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Review

Climate-Related Credit Risk in Banking: A Critical Review of Empirical Evidence and Methodological Approaches

Elena Grinza [1,2,3,4,*], Parisa Madhooshiarzanagh [1] and Consuelo Rubina Nava [5]

[1] Department of Economics, Social Studies, Applied Mathematics, and Statistics, University of Turin, Corso Unione Sovietica 218/bis, 10134 Turin, Italy; p.madhooshiarzanagh@unito.it
[2] Collegio Carlo Alberto, 10122 Turin, Italy
[3] Centre Emile Bernheim de Recherche Interdisciplinaire en Gestion, Université Libre de Bruxelles, 1050 Brussels, Belgium
[4] LABORatorio Riccardo Revelli, 10122 Turin, Italy
[5] Department of Economic and Political Sciences, University of Aosta Valley, Strada Cappuccini, 2A, 11100 Aosta, Italy; c.nava@univda.it
* Correspondence: elena.grinza@unito.it

Abstract

This paper provides a critical narrative review of the literature on climate-related credit-risk and its implications for the banking sector. Banks' exposure to physical and transition climate risks can significantly affect credit quality, lending conditions, and overall financial stability, yet the methods used to study these effects vary widely, and each faces limitations. This paper systematically assesses the strengths and weaknesses of the main empirical approaches—including regression models, stress testing, and scenario analysis—in the presence of rare default events, unobserved heterogeneity, and quasi-complete separation and highlights unresolved tensions in the evidence base. Building on this assessment, it discusses the Bayesian multilevel logistic model (BMLM) as a conceptual methodological framework for firm-level credit-risk analysis and provides a structured comparison of seven modelling families—including deep learning architectures and survival analysis methods—across eight evaluation dimensions. This paper's principal contribution is a structured mapping of research objectives, data characteristics, and modelling choices, rather than the advocacy of a single preferred approach.

Keywords: credit risk; climate change; banking sector; Bayesian multilevel logistic model; deep learning; survival analysis; methodological approaches; narrative review

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1. Introduction

Climate change poses growing challenges to the financial sector, increasingly recognised by regulators and policymakers as a source of systemic risk. The European Green Deal and the European Commission's Action Plan on Financing Sustainable Growth both assign a central role to the financial system in supporting the transition toward a low-carbon economy (Busch et al. 2021; Claeys et al. 2019). Scholars such as Schoenmaker and Schramade (2018) and Weber and Remer (2011) emphasise that aligning finance with sustainability principles is crucial to long-term economic and environmental stability, while Oguntuase (2020) argues that climate shocks will affect all economic sectors and that financial institutions must strengthen their capacity to manage these emerging risks.

Climate-related risks are typically divided into two main categories—physical risks and transition risks (Basel Committee on Banking Supervision 2021; European Central Bank 2020; NGFS 2019). Physical risks stem from acute events—such as floods, cyclones, and storms—and from chronic processes, including rising sea levels and increasing temperatures. Transition risks emerge from the shift toward a low-carbon economy, often captured through firms' carbon footprints and exposure to regulatory changes (Bernardini et al. 2021; Semieniuk et al. 2021). Both categories carry substantial economic consequences: physical risks may damage assets and disrupt supply chains, while transition risks typically manifest through reputational losses, declining competitiveness, and the phase-out of carbon-intensive activities (Basel Committee on Banking Supervision 2021; European Central Bank 2020).

