

Artificial Intelligence, Fintech, and Green Investment: Examining the Role of AI-Driven Climate-Risk Assessment in Sustainable Financial Decision-Making

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Abstract

Artificial Intelligence (AI), financial technology (fintech) and the global sustainability agenda have created a new analytical infrastructure for analyzing climate-related financial risk. The combination of financial technology (fintech), artificial intelligence (AI) and the global sustainability agenda has led to the development of a new analytical infrastructure for the assessment of climate-related financial risk. Financial institutions have embraced machine learning, natural language processing, and geospatial analytics derived from satellite data to measure physical and transition climate risks at a scale and speed that would otherwise be impossible using traditional actuarial and econometric approaches as regulators step up to mandate climate disclosures and investors look for reliable ways to invest trillions of dollars towards decarbonization. This paper reviews the existing literature, regulatory frameworks, and industry practices related to climate-risk assessment tools that can be used for sustainable financial decision making between 2022 and 2026. It establishes a taxonomy of AI applications in physical-risk

modelling, transition-risk analysis and scenario analysis, greenwashing identification, credit underwriting and robo-advisory portfolio construction, and maps these applications to an evolving regulatory framework that includes the Task Force on Climate-related Financial Disclosures (TCFD), the International Sustainability Standards Board (ISSB), the European Union's Corporate Sustainability Reporting Directive (CSRD) and the Network for Greening the Financial System (NGFS). Based on data from both developed and emerging markets, the paper proposes that AI is a valuable extension of analytical capacity for sustainable finance, but it also raises new epistemic risks, including from the low-quality or biased climate data used to create AI models, from persistent differences between the different ESG ratings enhanced by AI, from the lack of explainability of the models and the risk of regulatory non-accountability, from the rise of “AI-washing” as a second-order greenwashing risk, from the lack of access to advanced climate-analytics infrastructure in emerging markets, and from the unexamined carbon footprint of the AI systems. The paper ends with a governance design for the responsible use of AI in climate finance and priority fields for further research.

Keywords: Artificial intelligence, fintech, green finance, climate risk assessment, ESG, sustainable investment, machine learning, NGFS, TCFD, ISSB

1. Introduction

Climate change has gone mainstream in financial risk management. Climate exposure is now seen as a material financial risk driver, affecting asset value, credit quality, and the systemic stability and longevity of financial systems, by central banks, prudential regulators, institutional investors and, more recently, retail savers. This change has occurred in tandem with another and similarly significant evolution: the quick advancement of artificial intelligence (AI) as a general-purpose technology that can process the volume, velocity and heterogeneity of data needed for climate-risk analysis. While climate finance used to be based on financial statements from past periods and sectoral classification, it increasingly uses satellite imagery, sensor networks, unstructured corporate disclosures, and probabilistic climate-model outputs combined using machine-learning pipelines that were not feasible 10 years ago. These AI capabilities are now being delivered through an ecosystem of digital platforms, application programming interfaces (APIs), and algorithmic services known as fintech, which serve as an intermediary for financial transactions.

Climate risk has become a first-class citizen in the core banking and asset-management infrastructure, with platforms like BlackRock's Aladdin increasingly incorporating climate risk as a key input alongside credit and market risk, and also adopting natural language processing (NLP) to check the use-of-proceeds claims in green bond issuance platforms (Discover Sustainability, 2026). The outcome is a fast-growing, mutually reinforcing triad: Artificial Intelligence (as the analytical engine), Fintech (as the distribution and integration layer), and green investment (as the goal of capital allocation). This paper focuses on an important question: What benefit can climate-risk assessment using AI bring to sustainable financial decisionmaking and what are the real capabilities, weaknesses, and governance issues of this benefit? The question is important because the answer is not always an unequivocal celebration or an unequivocal skepticism. On the other hand, a large and increasing empirical literature confirms measurable benefits of AI in green finance: for example, a research on implementation of AI green finance tools in Punjab, Pakistan, correlates a 0.90 percent rise in the efficiency of carbon dioxide emission reduction with a one-million-rupee increase in green finance (di Pietro et al., 2026, citing Lee et al., 2025), while firms in the energy sector, which use AI tools, report measurable increases in capital expenditure linked to green innovation (diPietro et al., 2026). At the same time, the same literature identifies structural issues that reduce confidence in the reliability of AI-generated climate-risk metrics, such as data scarcity, rating divergence, opacity, and inequitable access (Berg, Kölbel, & Rigobon, 2022; Quotb, 2026). The paper then moves on as follows. Section 2 summarizes theoretical and definition aspects of sustainable finance, fintech and AI based risk assessment as well as the definition of climate physical and transition risk taxonomy. Section 3 elaborates on the main applications of AI in climate-risk assessment: physical-risk modelling, transition-risk and scenario analysis, NLP-based ESG and greenwashing analysis, AI enhanced credit underwriting and robo-advisory portfolio construction. In Section 4, these applications are placed in the regulatory framework that has developed since 2017, such as the TCFD, ISSB, CSRD/ESRS, the U.S. SEC climate-disclosure rule, and the NGFS climate scenario framework. Case evidence from developed and emerging markets is provided in Section 5. Section 6 challenges the conflicts and risks involved in the use of AI in the context of sustainable financial decision-making. A governance framework and policy recommendations are proposed in Section 7 while Section 8 concludes.

2. Literature Review

2.1 The Evolution of Sustainable Finance and Green Investment

Sustainable finance is a general term for financial services and investment activities that consider environmental, social and governance (ESG) factors in investment decisions, aiming to deliver both financial and environmental/social returns. Green investment refers to that part of sustainable finance that targets environmentally positive activities in particular: renewable energy generation, energy efficiency, low carbon transport, sustainable agriculture and climate adaptation infrastructure. The tools employed to implement green investment have increased significantly over the last ten years, including green bonds, sustainability-linked loans, green exchange-traded funds, and voluntary and compliance carbon markets, among others; overall growth was estimated at 25.52 percent compound annual rate in the green bond market between 2019 and 2023, with digital issuance increasingly driving growth (Appinventiv, 2026). A tightening-up in expectations regarding disclosures relating to climate change has coincided with and contributed to this growth. Global climate finance flows in 2024 amounted to around two trillion dollars, but the distribution of these flows is very uneven, with sub-Saharan Africa receiving less than three per cent of all flows, when it requires an estimated 600 billion dollars annually to achieve its climate targets by 2030 (Discover Sustainability, 2026b). The imbalance between the volume of capital that is raised in advanced markets and the consistent undercapitalization of climate-sensitive developing economies is recurring throughout this paper as a lens through which to explore the impacts of climate-risk tools powered by AI on access to sustainable finance.

