated for random seeds 11, 42, and 2026. The test sample is not used for model or hyperparameter selection.

3.3 Portfolio optimization with trading constraints

Following forecasting, portfolio optimization is conducted with three continuous-action actor-critic algorithms: DDPG, TD3, and SAC. Q-Learning is removed from the revised empirical framework because it was not used in the implementation and is not naturally suited to the continuous portfolio-weight action space considered here. DDPG, TD3, and SAC are retained because they can learn dynamic continuous allocations under changing market states.

Table 2. Summary of the model's predictive performance

Metrics	Definitions	Formulas
Mean absolute error (MAE)	-We choose the Mean Absolute Error (MAE) as a measure of the average difference between predicted and actual values. The MAE is straightforward to interpret and calculate	$MAE = \frac{1}{n} \sum_{i=1}^n \hat{y}_i - y_i $
Mean squared error (MSE)	-The Mean Squared Error (MSE) is calculated by averaging the squared differences between the actual values and the predicted values from the model. It quantifies the variance of the residuals	$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n}$
Root mean square error (RMSE)	-The Root Mean Square Error (RMSE) is sensitive to outliers in prediction errors. A lower RMSE indicates better predictive performance, as it reflects smaller absolute variance in the model's predictions	$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y(t) - \hat{y}(t))^2}$
Coefficient of determination (R^2)	-The Coefficient of Determination (R^2) serves as a key evaluation metric for assessing the accuracy of the prediction model	$R^2 = 1 - \frac{\frac{1}{N} \sum_{t=1}^N (y(t) - \hat{y}(t))^2}{\frac{1}{N} \sum_{t=1}^N (y(t) - \bar{y})^2}$

Note(s): This table presents the evaluation metrics used to assess the predictive performance of the hybrid forecasting models. MAE, MSE, RMSE, and R^2 are reported along with their definitions and mathematical expressions to facilitate the interpretation of forecasting accuracy

This table presents the evaluation metrics used to assess predictive performance. MAE, MSE, RMSE, and R^2 are retained for comparability with the original specification

Source(s): Created by the authors

The flowcharts presented in [Figure 2](#) depict the operational processes of the Deep Reinforcement Learning algorithms (DDPG, SAC, and TD3).

Implementation clarification for the revised empirical analysis: [Figure 2](#) is retained as the original conceptual diagram. In the actual estimation, portfolios are self-financing and rebalanced every five trading days. The ESG and conventional opportunity sets each contain

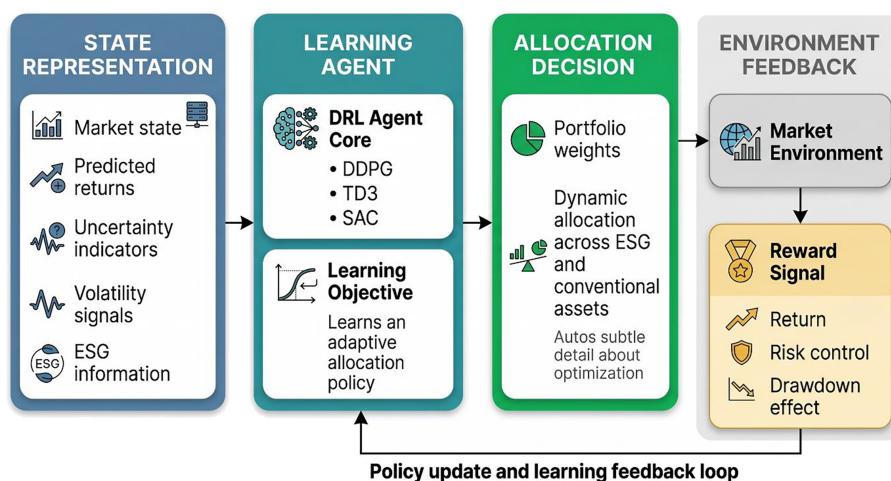


Figure 2. Deep reinforcement learning portfolio optimisation process. Note: At each step, the DRL agent observes the market state, selects portfolio weights, receives a reward based on return and risk, and updates its allocation policy through repeated interaction with the environment. Source: Authors' elaboration

the three regional equity indices, the S&P Green Bond Index, Gold, and Brent. VIX is used as a state variable rather than an investable asset. Portfolios are long-only and fully invested, individual weights are capped at 40%, one-way turnover is defined as $0.5 \times \Sigma |w(\text{target}) - w(\text{pre-trade})|$, and the baseline proportional transaction cost is 10 bps. The same accounting rules are applied to all DRL strategies and benchmark portfolios.