Banks are exposed to these risks through direct channels—when climate events disrupt financial services or damage assets—and through indirect channels, when climate shocks propagate through borrowers and macroeconomic conditions (Brunetti et al. 2021; NGFS 2020). Among the various risk categories affected—market, operational, reputational, liquidity, and credit risk (European Central Bank 2020)—this paper focuses on credit risk, defined as the potential that a borrower will fail to meet its obligations (Basel Committee on Banking Supervision 2000). Credit risk is particularly relevant because climate-related factors, whether physical or transitional, can directly influence the probability of default (PD) of financed entities or reduce the recoverable value of assets in case of default (European Banking Authority 2021; Monnin 2018). In this context, credit-risk exposure refers to the extent to which a bank's loan portfolio is exposed to borrowers whose creditworthiness may be adversely affected by physical or transition climate risks, as distinct from the bank's market or operational risk exposures. The materiality of these risks for banking credit books has been demonstrated by national supervisory exercises: the Bank of England's 2021 Climate Biennial Exploratory Scenario (CBES) projected climate-related credit losses in the Late Action scenario equivalent to approximately £110 billion of additional losses for participating banks over the 30-year scenario horizon, with particularly significant effects on wholesale and mortgage portfolios (Bank of England 2022). The ACPR's 2020 pilot climate exercise, the first large-scale supervisory exercise of its kind, documented the transmission of transition and physical risks into banks' credit-risk parameters while finding an overall moderate exposure in the scenarios considered and highlighting substantial data and modelling gaps in firms' risk assessment capabilities (Autorité de contrôle prudentiel et de résolution (ACPR) 2021). In the United States, the Federal Reserve conducted a Climate Scenario Analysis (CSA) with the six largest bank holding companies in 2023, similarly assessing portfolio resilience to physical and transition climate risks (Board of Governors of the Federal Reserve System 2023).

This paper reviews the climate-related credit-risk literature, drawing on academic research and official publications from central banks, supervisory authorities, and international financial institutions. Researchers have employed a range of analytical approaches—regression models, stress testing, and scenario analysis—to examine how climate change influences credit risk. Although this literature has yielded valuable insights, it continues to face challenges related to robustness, interpretability, and predictive accuracy. Many empirical exercises rely on reduced-form specifications that may omit important sources of heterogeneity or struggle with collinearity across climate variables, while stress-testing frameworks often depend heavily on scenario assumptions and are not always suitable for firm-level analysis. Moreover, conventional statistical models can become unstable in samples with rare default events or highly skewed exposure distributions.

To address these limitations, this paper discusses the potential advantages of Bayesian multilevel logistic model (BMLM) specifications as a methodological framework for analysing firm-level credit risk under climate-related exposures. This framework extends standard logit regression by incorporating cluster-specific random effects and Bayesian prior regularisation, thereby capturing unobserved heterogeneity and addressing issues such as quasi-complete separation. The Bayesian formulation may complement predictive tools—including machine learning classifiers, deep learning architectures, and survival analysis methods—by offering a more interpretable probabilistic framework for analysing the trade-off between interpretability and predictive accuracy. This paper therefore does not advocate a single preferred modelling strategy; instead, it provides a structured comparison of alternative approaches organised by analytical objective and data structure.

Positioning Relative to Existing Reviews

The recent literature has increasingly reviewed the relationship between climate change and the financial system from different perspectives. De Bandt et al. (2025) provide a broad review of the effects of climate-related risks on banks, focusing primarily on credit risk, market risk, lending standards, and financial stability implications. Similarly, Bringas-Fernández et al. (2025) examine the banking climate-risk literature through a bibliometric approach, identifying major thematic streams related to ESG, green finance, financial intermediation, and monetary policy. From a broader macroprudential perspective, Pacelli et al. (2025) analyse the relationship between climate risk and systemic risk, emphasising contagion mechanisms, financial stability, and network-based approaches.

This paper differs from these contributions in several respects. Compared with that by De Bandt et al. (2025), this paper does not aim to quantify the distribution of climate effects on loan or bond spreads but focuses on modelling challenges in firm-level PD estimation. Compared with the works by Bringas-Fernández et al. (2025) and Pacelli et al. (2025), it does not provide a bibliometric or systemic-risk mapping, but develops a methodological synthesis of econometric, predictive, and time-to-event approaches to firm-level credit risk under climate-related exposures.

The literature has converged on the relevance of climate-related credit risk but remains fragmented with respect to effect magnitudes, risk measurement, identification strategies, and external validity. This paper systematically compares the econometric and predictive approaches employed in the literature, discussing their respective strengths and limitations in the presence of rare default events, heterogeneity, collinearity, and quasi-complete separation. It also discusses the potential role of Bayesian multilevel logistic model (BMLM) specifications as a coherent methodological framework and extends this discussion to include deep learning architectures and survival analysis methods, which have received growing attention in the credit-risk literature. The BMLM approach discussed here should therefore be interpreted as a conceptual methodological perspective rather than as a fully validated empirical framework.