2.2 Fintech as the Distribution and Integration Layer

The fact that fintech is not a risk-assessment methodology doesn't mean it's not a part of the method, but rather a tool through which the risk assessment — however it is created — is sold to decision makers. Out of the three functions of fintech, three are particularly significant in the context of green investment. Among the three, there are three functions in fintech that are particularly significant in the context of green investment. Robo-advisory and digital wealth-management platforms, in particular, convert these ESG and climate-risk scores into retail-level products, effectively democratizing access to sustainability-screened portfolios, which remained limited to institutional investors (Springer Nature, 2026a). Second, green bond and carbon-market

platforms are increasingly incorporating DLT and AI analytics to produce verifiable, immutable proof of both use of proceeds and environmental impacts—countering the risk of double counting and fraud in carbon-market transactions (Springer Nature, 2026a; Appinventiv, 2026). Third, regulatory technology (regtech) platforms integrate AI-powered compliance screening into the reporting process, allowing institutions to navigate a fragmented and ever-expanding landscape of disclosure requirements (Appinventiv, 2026). This distribution layer is of significant economic importance. According to Intel Market Research, the global market for RoBo Advisory Services for Sustainable and ESG Investment was valued at around 5.21 billion dollars in 2025, with a compound annual growth rate of approximately 14.6 percent projected to reach 19.35 billion dollars by 2034. The trend shows that AI-enabled climate-risk assessment is no longer an institutional specialty, but a growing commonplace of the retail and institutional investment space.

2.3 Artificial Intelligence as an Analytical Technology for Financial Risk

Artificial Intelligence (AI), in this paper, is defined as supervised machine learning and unsupervised machine learning, deep learning architectures such as convolutional networks for geospatial imagery and transformer-based large language models for text, and the wider category of predictive analytics techniques that learn a statistical pattern from data, but are not explicitly programmed. Unlike previous generations of a quantitative finance that typically focused on linear data, high-dimensional data, and structured information, AI's ability to integrate multimodal data like satellite imagery, financial statements, sustainability reports, and output from physical climate models into a single analytical pipeline is what makes it a significant advancement in climate-risk assessment (Ji, Guo, & Zhang et al., 2025). Traditional statistical techniques and econometrics, which are usually calibrated using past financial time series, are not well suited to a domain where the risks of primary interest – catastrophic physical climate events, abrupt policy-driven repricing of carbon-intensive assets – are by design poorly represented or outright missing from historical data (Ji et al., 2025).

Recent systematic reviews have proposed a useful categorisation of the types of applications of AI in sustainable finance across four areas, namely: integration of ESG data and ESG scoring; predictive analysis and indicators of climate and transition risks; impact measurement and verification; and portfolio-level risk management (Future Business Journal, 2025). The approach

taken in this paper in Section 3 follows a closely related structure, grouping the IA applications around the specific financial function they serve, as this functional lens better maps AI capability to the decisions financial institutions need to make: physical-risk modeling, transition-risk and scenario analysis, disclosure and greenwashing analysis, credit underwriting, and portfolio construction.

2.4 Climate Risk Taxonomy: Physical and Transition Risk

Climate-related financial risk is typically structured into physical risk and transition risk, based on the taxonomy popularised by the Bank of England and formalised by the TCFD (Battiston et al., 2017 (as cited in Future Business Journal, 2025)). Physical risk is the immediate financial damage caused by climate and weather events, including acute risks like floods, wildfire, and tropical storms, as well as chronic risks like sea-level rise, heat stress, and changing precipitation patterns on physical assets, supply chains and collateral. Transition risk is the financial risk associated with transitioning to a lower carbon economy – including policy changes like carbon pricing, technological disruption that locks in high carbon assets and changes in market and consumer demand for carbon intensive products and services. A third, less structured, category: liability risk that stems from litigation against actors that are seen to have contributed to or misrepresented climate harm, is growing in importance alongside the first two, but is less suited to quantification by AI tools and is addressed here only cursorily. The taxonomy is important for AI system design because physical and transition risk data inputs, modeling horizons, and validation strategies are vastly different. Physical-risk models rely on high-resolution geospatial and climatological data, and are validated against observed losses of weather, while transition-risk models rely on policy, technology and market-sentiment data, and are validated, if possible, against consistency criteria rather than losses experienced in the past, since transition is a structural break from the past. Each of these is discussed separately in Section 3.

3. AI-Driven Climate-Risk Assessment: Methods and Applications

In this section, five areas in which AI has been put into practice in fintech and institutional finance to help with climate-risk assessment and, consequently, sustainable financial decision-making will be explored: physical-risk modeling; transition-risk and scenario analysis; natural-language

processing to extract ESG disclosure and detect greenwashing; AI in credit underwriting; and robo-advisory portfolio construction.

3.1 Physical-Risk Modeling

Physical climate-risk modeling integrates geospatial data (satellite imagery, DEM, land-use classification), and probabilistic climate projections, to estimate the exposure of specific, geolocated assets to hazards like flood, wildfire, drought, and extreme heat. Commercial firms such as Jupiter Intelligence, Climate AI and even Moody's (via its acquisition Four Twenty Seven) offer physical-risk scores to banks, insurers and asset managers—for example, on a per-facility, per-collateral or per-portfolio basis. The pipeline plays a central role for machine learning in two ways: convolutional neural networks and related deep-learning computer-vision techniques are used to gain insight into the conditions visible in the satellite and aerial images, such as vegetation density more relevant for wildfire risk and floodplain encroachment; the outputs from global climate models are coarse, requiring machine-learning ensemble and deep-learning techniques to scale them down to the resolution desired by asset-level underwriting and portfolio management decisions. A new study, which used the same approach to allocate adaptation funds to six climate vulnerable LMICs (Bangladesh, Colombia, Kenya, Morocco, Pakistan, and Vietnam) provides some indication of the analytical sophistication that is now possible. It combined socio-economic information with climate-hazard data from 2000-2024, applying principal component analysis to generate a set of eight indicators with a Compound Vulnerability Score; K-means and DBSCAN clustering to identify different vulnerability regimes; XGBoost to measure the relative importance of indicators of vulnerability; and graph neural networks to capture the systemic interconnections across countries and sectors. Projected drought risk (31.2 percent of feature importance), precipitation change (18.1 percent) and poverty headcount (14.3 percent) were the key factors driving compound vulnerability (Economies, 2026) in the XGBoost analysis. This whole-of-pipeline system, from discovering unsupervised regimes of climate risk, to identifying causal drivers of climate risk, to optimizing policy under budget constraints, constitutes a shift in paradigm from a diagnostic to a prescriptive approach to capital allocation (Economies, 2026). In spite of these developments, physical-risk models are still limited by the quality and scarcity of ground-truth data, especially in the most vulnerable areas where physical-risk assessment is most needed – low-income and climate-prone countries. Model outputs calibrated on high data contexts,

like the U.S. or Western Europe, may not readily transfer to low data contexts, as will be further discussed in Section 6.