3.3.1 Deep deterministic policy gradient (DDPG). DDPG adopts an actor–critic architecture with deterministic policies. The optimal Q-value follows the Bellman equation:

$$Q^*(s, a) = \mathbb{E} \left[r(s, a) + \gamma \max_{a'} Q^*(s', a') \right] \quad (9)$$

Temporal-Difference error:

$$TD = r + \gamma Q(s', a') - Q(s, a) \quad (10)$$

Soft-updated target networks:

$$\phi' = \rho \phi + (1 - \rho) \phi' \quad (12)$$

The critic's loss:

$$J_Q(\phi) = \mathbb{E} \left[\left(Q_\phi(s, a) - \left(r + \gamma(1 - d) Q'_\phi(s', \pi'_\theta(s')) \right) \right)^2 \right] \quad (13)$$

Policy objective:

$$J(\theta) = \max_{\theta} \mathbb{E} [Q_\phi(s, \pi_\theta(s))] \quad (14)$$

3.3.2 Twin delayed DDPG (TD3). TD3 mitigates overestimation bias and improves stability through:

- target policy smoothing

$$a'(s') = \text{clip}(\mu_{\theta'}(s') + \epsilon, a_{low}, a_{high}) \quad (15)$$

- clipped double Q-learning

Two critics evaluate the next Q-value, and the minimum is used to compute the target.

3.3.3 Soft actor–critic (SAC). SAC introduces entropy regularization to encourage exploration, making it robust in volatile markets.

Objective:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t (r_t + \alpha H(\pi(\cdot | s_t))) \right] \quad (16)$$

Entropy-augmented Bellman equation:

$$Q^\pi(s, a) = \mathbb{E} [r + \gamma (Q^\pi(s', a') + \alpha H(\pi(\cdot | s')))] \quad (17)$$

SAC critic loss:

$$L(\theta) = \mathbb{E} \left[\left(Q_{\theta}(s, a) - \left(r + \gamma(1 - d) \left(\min_i Q_{\theta^{target}}(s', a') - \alpha \log \pi_{\phi}(a' | s') \right) \right) \right)^2 \right] \quad (18)$$

Value function:

$$V^{\pi}(s) = \mathbb{E}[Q^{\pi}(s, a) - \alpha \log \pi(a | s)] \quad (19)$$

3.3.4 Portfolio training, selection, and robustness. The portfolio state uses a 20-day history of asset returns, momentum and realized volatility together with VIX, GPR, FSI, TRI, and PRI. State variables are standardized using training data only. The sample follows the same 70/15/15 chronological train-validation-test principle. Each DRL model uses a two-layer [64,64] policy network and 12,000 training timesteps in the final weekly self-financing specification. Models are compared on the validation period; the validation-selected policy is then repeated with seeds 11, 42, and 2026. Equal-Weight and rolling Markowitz Minimum-Variance portfolios are evaluated over the identical test period. Transaction-cost robustness replays the selected target-weight path at 0, 10, and 25 bps without retraining.

Table 3 presents a comparative overview of the main structural features, advantages, and typical financial applications of the deep reinforcement learning algorithms employed for dynamic asset allocation under uncertainty.

4. Data description

This study examines the impact of climate risk uncertainty, specifically transition risks (TRI) and physical risks (PRI), alongside financial stress (FSI), geopolitical risk (GPR), and the S&P Green Bond Index on ESG markets and their MSCI conventional counterparts across three major regions: China, Europe, and the USA. The explanatory variables are selected based on sustainable finance theory and empirical evidence. ESG and conventional MSCI indices allow comparison between sustainability-oriented and traditional markets. The S&P Green Bond Index captures interactions with ESG equity dynamics. GPR and FSI are included due to their documented impact on financial asset behavior and predictability. TRI and PRI reflect the growing role of climate-related uncertainty in pricing ESG-sensitive assets.