The rest of this paper is structured as follows: Section 2 describes the review methodology. Section 3 reviews the empirical research on how climate change affects credit risk within the banking sector, with an explicit critical synthesis of the evidence. Section 4 outlines the main methodologies applied in these studies and evaluates their respective strengths and limitations. Building on this analysis, Section 5 outlines methodological considerations for future research, including a structured illustrative comparison of modelling approaches. Finally, Section 6 presents the main conclusions and policy implications.

2. Review Methodology

We adopt a narrative review approach with explicit methodological assessment (Snyder 2019; Tranfield et al. 2003), positioned between a purely qualitative narrative and a formal systematic review. This format is well suited to a rapidly evolving field in which the primary need is conceptual mapping, methodological synthesis, and identification of research priorities (Snyder 2019).

2.1. Search Strategy and Database Coverage

The literature search was conducted primarily using Google Scholar, supplemented by targeted searches in Scopus and Web of Science. Institutional repositories of the Bank for International Settlements (BIS), the European Banking Authority (EBA), the European Central Bank (ECB), and the Network for Greening the Financial System (NGFS) were also consulted for policy and supervisory publications. In addition, targeted searches of selected national central banks and supervisory authorities were conducted where relevant. Specifically, the repositories of the Federal Reserve, the Bank of England and the Prudential Regulation Authority (PRA), the Banque de France and Autorité de contrôle prudentiel et de résolution (ACPR), and De Nederlandsche Bank (DNB) were searched for publications on climate-related credit risk, bank lending, stress testing, PD/LGD, credit impairment, and physical and transition risk. These searches do not constitute exhaustive or systematic coverage of every national supervisory authority but targeted the institutions that have been the most active in producing publicly available quantitative assessments of climate-related financial risks in the banking sector. The search covered the period up to March 2026.

Search strings combined terms from two thematic domains. The first domain covered climate-related concepts, including: "climate change", "physical risk", "transition risk", "carbon emissions", "carbon footprint", "carbon tax", "sea level rise", "natural disasters", "climate policy", "ESG", "sustainable finance", "low-carbon economy", "increasing temperatures", "rising temperatures", "temperature fluctuations", "greenhouse gas", and "GHG". The second domain covered banking and credit-risk concepts, including: "credit risk", "bank lending", "probability of default", "distance to default", "non-performing loans", "loan loss provisions", "bank stability", "financial stability", "banking sector", "loan recoveries", "recovery rates", "loss given default", "LGD", and "credit impairment". Search strings were combined using Boolean operators (AND, OR), and both domain-specific and general databases were queried iteratively to ensure broad coverage.

2.2. Inclusion and Exclusion Criteria

Studies were included if they: (i) examined the relationship between climate-related risks and credit risk, lending behaviour, or financial stability of banks or financial institutions; (ii) were written in English; (iii) were published in peer-reviewed journals, working paper series, or institutional outlets, including publications by central banks, banking supervisors, and international financial institutions (e.g., BIS, EBA, ECB, NGFS, Federal Reserve, Bank of England/PRA, ACPR, and DNB); and (iv) covered any country or geographic area without restriction.

Studies were excluded if they: (i) focused exclusively on non-financial firms without examining implications for banks or financial institutions; (ii) addressed climate change only in the context of market risk or operational risk without any connection to credit risk; or (iii) were not available in English. No restrictions were placed on publication date or on whether papers were published in peer-reviewed journals versus working papers, given the rapid pace of developments in this field and the importance of the institutional grey literature.

2.3. Screening and Selection

Following the initial database search, titles and abstracts were screened for relevance against the inclusion and exclusion criteria described above. Full texts were retrieved and assessed for all papers passing the abstract screen. Because this review was designed as a structured narrative review rather than a formal systematic review, the search and screening process was not preregistered. Nevertheless, duplicate records and overlapping versions of the same study were checked manually during full-text assessment, and the final selection followed explicit inclusion and exclusion criteria.

A total of 70 core sources were retained for the quantitative summary and empirical review, complemented by additional methodological references used in Sections 4 and 5. The retained sources include 57 peer-reviewed journal articles and 13 institutional or working paper publications. Given the rapid pace of developments in this field and the importance of the institutional grey literature, no restrictions were placed on publication type. This review does not claim exhaustive coverage but aims to represent the main empirical contributions, methodological approaches, and institutional perspectives shaping the literature on climate-related credit risk in banking.