3.2 Transition-Risk and Scenario Analysis

The assessment of transition risk is heavily dependent on scenario analysis: the creation of internally coherent scenarios of the possible futures of policy, technical and market preferences and the calculation of the risk exposure of financial institutions to each scenario. The Network for Greening the Financial System (NGFS) has emerged as the de facto standard-setter in this area. The central banks and supervisors of over 140 jurisdictions have adopted NGFS scenarios, some of which have been adapted (Carbon Tracker Initiative, 2025). The NGFS released new short-term scenarios in May 2025 which only cover the next decade up to 2030, specifically developed to be more “decision-useful” for institutional investors and corporate financial planners with business-cycle and not multi-decade time horizons, based on the IMF macroeconomic projections (Carbon Tracker Initiative, 2025). AI becomes a part of this process in multiple ways. First, the machine learning models perform the task of “downscaling” macro-financial variables that are coarse in nature, such as carbon price paths, sectoral output trajectories, energy-mix projections, into firm-level or asset-level financial impacts, which is conceptually analogous to the downscaling done in physical-risk modeling. Commercial climate-risk analytics providers now provide inference models to calculate future Scope 1, 2 and 3 GHG emissions (in the context of the 15 Scope 3 subcategories) for over 4 million companies by the year 2100, including disclosed emissions data, machine learning based emissions estimation for non-disclosing companies, and the NGFS climate scenario pathways to calculate forward-looking metrics, such as an implied temperature rise for an investment portfolio (ICE, 2026). Second, and more directly related to prudential regulation, the Nationally Determined Contributions scenario from the NGFS was integrated into the European Central Bank's EU-wide stress test, which also included it as a component of the European Banking Authority's adverse macroeconomic scenario. This was done via top-down statistical models that reflected sectoral transition-risk exposure in changes in corporate default probability and bank credit losses. The exercise revealed that transition risks arising from the repricing of prices for green-investment activities exacerbate credit losses, and depress Common Equity Tier 1 capital ratios, especially among banks focused on businesses and sectors that are highly sensitive to the transition (ECB, 2025). This is one of the more obvious applications of AI-

related quantitative modelling to guide a systemic financial-stability assessment, and not just on the basis of an individual institution's internal risk-management. Generative AI and large language models (LLMs) are now being added to this scenario-analysis infrastructure for synthesizing qualitative policy signals, such as legislative text, regulatory announcements, corporate transition plans, into structured inputs for quantitative models of these scenarios, and for providing plain-language explanations of these scenario outputs for non-technical stakeholders. This application is in its early stages compared to other physical-risk and disclosure-analysis applications described in this section.

3.3 Natural Language Processing for ESG Disclosure and Greenwashing Detection

One of the quickest evolving AI applications in the world of sustainable finance is the application of NLP and large language models to the ever-expanding universe of unstructured corporate sustainability reporting. Transformer-based foundation models had achieved what one review described as “production-ready capability” for ESG text analysis by 2024–2025: automated parsing of documents for structured data had surpassed 90 percent accuracy in extracting the information from unstructured sustainability reports; entity recognition of ESG topics and controversies was at over 0.85 accuracy and recall; and semantic detection of vague language and unmeasurable targets was approximately 85 percent accurate in peer-reviewed evaluations (ISDO, 2025). Since 2021, the cost of large-language-model inference has dropped by an estimated 90 percent, significantly reducing the barrier to scaling up the use of such techniques across an entire universe of investable stocks, as opposed to only a handful of large cap stocks (ISDO, 2025). There are several methodological developments in academic research about how to detect greenwashing. Using this method, one line of work has developed a Greenwashing Severity Index that compares the sentiment, topic distribution and term-frequency profile of the sustainability disclosure of firms with independent external media coverage, assuming that there is a high degree of difference between the two is itself evidence of greenwashing; this approach, applied to 204 large companies in eleven Central and Eastern European countries, revealed a moderate but widespread level of greenwashing across countries, industries and firm size, which was closely correlated with the maturity of national regulatory oversight (Davidescu et al., 2026). A second project develops supervised machine-learning classifiers (including deep-learning structures that combine several data sources) that directly predict greenwashing behavior from firm characteristics and disclosure

text, finding that these deep-learning classifiers significantly outperform earlier logistic-regression and rule-based classifiers (Journal of Environmental Management, 2026). A third line is used for claim-verification, cross-referencing specific quantitative and qualitative claims in ESG reports with external controversy databases and revealed performance data, generating a per-claim and per-company verification score (ACL Anthology, 2025a). These NLP tools also have a compliance role. China's central bank guidance in March 2024, for example, explicitly called for the financial institutions to further establish disclosure-based constraint mechanisms in green and low-carbon development policy, a policy signal which has spurred financial institutions in China to seek scalable, automated disclosure-verification solutions (PMC, 2025a). More broadly, between 2020 and 2025, at least nineteen jurisdictions require institutions to disclose on the subject of climate change, and greenwashing-detection capability has become more of a compliance necessity for institutions that are required to report climate change under double-materiality reporting standards, like the EU's European Sustainability Reporting Standards (ISDO, 2025).

3.4 AI-Augmented Credit Risk and Underwriting

When it comes to lending and underwriting, AI-based climate-risk assessment works by adding alternative and geospatial data, such as satellite-derived estimates of crop yields, weather-pattern data, and readings from the Internet-of-Things (IoT) sensor networks, to credit scoring and underwriting models, especially in the area of agricultural lending, infrastructure project finance and property-secured lending in climate-exposed areas. This is one area where the role of fintech as a distribution and access layer is most impactful: while the climate-risk signal may not matter much for borrowers with existing credit history and collateral, it can be very relevant for those who would not otherwise have access to formal credit markets because they lack such collateral or such a credit history. This has been furthered by decentralized finance (DeFi) platforms, as in a popular instance, a blockchain-based platform in Africa for renewable-energy microloans, where distributed-ledger infrastructure was used to allow loan amount proceeds to be tracked transparently to their indicated renewable-energy application (Appinventiv, 2026). This evidentiary basis for AI-augmented climate-informed credit underwriting is, however, significantly less robust than that of physical-risk modeling or disclosure analysis in the ESG space, partly because of the commercial confidentiality of the credit models being developed internally by banks and partly because academic studies directly quantifying the accuracy gains of

AI-driven default predictions, specifically those driven by climate-risk features, are relatively underdeveloped. Despite the fact that the exact economic significance of the information content of this signal has been actively debated, LSTM network architectures have been successful in forecasting financial distress, based on ESG data, 12 to 18 months ahead, with area-under-curve scores over 0.78 in peer-reviewed studies (ISDO, 2025).