Table 3. Comparison of deep reinforcement learning algorithms

Algorithm	Key features	Advantages	Applications
DDPG	Continuous action spaces, Actor-Critic architecture	Precise control in continuous action spaces	Asset allocation with precise control requirements
SAC	Entropy regularization, Actor-Critic architecture	Balances exploration and exploitation, Effective in high uncertainty environments	Portfolio optimization under uncertainty
TD3	Twin critics, Delayed policy updates	Addresses overestimation bias, Stability and robustness	Financial applications requiring accurate value estimation

Note(s): This table provides a comparative overview of the deep reinforcement learning algorithms employed in the portfolio optimisation stage. It summarizes their main structural features, advantages, and typical financial applications in dynamic asset allocation under uncertainty

Source(s): Created by the authors

The dataset consists of daily observations on ESG indices, MSCI conventional indices, the S&P Green Bond Index, VIXCLS, Gold, Brent crude oil, GPR, FSI, PRI, and TRI, covering July 2013 to January 2025. The starting date is determined by joint data availability. Transformations differ by empirical purpose: the forecasting module predicts one-day log returns and reconstructs index levels from the predicted return and the previous observed level, whereas the self-financing portfolio module uses simple asset returns because portfolio wealth compounds multiplicatively. Decision variables are lagged so that the information set at t contains no future observations.

4.1 Climate risk measures

Research in climate finance highlights the importance of distinguishing between physical and transition climate risks due to their heterogeneous effects on financial markets (Bua *et al.*, 2024; Engle *et al.*, 2020; Faccini *et al.*, 2023). According to the Task Force on Climate-related Financial Disclosures (TCFD), physical risks arise from extreme weather events, such as floods, droughts, heatwaves, or gradual shifts in climatic conditions including rising sea levels and long-term temperature increases. In contrast, transition risks reflect the economic and financial implications associated with the shift toward a low-carbon economy. These risks are driven by regulatory reforms, technological innovation, changes in market conditions, and evolving societal preferences (Breitenstein *et al.*, 2022). Recent evidence suggests that stock markets react significantly to climate-related uncertainty. Rubtsov and Shen (2024) document the strong sensitivity of stock investments to climate uncertainty, while Awijen *et al.* (2024) demonstrate that integrating both transition and physical climate risk indices into forecasting models improves the prediction accuracy of ESG stock prices. These findings underscore the critical role of climate-related variables in understanding financial market dynamics and justify their inclusion in our forecasting framework.

4.2 Financial stress index (FSI)

The Financial Stress Index (FSI) captures the prevailing level of instability within a country's financial system by aggregating multiple stress indicators across key market segments into a single composite measure (Drira *et al.*, 2025; Soltani *et al.*, 2025; Soltani and Abbes, 2025). The index is constructed following the methodology of Balakrishnan *et al.* (2011), with country-specific refinements based on the steps outlined by Soltani *et al.* (2021). In a recent contribution, Soltani *et al.* (2024) show that financial stress plays a decisive role in driving the forecasting performance of green and clean energy assets. Both the FSI and the Panic Index (PI) emerge as central determinants of price dynamics, highlighting the importance of incorporating financial stress indicators into advanced forecasting models. Given its relevance, the FSI is included in our variable set to capture systemic instability and its influence on ESG and conventional stock returns.

4.3 Geopolitical risk index (GPR)

The Geopolitical Risk (GPR) index measures the threat, occurrence, and escalation of adverse geopolitical events, including conflicts, terrorism, and political tensions, that disrupt international stability. The index is computed daily based on the textual methodology developed by Caldara and Iacoviello (2022). Several studies have emphasized the impact of geopolitical tensions on sustainable investments. Adekoya *et al.* (2025) demonstrate that global GPR significantly amplifies the volatility of green investment assets, particularly during episodes of geopolitical threats. Similarly, Mnif *et al.* (2025) highlight that environmentally friendly and energy-intensive cryptocurrencies can act as hedging tools during geopolitical instability, reinforcing the need to integrate geopolitical indicators into sustainable investment models. The GPR index is therefore included to capture exogenous shocks stemming from political and security disruptions.

4.4 S&P green bond index (S&P_GB)

Green bonds (GB) have emerged as one of the most effective financing tools for environmentally sustainable projects (Maltais and Nykvist, 2020; Bhutta *et al.*, 2022). They promote climate mitigation through investments in energy efficiency, renewable energy, and climate-resilient infrastructure (Park *et al.*, 2020; Sartzetakis, 2021). The interactions between green bond markets and traditional financial markets have received increasing scholarly attention, particularly regarding volatility transmission and diversification benefits. Aloui *et al.* (2025) and Gupta *et al.* (2025) show that volatility spillovers from green bonds to conventional assets play a crucial role in portfolio construction. Furthermore, understanding the correlations between green bonds and other asset classes is essential for international investors seeking to optimize risk–return trade-offs (Azad and Devi, 2025; Yousfi and Bouzgarrou, 2024). Given its importance, the S&P Green Bond Index is incorporated into our model to assess the predictive role of the green bond market in forecasting ESG and MSCI index fluctuations and in shaping portfolio optimization strategies.

