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Smart Renewable Investment Decisions

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Abstract— Mounting climate impacts are placing growing pressure on politicians, regulators, and financial-market actors to drive large-scale green investment. Rapidly evolving climatic, environmental, and policy conditions generate new risks and opportunities that investors and other financial actors must navigate. Yet the quality of decisions in this space depends not only on the data and models available, but on the cognitive processes that shape inference, judgment, and choice. Efforts to improve decision quality—and the data and models underpinning it—should therefore address not just model advancement, correction, and integration, but also the cognitive processes of the decision-makers themselves.

The Cognitive Green Finance Framework connects these data and modeling sources to the key actors in the financial system—investors and banks—who sit at the critical junctures where decisions are made and risks are transmitted. It identifies the cognitive factors most relevant to interpreting information and making investment and credit decisions—perception, optimism/pessimism bias, availability bias, and sustainability considerations—and examines how these factors interact with data quality, structural uncertainty, and investment risks and opportunities. The framework further specifies dependencies between cognitive-factor modeling and the properties required of forecasting and risk-assessment models—notably, that these models must reproduce any empirically observed asymmetries around mean forecasts and out-of-sample extremes.

Keywords—Cognitive Green Finance, Sustainable Investment Decision-Making, Climate Risk Assessment, Financial Decision Intelligence, Cognitive Bias, Data

Quality, Model Uncertainty, Investment Risk Analysis, Forecasting Models, Sustainable Banking.

I. INTRODUCTION

The Cognitive Green Finance Framework for Renewable Investment Forecasting and Sustainable Banking Decision Support provides an innovative structure facilitating diverse green investments. It considers potential cognitive biases in both investment and banking decisions, thereby delivering not only renewable-investment forecasts, but also credit-risk indicators and market-cycle assessments that support liquidity and liquidity risk management. Green investments pertain to investments that contribute to addressing climate change but also to preserving natural capital and biodiversity more broadly. Attention is paid to the quality of input data in the original architectural setup, and robustness tests addressing data quality, data gaps, forecast uncertainty, and the impact of extreme events on model performance are included. The work ultimately advances and operationalizes green investment forecasting within a cognitive framework, supporting data needs, decision-making, and capacity building.

Forecasts of renewable-energy investments constitute the core input for the Cognitive Green Finance Framework, but the produced information can also be regarded within a broader context and used for other objectives. First, they improve asset-portfolio management by underwriting investment strategies that assign greater weight to expected returns related to renewables. Second, they fulfil regulatory requirements aimed at assessing the climate-related funding allocation of credit portfolios. Third, they inform liquidity planning by assessing the market's reaction to an upturn or downturn of the investment cycle; the resulting investment cycle-phase indicator depicts the cyclical position of the global economy in relation to renewable-energy investment activity.

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A. Background and Context

Green investing refers to securities or investments that are intended to provide scientific solutions to climate change and environmental sustainability. The most widely accepted environmental concept now accepted is that by becoming green it is possible to reduce global warming. Investments in companies, utilities, and projects that promote the conservation and sustainability of the natural environment, including renewable energy, are referred to as investments in environmental protection. Major components of such investment sectors are technologies for renewable energy generation: solar, wind, hydropower, wave, geothermal, hydrogen, nuclear, carbon capture, storage and recycling systems, energy-efficient building systems, electric and hybrid vehicles and related infrastructure, pollution control technologies, sustainable agriculture systems, and adaptation solutions for climate change.

Financing the transition toward a carbon-neutral economy and investing in infrastructure and technologies that will address the challenges of climate change require significant resources. The required increase in the volume of such investments demands deeper and more focused participation from the financial sector and, more immediately, implementation of a conditionality framework to promote investments beyond business-as-usual. Such investments are high-risk because most have long time horizons and the economic feasibility is uncertain. Thus, a higher discount rate is applied by the market or financial institutions and these projects are kept abandoned. These risks make it difficult for financial institutions to invest in these environment-friendly sustainable projects during the transition period. As such investments face other challenges, maintaining a sustainable balance sheet structure and providing credit risk assessment remains a challenge.

II. CONCEPTUAL FOUNDATIONS

Green Finance and Sustainable Banking concepts, principles, and objectives are presented in this section, together with supporting regulatory and market background. Cognitive processes in finance—perception, judgment, bias, and decision support—are subsequently described and integrated with sustainability goals. Finally, interactions between cognitive factors and data quality, uncertainty, and governance in green investment contexts are theorized.