3.5 Robo-Advisory and AI-Driven Portfolio Construction

A key strength of AI-powered robo-advisory platforms is that they embed climate and ESG risk scores when making an investment decision. A handful of fintechs are beginning to mechanise green-bond and renewable-asset diligence for smaller institutional and retail investors, while institutional platforms like BlackRock's Aladdin are just examples of ESG-integrated rebalancing processes across trillions of dollars in assets under management (Discover Sustainability, 2026a). The platforms usually include three AI-enabled tools: Natural Language Processing to analyze sustainability disclosures, Computer Vision to monitor the real-world environmental effects of projects financed with green bonds (for instance, by verifying via satellite or drone imagery that a solar or wind power plant financed with a green bond has been actually built and is functioning), and Predictive Modelling to forecast the long-term economic and environmental outcomes of green-labelled instruments. The evidence of the benefits of this integration on the portfolio level is slightly positive: AI-based ESG-constrained portfolio optimization has yielded lower volatility and higher climate shock resilience compared to traditional mean-variance optimization (Discover Sustainability, 2026a). Investor appetite for "explainability" is growing, not just a numeric ESG or climate-risk score, but an auditable reason behind a green bond's rating: for instance, a statement that a particular green bond received a high score because it funds renewable energy in a jurisdiction where clean-technology subsidies are increasing and the bond meets a clear threshold for biodiversity impacts. The need has fueled the use of explainable-AI (XAI) methods in robo-advisories, which we will discuss in more detail in Sections 4.3 and 6.3. Distributed ledger technology is also increasingly being used in robo-advisory services to enable the creation of an immutable record of investment decisions and the sustainability disclosures they are based on, aiming to improve the auditability of investments for both regulators and end investors and prevent double-counting in green bond and carbon credit trading (Springer Nature, 2026a). Finally, looking forward, the main policy issue is whether the real democratization of access to sustainability-

screened investing enabled by these platforms can be achieved without compromising systemic stability, investor protection, or the integrity of the underlying climate-risk claims (as this paper will explore in Sections 6 and 7).

4. Regulatory and Institutional Context

AI-enabled climate-risk assessment is not independent from regulation. It has been influenced, and to a great degree, hastened by a series of climate-disclosure laws and regulations that have turned climate-related reporting from a voluntary, mainly narrative process into a more quantitative and obligatory one from 2017 to 2026. We provide an overview of the key regulatory steps taken and their impact on AI use in sustainable finance.

4.1 From Voluntary Disclosure to Mandatory Standards: TCFD, ISSB, CSRD, and the SEC Rule In 2015, the Financial Stability Board (FSB) released its Task Force on Climate-related Financial Disclosures (TCFD), which presented a taxonomy for climate-related financial risks and transition risks, and four pillars of disclosure: governance, strategy, risk management, and metrics and targets, which are used by virtually all other climate disclosure regimes. In 2021, the International Sustainability Standards Board (ISSB) was established under the IFRS Foundation, which followed the TCFD framework and should "reflect and build upon" it, with the aim of combining a confusing mix of voluntary standards and frameworks into a worldwide common denominator for transparency in sustainability and climate disclosure. The European Union's Corporate Sustainability Reporting Directive (CSRD), which requires companies covered by the directive to report on both sustainability issues that are material to the company and the company's material impacts on the environment and society, along with scope 3 emissions reporting, and independent third party assurance, based on the European Sustainability Reporting Standards (ESRS) adopted by the European Commission in 2023, was launched. The European Union has delayed the implementation of the ISDOs by one to two years, because of the concerns about regulatory burden, but the underlying disclosure framework remains binding and will be implemented in April 2025 (Wave 1), April 2027 (Wave 2, which was delayed to April 2028) and April 2029 (Wave 3, which was delayed to April 2030) (ISDO, 2025). In the USA, the Securities and Exchange Commission published climate-disclosure rules in March 2024 that will initially apply to large accelerated filers (ISDO, 2025) with market value above 700m dollars, and will gradually be extended to other companies over the following years. By December 2025, at least nineteen jurisdictions had finalized or proposed climate-related financial disclosure

mandates consistent with the TCFD or ISSB (ISDO, 2025). This is not a novel phenomenon, as the number of overlapping but not fully aligned disclosure regimes is itself a major enabler of the use of AI tools for disclosure: the sheer complexity and diversity of required disclosures, ranging from double-materiality assessments to the twelve modular ESRS standards, the mandatory Scope 3 estimation across fifteen emission subcategories, and the various taxonomies across jurisdictions of what constitutes a 'green' economic activity to disclose' makes manual compliance processes difficult to sustain at scale and drives a significant increase in demand for disclosure-parsing and verification tools based on NLP as described in Section 3.3. The NGFS Framework is included in this section, along with Central Bank Climate Stress Testing. This section includes the NGFS Framework and Central Bank Climate Stress Testing. Climate scenario analysis has also been incorporated into the prudential supervisors' financial-stability toolkits over the years in parallel with disclosure regulation. The NGFS was established at the Paris "One Planet Summit" in December 2017 and now includes 144 central banks and supervisors and 21 By March 2025, the Carbon Tracker Initiative (CTI) aims to have its observer institutions. It is explicitly designed to be a stress testing tool (not a point forecasting one) and its 4th phase (as of January 2025) includes for the first time short-term scenarios extending only to 2030, in addition to the long-term scenarios extending to 2050 and beyond. This new focus on shorter, more "decision-useful" time horizons is a growing realization among supervisors that acute physical risks can occur within any normal business-planning and electoral cycle, and not just over multi-decade time horizons. Some jurisdictions have customized their implementation of NGFS-based stress testing and have done so to different extents. Other jurisdictions have chosen to build climate stress scenarios with their own separately developed macroeconomic model, such as Colombia, rather than directly linking to NGFS scenarios; and the European Central Bank (ECB, 2025) in its 2025 EU-wide stress tests explicitly incorporated the NGFS Nationally Determined Contributions scenario into the European Banking Authority's official adverse macroeconomic scenario (ECB, 2025).

4.1. Explainability, Model Governance, and Regulatory Compliance

One common thread in disclosure regulation and prudential supervision is the conflict between the explanatory insight of deep-learning and large-language-models-based approaches and the explainability that financial regulation has increasingly demanded. ResearchGate, 2025, has conducted multiple reviews on the use of AI in the field of green fintech, with a consistent finding

that "algorithmic opacity" is a critical factor hindering wider adoption, along with data bias and misalignment of regulations. The policy recommendations that cross the literature are drawn from the implementation of explainable-AI frameworks as designed frameworks, and not after-the-fact fixes; a strengthening of the data-governance requirements particularly for climate and ESG data; and significantly more cross-sectoral cooperation between financial regulators, climate scientists and AI developers (ResearchGate, 2025). The process of regulatory harmonization will also need to be more agile, and disclosure and model-validation requirements should be made machine-readable, so as to be able to satisfy the ever-changing AI models and data sets (Springer Nature, 2026a).

5. Empirical Evidence and Case Illustrations

This section pulls together empirical evidence from real-world institutional practice in developed markets, emerging market financial-sector adoption studies, and the overarching empirical literature on ESG rating divergence, in order to provide examples of how AI tools for climate-risk assessment work — and, most of all, do not work — in practice.