To provide a clearer empirical overview of the dataset, Table 4 reports descriptive statistics for the ESG and conventional index levels in China, Europe, and the USA. The statistics show substantial cross-market differences in scale and dispersion, together with positive skewness in all six series. Kurtosis values range from approximately 2.19 to 3.30, indicating moderate distributional heterogeneity rather than uniformly heavy-tailed behavior. These descriptive patterns motivate flexible nonlinear modelling but are not, by themselves, evidence that one model class must dominate.

5. Empirical results and discussion

In this section, we present and analyze the results for ESG and MSCI conventional indices. We first discuss the LIME attribution results, then compare the out-of-sample performance of the three hybrid forecasting models, and finally evaluate TD3, SAC, and DDPG portfolio strategies. The section also reports explicit forecasting and portfolio robustness checks against naive/statistical benchmarks, multiple random seeds, and transaction-cost scenarios.

5.1 Factors contribution and feature importance

Understanding the behavior of machine learning models has become essential for portfolio managers, as it allows them to effectively communicate to investors how their funds are being managed. In constructing portfolios, managers can leverage machine learning models to justify their decisions, such as explaining the rationale behind portfolio diversification and optimization. This shift in the role of portfolio managers has positioned them as responsible for clarifying the use of machine learning models in portfolio management. Among the various explanation methods, Local Interpretable Model-agnostic Explanations (LIME) is particularly useful for understanding the proportional contributions of each component in accurately forecasting ESG and MSCI index prices.

Figure 3 presents local LIME explanations for ESG and conventional MSCI indices across China, Europe, and the U.S. The S&P Green Bond Index and the U.S. Financial Stress Index appear prominently in several local explanations, while GPR, TRI, and PRI contribute with smaller or more case-specific effects. Because LIME explains a particular fitted prediction, the displayed thresholds should be interpreted as local model-attribution patterns rather than structural or causal breakpoints. The figure therefore supports the relevance of green-finance and stress information for model decisions while also showing regional heterogeneity in the contribution of uncertainty variables.

5.2 Evaluating the forecasting performance of the models

Using MAE, MSE, RMSE, and R^2 , the revised out-of-sample analysis no longer identifies a universally dominant hybrid learner. As shown in Figure 4 and Table 5, reconstructed index-

Table 4. Descriptive statistics of ESG and conventional indices across China, Europe, and the USA

Region	Index type	Series	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
China	ESG	MSCI CHINA ESG	1413.690	411.192	805.332	2828.409	0.964	3.295
Europe	ESG	MSCI EUROPE ESG	94.034	14.527	69.646	128.006	0.491	2.186
USA	ESG	MSCI USA ESG	178.179	65.155	94.010	346.229	0.710	2.426
China	Conventional	CONV MSCI CHINA	7487.761	1617.966	4865.030	13270.780	0.887	3.166
Europe	Conventional	CONV MSCI EUROPE	1738.361	202.483	1152.700	2250.560	0.295	2.491
USA	Conventional	CONV MSCI USA	3037.688	1094.906	1559.690	5834.170	0.625	2.313

Note(s): This table reports the main descriptive statistics for the ESG and conventional indices used in the empirical analysis. The reported measures include the number of observations, mean, standard deviation, minimum, maximum, skewness, and kurtosis. These statistics provide a preliminary overview of the distributional properties and regional heterogeneity of the indices before the forecasting and portfolio optimization stages

This table reports the main descriptive statistics for the ESG and conventional index levels used in the empirical analysis. Each of the six series contains 2,925 daily observations over the common July 2013–January 2025 sample

Source(s): Created by the authors



Figure 3. Local interpretable model-agnostic explanations (LIME). Note: This figure reports the LIME-based local explanations for ESG and conventional MSCI indices in China, Europe, and the USA. Positive and negative bars indicate local contributions to a specific fitted prediction. Source: Authors' elaboration