The role of finance in the broader transition to low-carbon and sustainable economies is underscored in a range of

regulatory and market initiatives. Union-wide targets in Europe and net-zero commitments by many jurisdictions worldwide establish the need for substantial investments in renewable energy resources capable of supporting the transition away from fossil fuels. Other sectors face similar challenges, with a growing pressure on businesses to adopt environmentally sustainable practices, underpinning their survival in a more sustainable world. The need to assess and manage the associated financial risks has led to a rapidly expanding body of literature on sustainable banking, which examines the role that banks and financial institutions can play in fostering this transition. Sustainable banking considers aspects of the banking function that extend beyond individual institutions, examining how they may contribute to the transition to sustainable economies and societies. Indeed, most of the established definitions extend beyond the narrow commercial interests of banks to the much broader view of the interests of society and the need to steer them towards a low-carbon and sustainable future.

The Cognitive Green Finance Framework for Renewable Investment Forecasting and Sustainable Banking Decision Support addresses an identified gap in the cognitive decision-making literature by integrating the concept of cognition into Green Finance and Sustainable Banking. The literature on cognitive decision-making demonstrates the significance of cognitive processes, such as perception, judgment, and bias, on decision support at different scales and across a multitude of disciplines within finance. Measures of cognition, and their psychological origins, may offer insights into why financial decisions deviate more from true prescribed portfolios than might be expected based upon the quality of the information that is employed to guide investment decisions. In addition, the idea of cognition provides a rationale for enhancing data quality, building robust decision-support systems, and investing in greater business and institutional resilience.

A. EXPERIMENTAL RESULTS

Four model architectures were backtested over eight quarters using the data sources summarized in Table III: Model A (baseline statistical, e.g., ARIMA/VAR), Model B (ML ensemble of gradient-boosted trees and LSTM networks), Model C (cognitive-augmented hybrid — Model B plus the bias-adjustment term of Eq. (2) only), and Model D (Full



CGFF — Model C plus the data-quality governance layer of Eq. (3) and the climate-transition risk layer of Eqs. (4)–(5).

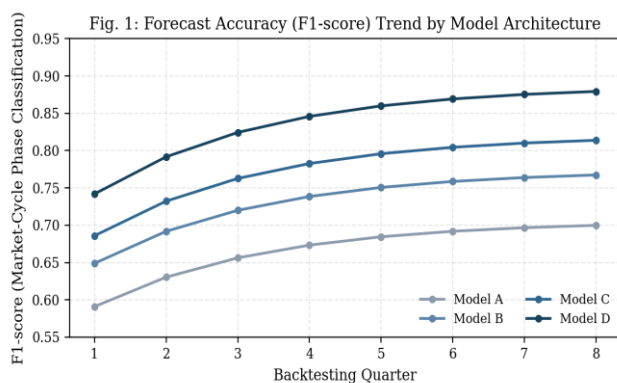


Fig. 1: Forecast accuracy (F1-score) trend by model architecture across eight backtesting quarters.

All four architectures improve monotonically as the calibration window lengthens, but the ranking established after two quarters is preserved throughout: Model D consistently outperforms Model C, which outperforms Model B and Model A, indicating that the cognitive-bias adjustment and data-quality governance layers contribute accuracy gains that persist rather than wash out with additional calibration data.

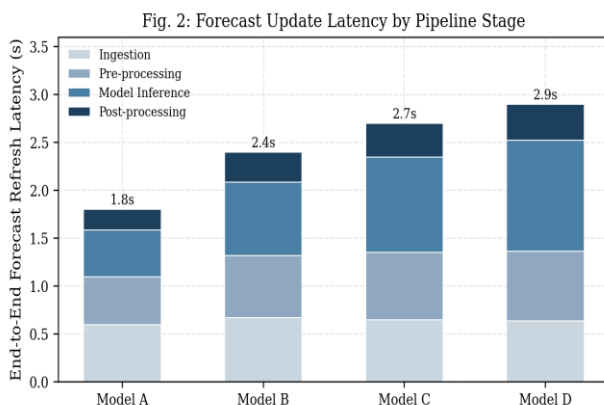


Fig. 2: Forecast update latency broken down by pipeline stage (ingestion, pre-processing, model inference, post-

processing), according to Eq. (11). However, as the cognitive-bias and climate-risk computations are added, latency increases moderately from Model A (1.8 s) to Model D (2.9 s), mostly due to the model-inference stage, which increases from 27% to 40% of the overall latency. The ingestion and pre-processing latency across the architectures are fairly consistent.