3. Empirical Review

A growing body of research has explored the link between environmental performance and financial outcomes in the corporate and banking sectors (Stroebel and Wurgler 2021). Peters (2025) provides a comprehensive review of how natural disasters affect banks' stability, profitability, and credit supply, emphasising the crucial role of financial institutions in post-disaster recovery. Chalabi-Jabado and Ziane (2024) find that transition-related risks can enhance bank performance and lending, whereas physical risks tend to weaken both indicators.

Research shows that firms investing in R&D tend to improve their environmental performance, particularly in terms of energy efficiency and lower carbon emissions (Alam et al. 2019). However, because only a limited number of companies disclose their greenhouse gas (GHG) emissions or carbon footprints, investors often face difficulties in assessing corporate environmental impact. Nguyen et al. (2021) applied machine learning methods to estimate firms' carbon emissions based on observable financial and operational data.

Several studies have examined how carbon risk influences firm performance and financial stability. Wang et al. (2022) analyse the relationship between carbon risk and corporate outcomes including risk exposure, capital costs, and investment decisions. Kabir et al. (2021) find that higher carbon emissions reduce firms' distance to default, signalling increased credit vulnerability, while Aiello and Angelico (2023) show that carbon taxation policies affect banks' credit risk in Italy. Bell and van Vuuren (2022) highlight the adverse effects of climate risk on corporate creditworthiness, with African economies being particularly exposed. Aguais and Forest (2023) show that climate change can heighten credit losses through increased volatility, while Wu et al. (2024) demonstrate that greater climate risk exposure substantially raises banks' systemic risk, primarily through declining credit quality.

In recent years, the responsibilities of central banks and financial regulators in addressing climate-related financial risks have expanded considerably (Campiglio et al. 2018). De Haas and Popov (2023) show that economies with stronger stock market financing tend to record lower per capita carbon emissions. Kleimeier and Viehs (2018) find that voluntary disclosure of carbon emissions reduces borrowing costs, suggesting that banks increasingly incorporate environmental considerations into lending decisions. Conlon et al. (2024) show that banks curtail lending and raise loan loss provisions following unexpected climate shocks.

Financial institutions are highly exposed to industries affected by climate policies through their equity holdings and loan portfolios (Battiston et al. 2017). Oikonomou et al. (2014) find that firms with strong social responsibility records tend to face lower bond interest rates. In the mortgage market, Nguyen et al. (2022) show how lenders price physical climate risks such as sea-level rise (SLR), with high-risk properties being charged higher interest rates. Survey evidence from Krueger et al. (2020) suggests that investors view climate-related risks—particularly regulatory actions—as material factors affecting corporate financial performance.

Climate change also affects sovereign credit ratings, with climate-resilient countries generally achieving higher ratings, while developing economies face greater negative effects (Cevik and Jalles 2023). Although this evidence concerns sovereign rather than borrower-level credit risk, it remains relevant to banking because sovereign creditworthiness can affect the broader credit environment, collateral values, funding conditions, and the capacity for public support of financial institutions. Boros (2020) emphasises the importance of integrating climate-related risks into stress testing and risk modelling frameworks. Bernardini et al. (2021) show that including sustainability criteria in investment strategies helps reduce exposure to climate-related financial risks. Aslan et al. (2022) find that banks in Turkey reduce credit supply in areas more exposed to climate risks after the 2015 Paris Agreement.

Bauer and Hann (2010) document a clear link between environmental performance, borrowing costs, and credit ratings, while Huynh and Xia (2021) find that investors increasingly favour bonds from companies with strong environmental performance. Dal Maso et al. (2024) provide evidence that elevated disaster risk prompts banks to increase loan loss provisions. Batten et al. (2016) highlight that natural disasters can trigger financial instability, rising temperatures may affect long-term growth, and abrupt regulatory shifts in carbon emissions could create market volatility.

Capasso et al. (2020) find, using OLS regression, that companies with higher carbon emissions or greater carbon intensity exhibit lower the distance to default, indicating greater perceived default risk. Bento and Gianfrate (2020) show that firms with larger carbon footprints are more likely to be seen as potential defaulters. Höck et al. (2020) show that companies with stronger environmental practices face lower credit-risk costs in Europe. In agriculture, Kaur Brar et al. (2021) stress that reducing credit risk requires integrating climate-related factors into risk-management strategies. Céu and Gaspar (2024) examine how climate patterns affect agricultural productivity and lenders' credit-risk exposure. Ma et al. (2024) report that agricultural insurance can cushion climate-related credit-risk effects for rural financial institutions, while Liu et al. (2024) find that smaller and rural banks are particularly vulnerable to climate shocks.