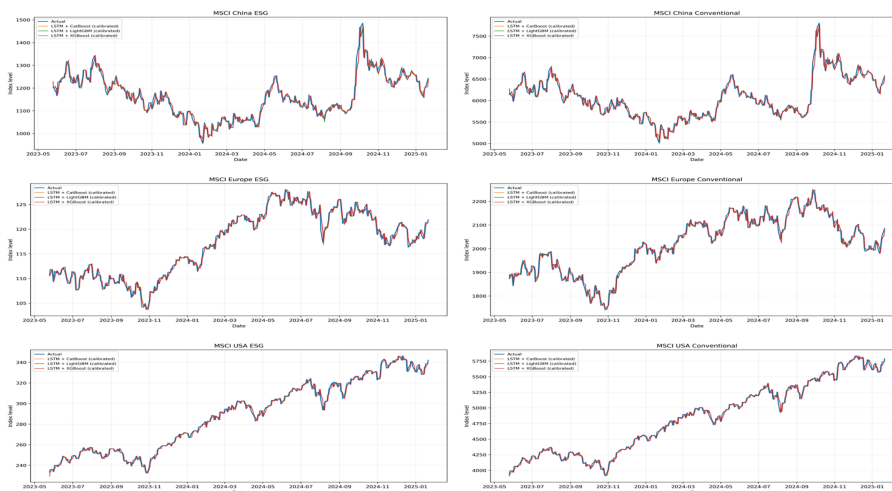


Figure 4. Actual versus predicted values from the revised hybrid forecasting models for ESG and conventional indices across China, Europe, and the USA. Note: The revised plots use the leakage-controlled out-of-sample forecasts from the chronological test sample. The three calibrated hybrid models are shown together with the observed index level. Source: Authors' elaboration

level forecasts remain close to observed levels, with R^2 generally above 0.95 after leakage-controlled estimation. However, the best model varies by market. Validation selects LSTM-LightGBM for China ESG and USA ESG, LSTM-XGBoost for Europe ESG, and LSTM-CatBoost for the three conventional indices. This market dependence is more consistent with

Table 5. Revised out-of-sample hybrid model prediction accuracy

Index	Hybrid model	MSE	MAE	RMSE	R^2
China ESG	LSTM + CatBoost	0.00009	0.00700	0.00967	0.9570
	LSTM + LightGBM	0.00009	0.00693	0.00967	0.9570
	LSTM + XGBoost	0.00009	0.00695	0.00972	0.9566
Europe ESG	LSTM + CatBoost	0.00029	0.01303	0.01710	0.9854
	LSTM + LightGBM	0.00030	0.01308	0.01718	0.9853
	LSTM + XGBoost	0.00030	0.01314	0.01723	0.9852
USA ESG	LSTM + CatBoost	0.00023	0.01101	0.01518	0.9946
	LSTM + LightGBM	0.00023	0.01098	0.01512	0.9946
	LSTM + XGBoost	0.00023	0.01101	0.01518	0.9946
China conventional	LSTM + CatBoost	0.00012	0.00793	0.01108	0.9608
	LSTM + LightGBM	0.00012	0.00801	0.01117	0.9602
	LSTM + XGBoost	0.00012	0.00799	0.01110	0.9607
Europe conventional	LSTM + CatBoost	0.00029	0.01332	0.01704	0.9805
	LSTM + LightGBM	0.00029	0.01323	0.01698	0.9806
	LSTM + XGBoost	0.00029	0.01329	0.01710	0.9803
USA conventional	LSTM + CatBoost	0.00017	0.00978	0.01321	0.9954
	LSTM + LightGBM	0.00018	0.00980	0.01325	0.9954
	LSTM + XGBoost	0.00018	0.00980	0.01325	0.9954

Note(s): Metrics are calculated for reconstructed index-level forecasts after train-fitted scaling. Model calibration and selection use validation data only; the test set is reserved for final evaluation

Source(s): Created by the authors

heterogeneous nonlinear structures than the previous claim that LSTM-LightGBM dominates every market.

The stricter return-space results are more modest than the high index-level R^2 values. In the main-seed comparison, the validation-selected model improves on the Random Walk in five of six markets, but the Diebold-Mariano difference is statistically significant at 5% only for USA ESG ($p = 0.016$) and is marginal at 10% for USA Conventional ($p = 0.075$). Thus, the evidence supports selective incremental predictability rather than universal forecasting superiority.

5.3 Portfolio optimization

In this section, we explore portfolio optimization for ESG and MSCI stock indices using Deep Reinforcement Learning (DRL) algorithms to mitigate market volatility. Three DRL algorithms, Deep Deterministic Policy Gradient (DDPG), Soft Actor–Critic (SAC), and Twin Delayed DDPG (TD3), are evaluated for their effectiveness in managing risk and optimizing returns.