5.1 Developed-Market Institutional Practice

The use of AI in assessing climate risks is more developed in developed markets, at the nexus of prudential supervision and large-scale asset management. The European Central Bank's stress test exercise outlined above is one of the most explicit cases of climate-risk modelling directly influencing a systemic financial-stability assessment, which has regulatory implications for individual banks' capital needs (ECB 2025). At the asset-management level, institutional platforms that incorporate AI-based ESG and climate scores into portfolio construction already operate on a scale to impact capital flows for entire asset classes, and commercial emissions-inference models for several million companies spanning the entire century are now part of the assessment of portfolio alignment with net-zero pathways (ICE, 2026).

5.2 Emerging-Market Adoption and the Access Gap

The emerging markets provide a more complex picture: while there is real technical promise, there are also structural barriers to adoption. The survey-based study of the financial sector in Ghana, with 317 respondents from banks, insurance companies, asset management firms and development finance institutions and analyzed using partial least squares structural equation modeling, revealed that the most important drivers of institutional willingness to adopt AI tools for climate finance were perceived usefulness and trust in AI (Discover Sustainability, 2026b). This discovery highlights that institutional trust and proven effectiveness in emerging markets is as much a governance and change management as it is a technical question, since technical availability of AI tools is not the main barrier to adoption. The low- and middle-income country vulnerability-assessment study presented in Section 3.1,

which includes Bangladesh, Colombia, Kenya, Morocco, Pakistan, and Vietnam, demonstrates the extent of analytical sophistication now available to development-finance institutions and the data constraints that remain in precisely the countries most vulnerable to climate risk (Economies, 2026). Despite the need for more than 600 billion dollars per year in climate finance by 2030, and SSA receiving less than three per cent of the world's climate finance, an increased capacity to quantify risk using AI has not, in itself, closed the gap in capital allocation between climate-vulnerable and climate-resilient economies (Discover Sustainability, 2026b).

4.2. ESG Rating Divergence: A Persistent Empirical Anomaly

One of the best documented empirical issues on the ability to have full confidence in AI-based climate-risk scores is that ESG scores issued by different providers do not always agree on the same score for a given firm. Berg, Kölbel and Rigobon (2022) have published a ground-breaking study that found the correlation between the various agencies rating the same company is around 0.99 – a figure significantly different from that of ESG ratings, which range from 0.38 to 0.71, and in some cases, two different agencies have arrived at opposite ratings for the same company (PMC, 2025b, citing Berg et al., 2022). A prime example of this is a large Chinese alcohol company which received a “C+” rating from one domestic rating agency and an “AA” rating from another in the same year (PMC, 2025b). The reasons for this divergence can be summed up in the following, and have been documented elsewhere: Providers' diverse definitions, composition and weighting of the sub-components of the environmental, social and governance (ESG) pillars; the presence of a “rater effect”, meaning that the divergence is not random but provider-specific; and the difference in disclosure requirements for the environmental, social and governance (ESG) sub-components, which has historically not been consistent and therefore not entirely accurate (Open Research Europe, 2025; Berg et al., 2022). Particularly, it is paradoxical that divergences in the granular sub categories partially balance each other when aggregation into more broadly defined environmental-dimension scores, resulting in an average score of 0.53 compared to the range of 0.36–0.38 of the correlations between paired rating providers at the granular sub categories level (Berg et al., 2022). This disparity in financial effects is no trivial matter. Empirically, the more disagreeing among ESG-raters, the higher the cost of capital, even for firms that actually are good for the environment, as the following quote b (Quotb, 2026 citing Avramov et al., 2022, and Gibson Brandon et al., 2021) states. Similarly, in China, the conflict over ESG ratings has been

linked to a decline in the availability of bank loans and this has led to a decline in investment. (PMC, 2025b). It is a continuing and unabbreviated topic of research as the literature in this field is still split into studies on the determinants of divergence and studies on the downstream implications of divergence, and conceptual and methodological difficulties remain in making cross-provider comparisons of ESG ratings (Review of Managerial Science, 2026). Whether this gap is narrowing or widening due to the increased adoption of AI is yet an unconfirmed question. While machine-learning based ESG scoring models that employ more consistent sets of data inputs have the potential to reduce idiosyncratic rater effects, they may not be as effective at capturing the idiosyncratic rater effects curated scoring processes. Conversely, the systematic review of 43 peer-reviewed articles and 23 institutional reports of whether adoption of machine learning surpasses adoption of rules in ESG data's predictive power of sustainable investment performance found that ESG data is still quite fragmented, inconsistent and susceptible to methodological opacity, especially in the context of climate-related investments, precisely because there is none to date on whether AI adoption resolves or simply automates the existing rating inconsistency (Future Business Journal, 2025).

5. Critical Challenges and Tensions

The previous paragraphs show how much AI has become integral to the sustainable financial decision-making system. In this section, the tensions arising from this embedding are examined, with the six following challenges organised around them: Data quality and false precision; Divergence in ESG-scores despite the uptake of AI; Explainability of the model versus regulatory accountability; The rise of AI-washing as a second-order greenwashing risk; Unequal access to AI-based climate-analytics infrastructure; Environmental impacts of the AI systems themselves.

Data Quality, Sparse Ground Truth and False Precision

6.1 Climate-financial data continues, in many respects, to be sparse, non-stationary and geographically uneven, and AI models are only as reliable as the data that they are trained and validated on. The problem of transferability is real for physical-risk models which are calibrated primarily in data-rich contexts in North America and Western Europe and are applied to the climate-vulnerable, data-poor contexts where accurate physical-risk assessment is most urgently needed (Economies, 2026). Transition-risk models are similarly confronted with a problem, though one of a different nature: the transition to low carbon is by definition a shift from historical patterns, and therefore cannot be validated against historical

outcomes, unlike traditional credit-risk models, but rather by the consistency of the scenarios with respect to one another, which impose assumptions on future policy and technology developments that are inherently uncertain (Ji et al., 2025). The practical caution is that AI models, especially deep-learning models that can predict very precise-looking point estimates, can promote false confidence: a given portfolio's "implied temperature rise" rounded to two decimals, or a firm's flood-risk score expressed as a percentile, may suggest a level of certainty that the actual, far more sparse and uncertain climate and financial data is unable to substantiate. This is not just a technical issue that can be solved by a good algorithm – rather, it is an epistemological feature of making novel predictions about rare, high-impact events from climate risk forecasts built using statistical methods traditionally used to predict real-world events, and one that advocates for not presenting climate risk outputs as a single point prediction, but rather as a range of uncertainty and dependence on multiple scenario options, something which is recommended but not yet practiced widely by commercial climate risk analytics providers.