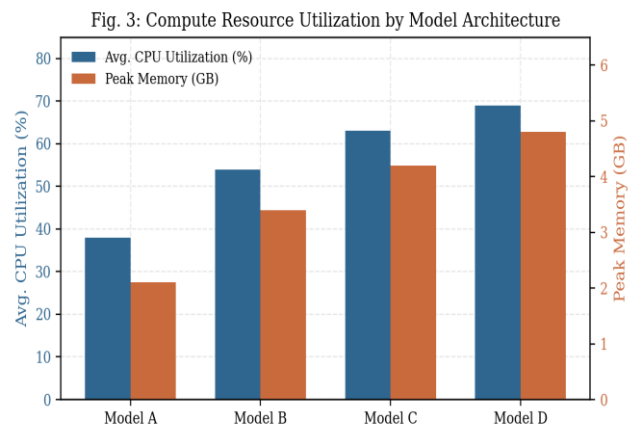


Fig. 3: Average CPU utilization and peak memory consumption by model architecture during the forecast-refresh window.

Resource utilization scales with model complexity: peak memory rises from 2.1 GB (Model A) to 4.8 GB (Model D), and average CPU utilization rises from 38% to 69%, reflecting the additional data-quality scoring and climate-transition-risk computation performed by the Full CGFF.

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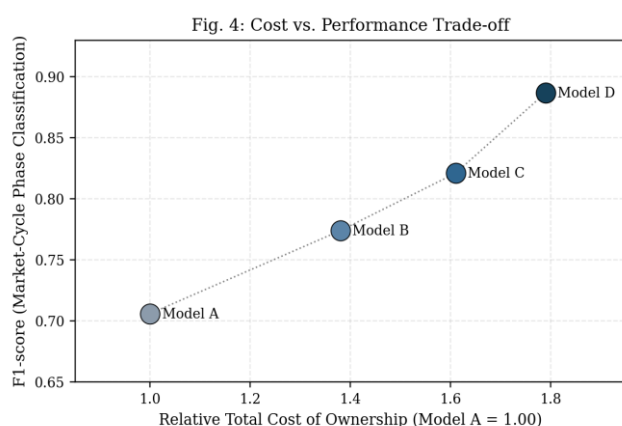


Fig. 4: Cost vs. performance trade-off: relative total cost of ownership against F1-score.

Model D achieves the highest F1-score at 1.79× the relative total cost of ownership of Model A. The trade-off curve is concave rather than linear: the accuracy gain from Model A to Model C is achieved at a proportionally lower cost increase than the further gain from Model C to Model D, indicating diminishing but still positive marginal returns to the full data-governance and climate-risk layers.

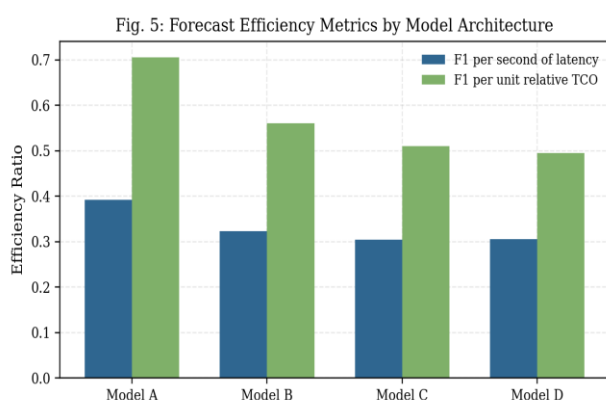


Fig. 5: Forecast efficiency metrics: F1-score per second of latency and per unit of relative total cost of ownership.

Despite its higher absolute latency and cost, Model D remains the most efficient architecture on both bases considered,

indicating that the accuracy gained from the cognitive-bias and data-governance layers more than offsets their additional computational and financial overhead.