5.3.1 Comparison ESG and conventional performance with deep learning reinforcement. Using Deep Reinforcement Learning, we construct weekly self-financing portfolios for ESG and conventional opportunity sets. Each set contains the three corresponding regional equity indices, the S&P Green Bond Index, Gold, and Brent, while VIX and the uncertainty indicators enter the state rather than the investable set. Figure 5 compares portfolio values over the independent test period, which begins in 2023 and ends in January 2025.

Figure 5 shows substantial variation across algorithms rather than uniform ESG dominance. On the test sample, TD3_CONV attains the highest terminal value among the six DRL strategies, while SAC_ESG is the strongest ESG DRL strategy. The comparison therefore indicates that performance depends jointly on the algorithm and opportunity set. This heterogeneous result is retained rather than interpreting ESG status alone as sufficient to guarantee superior portfolio outcomes.

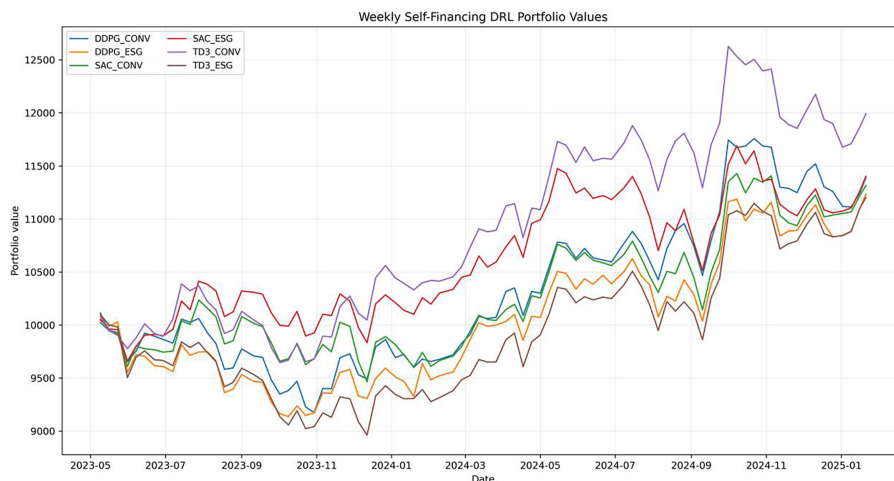


Figure 5. Portfolio values for the revised weekly self-financing DRL strategies. Note: All strategies are evaluated with long-only fully invested weights, a 40% position cap, one-way turnover, and a 10-bps baseline transaction cost. Source: Authors' elaboration

5.3.2 Cumulative return trends. The cumulative-return paths in Figure 6 cover the independent 2023–2025 test period. Accordingly, the revised interpretation does not attribute these test results to the COVID-19 shock or the initial 2022 Russia-Ukraine invasion, which fall outside the test window. The figure instead documents the relative out-of-sample trajectories of TD3, SAC, and DDPG under the same self-financing and transaction-cost assumptions.

The ex-post ranking in Figure 6 is led by TD3_CONV, followed by the strongest ESG strategy, SAC_ESG. DDPG remains important because it is the policy selected ex ante on the

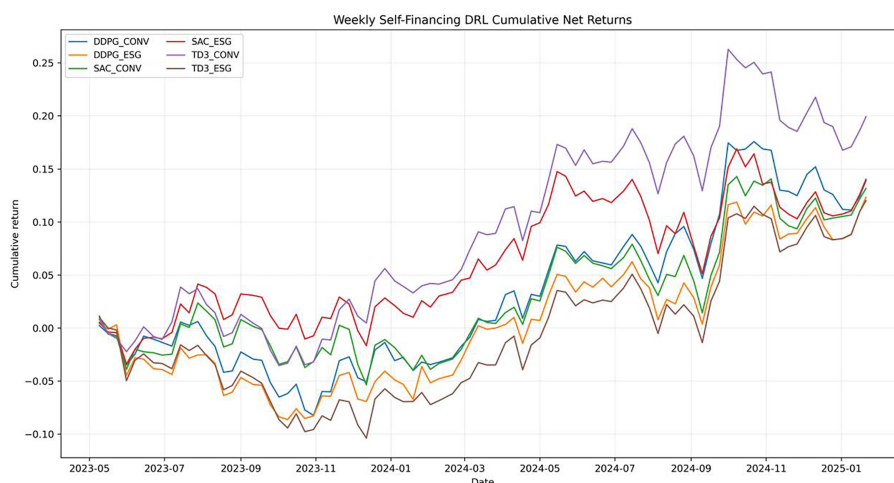


Figure 6. Cumulative net returns of the revised weekly self-financing DRL portfolio strategies. Note: Cumulative returns are computed from net self-financing portfolio returns over the independent test period after baseline transaction costs. Source: Authors' elaboration

validation period for both ESG and conventional opportunity sets. The fact that a different algorithm can lead on the subsequent test highlights model uncertainty and reinforces the need to distinguish validation-based selection from ex-post-test ranking.