6.2 ESG-Scoring Divergence is proving to be persistent. As explained in Section 5.3, differences in ESG ratings for the same company are significant and are, at least partly, caused by real disagreement over how to measure the E, S, and G components, as well as on the weightings applied to them, and by the fact that the definitions of ESG are unclear. The importance of this in relation to the central claim addressed in this paper is, however, that the use of AI for climate-risk assessment, if it is to have a genuine impact on sustainable financial decision-making, must be capable of making a significant contribution to this underlying inconsistency, rather than simply automating it. There is at present insufficient evidence to draw a definite conclusion either way. Machine-learning-based scoring, as applied to more homogenous and larger training datasets, has plausible mechanisms by which it can mitigate idiosyncratic rater effects; but so long as different providers continue to train models with different underlying definitions of materiality or different weighting schemes, the use of AI can be expected to simply accelerate and expand idiosyncratic rater effects, faking that divergence with the aura of rigor it brings in being produced by a sophisticated model instead of an analyst's judgment. Discuss the difference between explainability and regulatory accountability. Discuss the difference between explainability and regulatory accountability. As risk-relevant actions increasingly demand justifiability to the supervisors, auditors and, in many jurisdictions, to the counterparty itself, financial regulation is becoming increasingly complex. This is not exactly aligned with the "black-box" nature of many of the deep-learning and large-language-model architectures that are being applied

to climate risk assessment. For example, a CNN-based model that can predict flood risk from satellite images can give a high accuracy prediction of flood risk, while a transformer-based model that can predict indicators of greenwashing from text in sustainability reports can give a high accuracy prediction of greenwashing indicators, but the model does not provide an interpretable explanation of exactly what features in the satellite image led to a high score for a specific asset or in sustainability-report text led to a high score for a specific firm. The state of the art to date in dealing with this tension are the explainable-AI techniques discussed above and in this section, such as feature-attribution techniques, surrogate interpretable models, and structured natural-language explanations of the kind described in Section 3.5, where a green bond in a particular institution includes a stated “rationale” that references specific institutional subsidies and a “biodiversity threshold. Explainable-AI methods, including feature-attribution methods, surrogate interpretable models, and structured natural-language explanations of the type described in Section 3.5 (where a green bond in a particular institution is accompanied by a “rationale” that references specific institutional subsidies and a “biodiversity threshold”), represent the current state of the art in dealing with this tension, but, in most institutional deployments, are only a partial and imperfect solution — rather than a full solution to the underlying opacity problem.

6.4 is an AI-Washing Risk. 6.4 is a Second-Order Greenwashing Risk. What has remained comparatively under-researched in the field, though, is a risk that can be referred to as AI-washing: The risk that a fintech's marketing use of the word ‘AI-driven’ or ‘rigorous,’ in its description of a climate risk assessment, is an indication of actual analytical rigor rather than a more genuine substitute for it. The specific architecture, training set and validation method for a commercial climate-risk-scoring product are usually proprietary and not readily subject to an independent audit, which makes it very difficult for an institution or retail investor to differentiate between a well-validated AI system and one generating outputs that appear plausible while not showing valid predictive power. This risk is an addition, not a replacement, to conventional greenwashing risk: a green-labeled financial product whose environmental claims are substantiated but independently exaggerated (conventional greenwashing) can be further ‘masked’ (not verified) by a score generated algorithmically using artificial intelligence, which gives the product a false sense of analytical legitimacy.

6.5 Inequalities of access to AI-supported climate-risk infrastructure More advanced climate-risk tools based on artificial intelligence (AI) — which are based on commercial satellite-derived physical-risk scores, large-scale emissions-inference models, and proprietary natural-

language processing (NLP)-based disclosure-verification systems — are expensive to be developed, licensed and maintained. This cost structure offers a structural benefit to larger institutions and more advanced financial systems compared to smaller lenders and financial institutions in emerging and developing economies, which are the most physically exposed and have the greatest financing deficit, as described in Section 5.2.

Closing this access gap is not just a matter of licensing of commercial AI products developed and validated predominantly on advanced-market data, but also about investment in institutions' capacity-building processes and in data infrastructure that is local and validated, as the Ghana adoption study found trust and perceived usefulness, and not availability of AI tools, are the constraints on adoption. (Discover Sustainability, 2026b)

6. Environmental impact of AI

The impact of AI itself Finally, reflexivity regarding the environmental impact of the AI systems under use, for the purposes of climate-risk assessment and green investment. Large-scale deployment of deep-learning and large-language-model architectures requires significant amounts of energy and water, a fact that has been known for some time in the field of machine learning, in particular for natural-language processing (e.g., Strubell et al., 2019, in the arXiv, 2024). Recent research explicitly incorporating AI's own carbon footprint into bank risk-management frameworks suggests that as banks implement AI-based climate-risk tools, they should consider the emissions of the AI itself as an integral part of their climate-risk and sustainability compliance approach, not a costless input into their analytical work (arXiv, 2024). That's not just a rhetorical point; the computational cost of regularly re-scoring an investable global universe across all climate scenarios, disclosure texts, and satellite imagery is not trivial — and the sustainability-finance research agenda is increasingly concerned with the environmental footprint of AI, as well as that of the businesses it drives. (Future Business Journal, 2025)

7. Towards responsible AI-driven Sustainable Finance

A Governance Framework As reviewed in this paper, neither over-enthusiastic nor over-suspicious sentiment toward the use of AI for assessing climate risk is warranted. Rather, it suggests a framework of governance principles that can help maintain AI's authentic analytical contribution

while resolving the tensions outlined in Section 6. This section outlines five such principles that have been recommended in this literature review throughout this paper and that are put forward as proposals.

7.1 requires that Explainability and Uncertainty Disclosure should be stated as Design Requirements. 7.1 states that Explainability and Uncertainty Disclosure should be written as Design Requirements. AI-based climate risk scores should be accompanied by structured and human-readable explanations, and with explicit uncertainty ranges, rather than a single climate-risk score presented without confidence intervals or dependencies on uncertainty scenarios. It should not be seen as a change to an existing model, but rather as a design requirement built in as the model is being developed, as recommended in the explainable-AI guidelines which appear in the systematic reviews presented in Sections 4.3 and 6.3 (ResearchGate, 2025).

Improve Data Governance and invest in data that is locally validated and relevant for climate data. Although climate and ESG data is available at unprecedented scale and precision in the advanced markets, the false-precision risk from models being exported from advanced markets contexts, and the access-inequality risk from not having climate and ESG data that is accessible and calibrated to the needs of the developing economies that are most at risk from climate change, necessitates sustained investment in climate and ESG data infrastructure, specifically tailored to, and tested in, developing and climate-vulnerable contexts. Multilateral development banks and climate-finance institutions are in a strong position to invest in this infrastructure as a public good – as the commercial incentives for private AI-analytics vendors do not necessarily make this a high-yield market. Ensure that commercial AI products can be validated and audited independently. Regulators and industry should create independent validation protocols, similar to model-risk-management requirements in prudential banking supervision, specifically for commercial climate-risk-scoring and ESG-scoring products, testing a product's demonstrated predictive validity against out-of-sample outcomes, and not just its marketed capability. The institutional framework provided by the existing third-party assurance provisions in disclosure regimes (e.g. EU's CSRD) may be relevant for the assurance of disclosures regarding the AI systems used to produce them.