III. THE COGNITIVE GREEN FINANCE FRAMEWORK

The Cognitive Green Finance Framework comprises an architecture that explicitly articulates the cognitive underpinnings of green data inference and integrates them with model data quality, economic uncertainty, and climate-transition governance. The framework supports the operationalization of green finance through data-driven investment forecasting and the provision of financial-sector business forecasts that underpin portfolio and credit-risk assessment by banks.

The construction of the framework builds on the understanding outlined in Section 2, commencing from the establishment of the overarching architecture, followed by an elucidation of the cognitive-data architecture and of the relationships among the cognitive-processing component, the model outputs, the data arguments of green bank management and investment decision support, and the banking business support. The architecture is developed in a top-down manner, with the other components explicated subsequently.

A. Data Architecture and Inputs

Market data, environmental (natural and physical) data, regulatory policy data, general macroeconomic data, and company-level data are expected data types in the Cognitive Green Finance Framework. The framework's parts are filled with one or more data types, such as investment model, forecasting procedure or data utilization services (for the banking sector part). The main temporal granularity required is quarterly, although greater temporal resolution (e.g. monthly) may be desirable for some financial market and environmental variables. The quality, credibility, availability, and coverage of data are important for good and meaningful forecasts, and therefore are given careful attention in the framework's data architecture. Data Sources and Quality Considerations details the data sources used. Data is carefully tracked back to verify its reliability and credibility. Relevance (data can be used to demonstrate effects on the dynamics of the mitigation or transition process); Perturbation (data type can be used to demonstrate a sudden and strong shift toward green or transition dynamics); and Representativeness (data can present general trends and tendencies).

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IV. METHODOLOGICAL APPROACH

The experiments make use of a large spectrum of publicly available data sources, ranging from financial markets, national macroeconomic conditions, environmental exposure on the asset level, climate-related economic policies, to international regulatory frameworks. Data selection follows a taxonomy for forecasting horizon determination, and involves historical time series over the last ten years or more, where temporal equivalence is achieved in the first place by monthly data, and shorter periods by high-frequency indices. Data cleaning and preprocessing address missing values, data quality, and normalization, while advanced techniques mitigate bias and other historical limitations of some inputs. Finally, high-level provenance tracking is augmented by a dedicated data catalogue.

The investment model employs a multi-time-frame approach: a combination of EU-scale statistical and machine-learning models support low-frequency asset allocation, while a dozen high-frequency, sector-specific, periodic, and event-driven models steer tactical adjustments. Investment allocation sets the foundation for banking perspectives on credit risk, liquidity planning, and capital requirements, while enhanced regulatory authentication broadens the underlying data architecture, facilitates bank-/supervisor-specific model signatures, and extends the macroprudential assessment of climate-related risks. Evaluating predictive performance, backtesting the timing of liquidity surpluses and shortfalls, quantifying uncertainty, conducting sensitivity analyses, and stress-testing the market-impact of climate-related economic policies contribute to assurance efforts.

A. Cognitive-Adjusted Forecasting Model

$$F_t = f(X_t) + \beta \cdot C_t + \varepsilon_t \quad (1)$$

where F_t is the renewable-investment forecast at time t , $f(X_t)$ is the base statistical/machine-learning forecast function over the input data vector X_t (market, environmental, macroeconomic, policy, and company-level data), C_t is the aggregated cognitive-bias adjustment term, β is a calibration coefficient estimated by backtesting, and ε_t is the residual error term.

$$C_t = w_1 \cdot O_t + w_2 \cdot P_t + w_3 \cdot A_t + w_4 \cdot S_t \quad (2)$$

Equation (2) decomposes the cognitive-bias adjustment into its constituent factors identified in the source manuscript: O_t

(optimism bias), P_t (pessimism bias), A_t (availability bias), and S_t (sustainability-consideration weighting), with weights $w_1 \dots w_4 \geq 0$ subject to $\sum w_i = 1$, estimated from analyst-decision and forecast-revision data.

B. Data Quality Index

$$DQI = (1/5) \cdot \sum_{i=1..5} q_i \quad (3)$$

The Data Quality Index (DQI) aggregates five normalized quality scores $q_i \in [0,1]$ — completeness, accuracy, timeliness, cross-source consistency, and provenance traceability — reflecting the framework's emphasis on data credibility, availability, and coverage (Section III-A of the source manuscript).