The revised results do not support a universal claim that ESG-based DRL portfolios are always more resilient. Instead, the relative performance of ESG and conventional strategies varies with the algorithm, benchmark, and evaluation metric. This finding is consistent with treating ESG characteristics as one component of the market state rather than as a guarantee of superior return-risk performance.

5.3.3 Overall performance metrics. The Table 6 provides a comparative analysis of performance metrics for various portfolio allocation models, specifically contrasting ESG strategies with conventional investment approaches.

Table 6 shows that TD3_CONV records the strongest ex-post DRL performance, with an annualized return of 11.10%, cumulative return of 19.93%, Sharpe ratio of 0.776, and maximum drawdown of −7.54%. Within the ESG opportunity set, SAC_ESG is the strongest DRL strategy, with a 7.90% annualized return and Sharpe ratio of 0.555. These rankings differ from the validation-stage selection, where DDPG is retained for both opportunity sets. The revised interpretation therefore separates ex-ante model selection from ex-post-test performance and avoids the previous conclusion that ESG strategies uniformly dominate conventional portfolios.

5.4 Robustness checks

Forecasting robustness is assessed with both naive/statistical benchmarks and repeated seeds. Across seeds 11, 42, and 2026, the validation-selected hybrid model produces a positive average RMSE gain over the Random Walk in five of six markets. The two China series show the most stable gains, whereas Europe Conventional is essentially benchmark-equivalent on average. Main-seed Diebold-Mariano tests reject equal squared-error performance against the Random Walk at 5% for USA ESG and at the 10% level for USA Conventional. These results support selective, market-dependent predictive gains rather than universal superiority (see Table 7).

Portfolio robustness is evaluated for the DDPG policies selected ex ante on the validation period. Both DDPG_ESG and DDPG_CONV remain profitable across all three seeds, although conventional performance is more dispersed. Transaction-cost sensitivity also remains economically positive: annualized returns stay at 4.15% for ESG and 5.23% for conventional portfolios at 25 bps. However, Equal Weight remains a strong benchmark,

Table 6. Revised performance metrics of DRL portfolio allocation models

Metrics	TD3_ ESG	SAC_ ESG	DDPG_ ESG	TD3_ CONV	SAC_ CONV	DDPG_ CONV
Annual return (%)	6.792	7.901	6.965	11.102	7.427	7.833
Cumulative return (%)	12.011	14.027	12.325	19.929	13.163	13.902
Annualized volatility (%)	11.749	11.262	11.496	11.920	11.893	11.469
Sharpe ratio	0.449	0.555	0.471	0.776	0.495	0.542
Sortino ratio	0.690	0.854	0.702	1.306	0.786	0.878
Calmar ratio	0.603	0.942	0.772	1.473	0.985	0.890
Maximum drawdown (%)	−11.266	−8.385	−9.023	−7.536	−7.537	−8.796
Final portfolio value	11201.14	11402.74	11232.50	11992.86	11316.33	11390.22

Note(s): All DRL strategies use weekly self-financing accounting, 10-bps baseline transaction costs, and the common out-of-sample test window. Equal-Weight and Minimum-Variance benchmark results are reported in the robustness analysis below

Source(s): Created by the authors

Table 7. Forecasting robustness of validation-selected hybrid models

Index	Selected model	RMSE mean $\pm$ SD	Mean gain vs. RW (%)	Seeds B/T/L	DM <i>p</i> -value
China ESG	LSTM + LightGBM	0.01596 $\pm$ 0.00005	0.55	3/0/0	0.553
China conventional	LSTM + CatBoost	0.01474 $\pm$ 0.00001	0.97	3/0/0	0.370
Europe ESG	LSTM + XGBoost	0.00667 $\pm$ 0.00004	0.36	2/0/1	0.623
Europe conventional	LSTM + CatBoost	0.00817 $\pm$ 0.00002	-0.08	1/0/2	0.764
USA ESG	LSTM + LightGBM	0.00839 $\pm$ 0.00003	0.34	2/1/0	0.016
USA conventional	LSTM + CatBoost	0.00771 $\pm$ 0.00002	0.27	2/1/0	0.075

Note(s): B/T/L denotes the number of seeds beating, tying, or losing to the Random Walk. DM *p*-values refer to the main-seed validation-selected model versus Random Walk

especially in the ESG set, where its 9.30% annualized return and Sharpe ratio of 0.735 exceed the main-seed DDPG_ESG result (see [Table 8](#)).