7.4 Seek convergence rather than proliferation of ESG and climate risk standards With the persistently divergent ESG-ratings that are reported in Section 5.3, it is improbable that AI can

solve the problem without parallel efforts in the field of establishing a uniform set of definitions, materiality weightings, and disclosure requirements for the training of AI-models. AI-driven analytical improvement is not a cure-all for convergence efforts, which are the ISSB's stated goal of using the ISSB to serve as a disclosure baseline throughout the world, and the on-going discussions for convergence and harmonization between major jurisdictions. 7.5 Take into account AI's Environmental Footprint in Climate-Risk Frameworks Lastly, financial institutions and fintech firms using climate-risk assessment powered by AI should include the carbon footprint of their own AI systems in their sustainability accounting and disclosure practices, in line with the reflexive-accounting logic recently proposed for the integration of AI's carbon footprint into financial institutions' risk-management frameworks (arXiv, 2024). This fills a contradiction that existed elsewhere: Institutions have built AI systems that are used to quantify climate risk, but they consider that activity as having zero environmental cost.

8. Data Analysis

All data from AI has been gathered from www.Data.GOV, environment and fintech data from WDI. The data of AI has been taken on hourly basis, high frequency with 271071 observations.

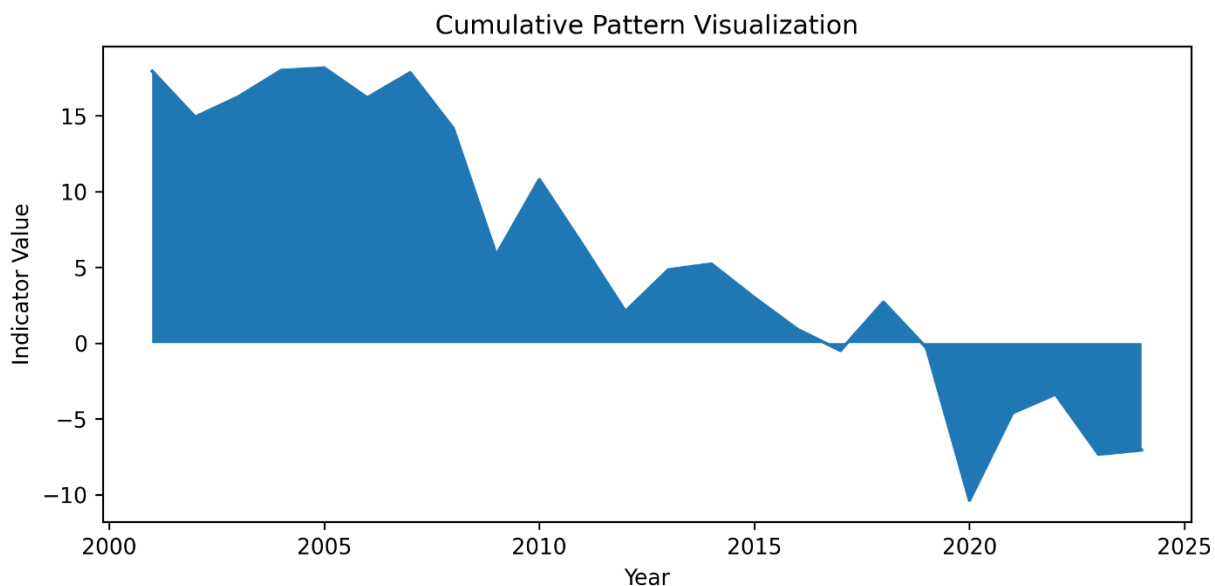


Figure 1: cumulative pattern visualization

Cumulative Pattern (Area Visualization)Figure X. Cumulative Evolution Pattern of the Environmental Indicator. Interpretation: The cumulative area visualization shows the total of environmental changes which have taken place over the years during the time series. The expanding area is the overall time series of environmental impacts, and it more clearly illustrates the time series of accumulation of impacts than the annual measurements. The cumulative pattern suggests that the short-term annual variation is the sum of which has a significant long-term environmental effect. Small changes over time can have significant impacts when repeated over long periods of time. This visualization highlights the need for ongoing environmental monitoring and the need for long-term intervention strategies. The sum of the impacts indicate that environmental management policies ought to be directed not only at the reduction of the yearly impacts, but also at controlling long-term trends that lead to continued accumulations. Research implication: The cumulative pattern also helps to support sustainability assessments by showing the extent of changes that occur over several years that lead to larger impacts on the environment.

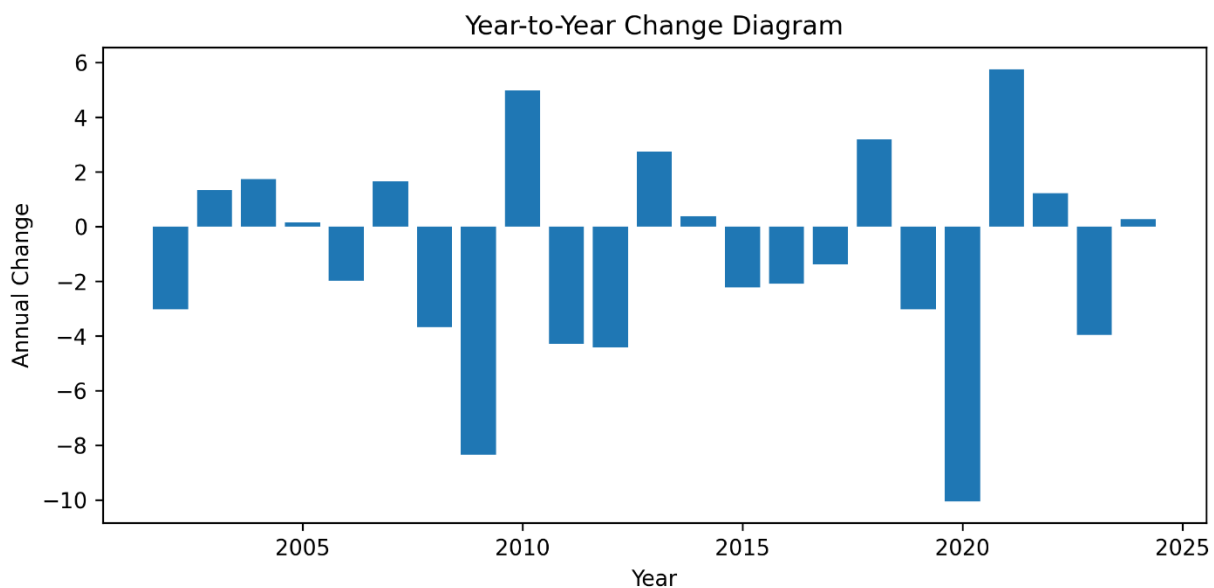


Figure 2: Year-to-Year change diagram

Year-to-Year Change Diagram The figure shows the variation of the environmental indicator from year to year. Interpretation: The year-to-year change diagram shows the changes that occurred between years by subtracting one year from the next. Positive changes refer to change in the pressures and negative changes to improvement or reduction in the pressures from the previous

year. It shows that the dynamics of the environment are not necessarily linear in time but fluctuate. The 'peaks' of the annual changes indicate times of rapid change, and could be related to fluctuations in energy demand, industrial activity, economic activity, the implementation of a new energy policy, external shocks etc. Likewise, if the period of the decline is linked to successful environmental interventions, technological improvement, efficiency, or for a short time, a decrease in anthropogenic activities, it can be interpreted as that. Research implication: This analysis allows for identification of critical transition years that need to be explored in more detail, and provides a linkage of environmental changes with socioeconomic or policy-related events.