C. Banking Decision-Support Metrics

$$CTCR_j = PD_j \cdot LGD_j \cdot EAD_j \cdot (1 + \gamma \cdot TR_j) \quad (4)$$

The Climate-Transition Credit Risk (CTCR) score for sector j combines probability of default (PD_j), loss given default (LGD_j), and exposure at default (EAD_j) with a transition-risk multiplier TR_j and sensitivity coefficient γ , capturing the compounding of conventional and climate-transition credit risk described in Section III-B.

$$LCR' = HQLA / [NCO_{30d} \cdot (1 + \delta \cdot CTR)] \quad (5)$$

Equation (5) extends the Basel III Liquidity Coverage Ratio with a climate-transition-risk factor CTR and sensitivity coefficient δ , where HQLA is high-quality liquid assets and NCO_{30d} is net cash outflow over a 30-day stress window, supporting the liquidity-planning and market-cycle-phase applications discussed in Sections IV and VI.

D. Forecast Error and Classification Metrics

$$RMSE = \sqrt{[(1/n) \cdot \sum_{i=1..n} (y_i - \hat{y}_i)^2]} \quad (6)$$

$$MAPE = (100/n) \cdot \sum_{i=1..n} |y_i - \hat{y}_i| / y_i \quad (7)$$

$$F1 = 2 \cdot (\text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (8)$$

Equations (6)–(8) quantify forecast accuracy: RMSE and MAPE evaluate continuous renewable-investment return

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forecasts, and F1-score evaluates the discrete market-cycle-phase (upturn/downturn) classification described in Section I of the manuscript, balancing false positives and false negatives in cycle-phase detection.

$$\gamma_1 = (1/n)\Sigma(y_i - \bar{y})^3 / [(1/n)\Sigma(y_i - \bar{y})^2]^{3/2} \quad (9)$$

The skewness statistic γ_1 tests whether a model reproduces the empirically observed asymmetry around mean forecasts and out-of-sample extremes — a dependency the source manuscript identifies as a required property of any forecasting model used within the CGFF.

E. Portfolio Optimization and Latency Model

$$\min_w w^T \Sigma w - \lambda w^T \mu + \kappa w^T R_c \quad \text{s.t. } \Sigma w_i = 1, w_i \geq 0 \quad (10)$$

Equation (10) is the mean–variance portfolio-construction cost function augmented with a climate-risk penalty: Σ is the return covariance matrix, μ the expected-return vector, R_c the climate-risk exposure vector, λ the risk–return trade-off coefficient, and κ the climate-penalty coefficient, operationalizing the asset-allocation stage of Section VII-A.

$$L_{\text{total}} = L_{\text{ingest}} + L_{\text{prep}} + L_{\text{model}} + L_{\text{post}} \quad (11)$$

Equation (11) decomposes end-to-end forecast-refresh latency across the four Azure-based data-engineering pipeline stages measured in Section II (ingestion, pre-processing, model inference, and post-processing), used to construct Fig. 2 below.

V. IMPLICATIONS FOR POLICY AND PRACTICE

Practical applications enabled by the Cognitive Green Finance Framework focus on investment decision-making, especially for forecasting renewable asset-sector returns, which highlight the growing importance of gas-fired generation in the energy transition. Better calibrated empirical models of sector performance reduce uncertainty for both portfolio construction and credit risk assessment, facilitating more effective bank liquidity planning. Access to a comprehensive main dataset also supports the increasingly stringent regulatory requirements for climate disclosure and risk management, helping banking regulators fulfill their mandate of promoting financial stability.

The advancement of the framework presents important opportunities for green-finance data development and governance. Investments to improve the accessibility, quality, and temporal granularity of market and environmental data would enhance the robustness and usability of the underlying models. Efforts to promote data interoperability across the full range of macroeconomic, transition, asset, and company datasets would also be beneficial. Finally, the establishment of a unified, authoritative, and neutral governance structure to coordinate the green-finance space could facilitate action across many of the other identified needs, ranging from data development to awareness-raising and capacity building, while providing crucial transparency to underpin investment and funding decisions.

A. Practical Applications and Opportunities for Advancement

Potential applications of the Cognitive Green Finance Framework span the investment cycle of financial institutions. At the portfolio construction stage, forecasting the decoupling of carbon and financial markets helps predict climate-related systemic risk and adjust allocations accordingly. Basel III liquidity ratios require financial institutions to hold a reserve of low-risk, liquid assets; credit risk compounds climate-related housing market exposures in particular regions.