6. Theoretical, managerial, and policy implications

This study offers several theoretical, managerial, and policy implications. From a theoretical perspective, the joint inclusion of PRI, TRI, FSI, GPR, and the S&P Green Bond Index shows that ESG-sensitive forecasting is shaped by multiple interacting sources of uncertainty. At the same time, the heterogeneous forecasting and portfolio results indicate that these variables do not create a uniform ESG premium or a universally superior AI model. The evidence therefore supports a conditional, market-dependent interpretation of sustainability and uncertainty effects.

From a managerial standpoint, the main implication is the importance of benchmark-oriented model governance. High index-level R^2 should not be interpreted as sufficient evidence of exploitable return predictability, and DRL strategies should be evaluated under the same wealth accounting and transaction-cost assumptions as simple alternatives. Equal Weight is difficult to beat in the ESG opportunity set, whereas TD3 provides strong ex-post performance in the conventional set. Portfolio managers should therefore allow model choice to vary by market and retain simple benchmark allocations as live reference strategies rather than assuming ESG or DRL dominance.

Finally, the findings offer practical implications for both investment practice and policy. LIME can help portfolio managers communicate which uncertainty factors contribute to a particular model prediction, but these attributions should not be interpreted causally. The multi-seed and transaction-cost results also show that implementation risk must be monitored explicitly. For policymakers, the relevance of green-bond conditions, climate-risk indicators, geopolitical risk, and financial stress supports efforts to improve the consistency and availability of sustainable-finance data. However, the heterogeneous performance results

Table 8. Multi-seed, transaction-cost, and benchmark robustness of validation-selected DDPG policies

Portfolio	Selected policy	Ann. Return mean $\pm$ SD (%)	Sharpe mean $\pm$ SD	Max DD mean $\pm$ SD (%)	Return @ 0/ 10/25 bps (%)	Benchmark return EW/ MV (%)
ESG	DDPG	6.80 $\pm$ 2.29	0.455 $\pm$ 0.190	-8.43 $\pm$ 0.58	8.88/6.96/4.15	9.30/2.93
CONV	DDPG	7.69 $\pm$ 4.80	0.505 $\pm$ 0.362	-8.66 $\pm$ 0.25	9.60/7.83/5.23	9.34/5.50

Note(s): Multi-seed statistics use seeds 11, 42, and 2026. Cost sensitivity replays the main-seed target-weight path without retraining. EW = Equal Weight; MV = Markowitz Minimum Variance

7. Conclusion

This study evaluates hybrid machine-learning forecasting and continuous-action DRL portfolio optimization for ESG and conventional indices in China, Europe, and the USA under a common uncertainty information set. The revised methodology uses strict chronological train-validation-test separation, train-only preprocessing, explicit forecasting benchmarks, and a weekly self-financing portfolio environment with realistic turnover and transaction costs. Forecasting results are heterogeneous: validation selects different LSTM-boosting combinations across markets, and multi-seed tests show positive average RMSE gains over the Random Walk in five of six series, with the most stable improvements in China and statistically significant main-seed evidence for USA ESG. In portfolio allocation, TD3_CONV provides the strongest ex-post DRL performance, while SAC_ESG is the strongest ESG DRL strategy; nevertheless, Equal Weight remains a demanding benchmark and outperforms the main ESG DRL strategies on several risk-adjusted measures. DDPG, selected ex ante on validation for both opportunity sets, remains profitable across three seeds and under transaction-cost scenarios up to 25 bps. These findings indicate that AI and ESG information add value selectively rather than universally.

A limitation of this study is the reliance on broad regional indices and a specific set of uncertainty proxies. In addition, LIME provides local model attribution rather than causal identification, and the relative ranking of DRL policies remains sensitive to the random seed and market opportunity set. Future research could extend the framework to additional emerging markets, alternative ESG taxonomies, regime-specific validation designs, richer liquidity and market-impact costs, and direct integration of strictly out-of-sample forecast signals into the DRL state.

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