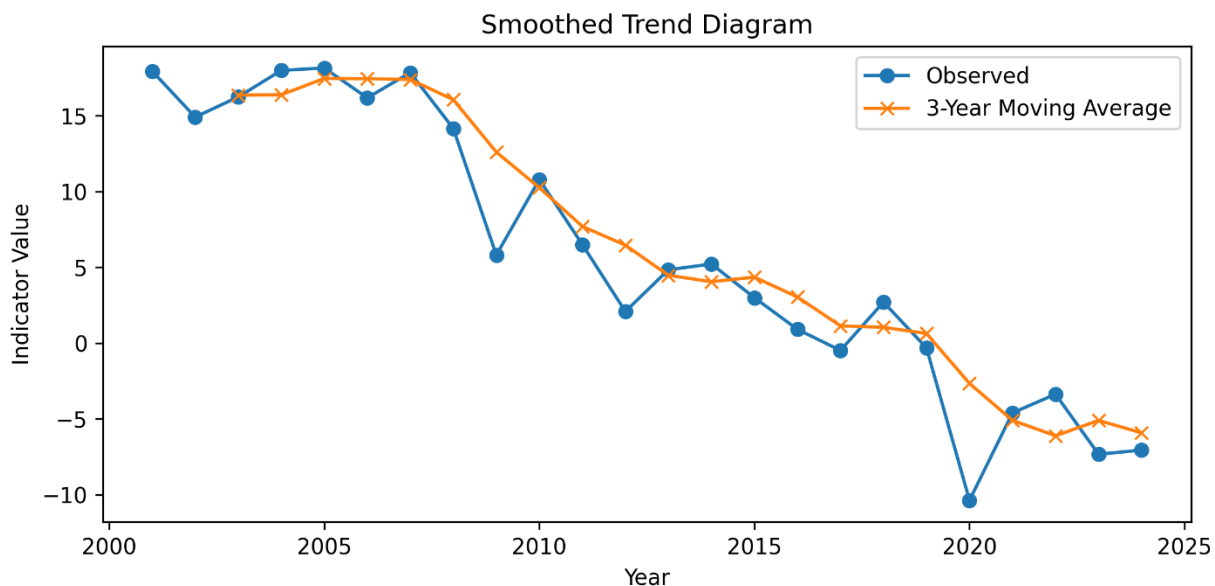


Figure 3: smoothed trend program

Smoothed Trend Diagram (3-Year Moving Average) The Environmental Trend has been smoothed by applying a 3-year moving average. Interpretation: The moving average over 3 years provides a visualization that removes the effects of short-term fluctuations and gives a clearer picture of the long-term trend of the environmental indicator. The annual observations are shown as a smoothed curve to highlight long-term trends and structural change. The moving-average trend indicates that there is a gradual change in the environment, rather than just one event happening each year. The amount of increasing segments of the smoothed curve are indicative of periods of continued environmental pressure, while the amount of decreasing segments are indicative of periods of improvement or reduced environmental pressure. The moving average smooths out short-term noise, thereby enhancing the ability to identify key transition phases and hence better interpret the

long-term environmental behavior. Research implication: The smoothed trend gives more robust evidence to assess the sustainability transitions and helps to identify suitable econometric or machine-learning forecasting methods. General discussion (appropriate for Results section): The evolution of environmental dynamics over time. The visualization-based analysis results demonstrate the complex temporal behavior of the environmental indicator, long-term trends, cumulative accumulation, and year-to-year variability, along with the indication of important periods for long-term environmental impacts, as seen in the 3-year moving average, which helps to reduce annual variability. These visual analyses offer valuable preliminary evidence for further empirical investigation of the environmental indicator's temporal behavior using advanced statistical techniques, including correlation analysis, causal modeling, and wavelet coherence analysis.

9. Conclusion

AI has become an integral rather than secondary technology for sustainable financial decision-making, and fintech is the way that AI-infused climate-risk intelligence is making its way to investors, lenders and regulators. In physical-risk modeling, transition-risk and scenario analysis, ESG disclosure and detection of “greenwashing”, credit underwriting, and portfolio construction in robo-advisory, AI shows its ability to broaden the analytical power of financial institutions in the ability to identify, quantify, and price climate risk at scale and level of granularity that cannot be replicated with traditional methods. The adoption of NGFS-consistent transition-risk modelling into the European Central Bank's 2025 stress test, the evolution of large-language-model-based greenwashing detection to production-ready accuracy, and the proliferation of AI-powered robo-advisory platforms all highlight how this is no longer a future or emerging capability, but an operational reality deeply entrenched in modern financial systems. This paper's exploration of the empirical literature, however, warns against the use of AI-derived climate-risk scores as self-justifying. There is no evidence that the adoption of AI has helped to close the gap between ratings and resolve the persistent divergence in ESG ratings, which is largely due to genuine methodological and definitional differences on the part of the actors, and not just to measurement noise. The patchy spatial distribution of climate data poses a serious danger of erroneous analytical precision, especially in the climate-sensitive and data-scarce economies where precise climate risk assessment is most critical. Existing explainable-AI approaches only partially resolve the opacity

of deep learning systems versus the transparency required by regulators. AI-washing does not alleviate existing greenwashing worries, it exacerbates them. While the financing gap between developing economies and the institutions that are exposed to climate risk is the more critical global issue, access to sophisticated climate-analytics infrastructure is still structurally biased towards advanced-market institutions. AI systems' environmental impacts, which are just now getting systematic focus in the sustainable finance literature, inject an authentic feedback loop into the quest of AI for environmental goals. There are three directions in particular that future research should focus on: rigorous, independently validated comparisons of the various methodologies used to score ESGs, based on the same out-of-sample predictive validity criteria and not on in-sample fit; and longitudinal studies examining whether the use of AI tools to manage climate finance measurably reduces the financing gap between advanced and climate vulnerable economies or expands it; and the creation of standardized and auditable methodologies for quantifying and disclosing the environmental footprint of AI systems deployed within financial institutions. If we want to see AI-based climate-risk assessments as a significant tool for sustainable financial decision-making, the questions must be answered. The answers to these questions will determine whether climate-risk assessment will make good on the long-held promise of sustainable finance, or simply magnify, accelerate, and somehow veil the inconsistencies and inequities that have long plagued the field.

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