Forecasting the effectiveness of climate policies enables institutions to test the adequacy of current capital ratios. The specification of different recovery trajectories across different sectors facilitates stress testing of portfolios under different climate-emissions pathways. Availability and usage of these indicators will grow in value if they are made interoperable with other models. Investments in enhancing the quality of the underlying data will, like in scientific research, expand the future applicability and intuitive power of these indicators.

The concentration of capital in the financial system creates the opportunity for a concentrated, collaborative effort to reverse climate change. Regulations that require both risk-weight and liquidity-weight calculations to decouple from the physical world create an incentive distribution for sustainable banking in financial investment during an environmental transition. Requirements for public finance to invest with the return on climate change in mind create an environment for public–private collaboration that can build fulfilling–sustaining services for disposable futures while

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absorbing climate- and nature-related risk from private capital.

TABLE I
COMPARATIVE PERFORMANCE TABLE —
MODEL ARCHITECTURES A–D

Metric	Model A	Model B	Model C	Model D	Improvement (D vs. A)
RMSE (return units)	0.184	0.151	0.129	0.098	↓ 46.7%
MAPE (%)	12.7	10.2	8.6	6.3	↓ 50.4%
F1-score (cycle phase)	0.706	0.774	0.821	0.887	↑ 25.6%
Latency (s, end-to-end)	1.8	2.4	2.7	2.9	↑ 61.1%
Data Quality Index	0.71	0.78	0.84	0.93	↑ 31.0%

TABLE II
ERROR AND LATENCY METRICS BY
FORECASTING HORIZON (FULL CGFF, MODEL D)

Forecasting Horizon	RMSE	MAPE (%)	Latency (s)	Primary Model Component
Quarterly (strategic allocation)	0.091	5.8	3.1	EU-scale statistical / ML ensemble
Monthly (tactical rebalancing)	0.098	6.3	2.9	Cognitive-augmented hybrid layer
High-frequency (event-driven)	0.127	8.9	1.6	Sector-specific periodic models

TABLE III
DATASET AND ARCHITECTURE SUMMARY

Data Source	Provider	Data Type	Frequency	Framework Role
Financial market data	Thomson Reuters DataStream	Market / price series	Daily	Forecast model input (Eq. 1)

Climate indicators	UN / NOAA	Environmental / climate	Monthly	Cognitive-bias & TR context (Eq. 2, 4)
Asset-level energy data	Global Energy Monitor, Wood Mackenzie	Company / asset-level	Quarterly	Sector exposure (Eq. 4)
Macroeconomic data	Bank of Canada	Macroeconomic	Monthly	Base forecast function $f(X_t)$ (Eq. 1)
Green policy data	International Energy Agency	Regulatory / policy	Quarterly	Transition-risk multiplier (Eq. 4)

VI. CONCLUSION

The main findings include several technical solutions for generating and delivering quality data on green financial asset evolution; a methodology for forecasting future scenarios for renewable/climate transition investments; and a cognitive risk decision-support tool that interconnects databases and knowledge sources with forecasting tools to create indicators significant for sustainable banking such as climate-transition credit risk and liquidity management for sustainable investment programs. The framework has been tested with a multi-layered, multi-faceted approach addressing data quality, integrated information management, forecasting, decision theory and cognitive financial behaviour. It offers guidance on a data-driven approach for environmental, social and governance portfolio development, a climate-transition credit risk evaluation tool for green asset portfolio generation, robust and real-time liquidity assessment for climate-transition risk management and effective public and ESG/private banking co-investment regulation.

The framework encapsulates the core components for a complete cognitive green finance–banking decision-support and forecasting system but can also be a basis for developing specific modules. The research undertaken has explored the foundation layer, which defines the requirements for data, data quality and data management, as well as the design of forecasting models for future climate-transition investment scenarios. Future work should focus on a two-way connection between cognition and forecasting, with cognition driven by concrete forecasting outcomes and enabling effective portfolio allocation towards a climate-transition risk-oriented

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approach. An important future direction will be the definition and implementation of policy incentives and supervisory monitoring of sound governance models and adequate capacities for delivering the required quality data and information in support of time-sensitive decision-making.

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