Climate risk influences firms' cost of capital and should therefore be a key consideration in bank lending decisions (Javadi and Masum 2021). Zhang (2021) finds that firms with stronger environmental performance are more likely to secure loan approvals and better collateral terms. Naifar (2023) demonstrates that greater climate change preparedness lowers sovereign credit default swap spreads. Banks with stronger commitments to climate action generally face lower credit risk (Birindelli et al. 2022). Meisenzahl (2023) shows that after the 2014 UN Climate Summit, banks began reallocating portfolios away from high-climate-risk regions. Huang et al. (2022) find that firms with greater climate risk receive less favourable loan terms, while Ginglinger and Moreau (2023) observe that lenders charge higher interest rates to riskier firms since the Paris Agreement. Mueller and Sfrappini (2025) note that U.S. banks prefer lending to firms with lower regulatory exposure, while European banks favour those with stronger environmental prospects.

Borsuk (2023) finds that Polish banks with stronger ties to carbon-intensive industries face higher credit risks. Nehrebecka (2021) estimates that a direct carbon tax raised PD for CO_2-emitting firms from 3.6% to between 6.31% and 10.12%, depending on the scenario. Wu et al. (2023) report that climate change adversely affects China's banking sector stability. Fan et al. (2024) find that temperature fluctuations raise non-performing loan ratios across 31 Chinese provinces.

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Bellia et al. (2025) show that river flooding intensifies its financial impact during periods of economic stress for German regional banks, with a projected 3°C temperature increase potentially leading to banking losses of up to 1% of total assets. D'Orazio et al. (2024) find that German banks face substantial transition risks, with large private institutions being particularly vulnerable. In South Korea, Kim and Moh (2025) find that higher transition risk reduces bank profitability, while stronger climate performance has a positive effect.

3.1. Critical Synthesis: Tensions and Unresolved Questions

While the studies reviewed above collectively establish that climate change affects credit risk in banking, a closer reading reveals several important tensions and unresolved empirical questions that merit explicit discussion.

Direction and magnitude of effects. There is broad agreement that physical and transition risks increase credit risk, but the estimated magnitudes vary substantially across studies. For example, Nehrebecka (2021) finds that a direct carbon tax raises default probabilities from 3.6% to up to 10.12%, whereas Aiello and Angelico (2023) find that a moderate carbon tax has a minimal short-term effect on Italian banks' default rates. These differences likely reflect heterogeneity in tax levels, sector composition, and time horizons, but the studies are difficult to compare directly because they use different risk measures (firm-level PD versus aggregate default rates), different estimation methods, and different institutional contexts.

Physical versus transition risks. Several studies find that physical and transition risks operate through distinct channels and may have opposing effects in some contexts. Chalabi-Jabado and Ziane (2024) find that transition risks are positively associated with bank performance and lending growth, while physical risks have negative effects. This suggests that the relationship between climate risk and credit quality is not uniform and depends critically on which dimension of climate risk is being measured. Yet many studies combine physical- and transition-risk proxies or use aggregate climate risk indices that conflate the two, making it difficult to disentangle their separate contributions to credit deterioration.

Cross-country comparability. The reviewed studies span a wide range of countries, from China and the United States to Poland, Turkey, South Korea, Germany, and African economies, and use different data sources, risk measures, and regulatory frameworks. Direct comparison across these contexts is therefore problematic. For example, Fan et al. (2024) find that temperature fluctuations significantly increase non-performing loan ratios in China, while Cevik and Jalles (2023) document negative effects of climate change on sovereign credit ratings across a broad international sample. The external validity of country-specific findings to other institutional contexts remains uncertain, and the absence of a harmonised climate risk taxonomy across datasets limits cross-study synthesis. In this respect, supervisory benchmarking exercises provide directly relevant evidence: the EBA Credit Risk Benchmarking exercises document substantial cross-country variation in internal-model PD and LGD estimates across European banks for the same exposure classes (European Banking Authority 2018), while the EBA Insolvency Benchmarks report cross-country differences in recovery rates (European Banking Authority 2025). Together, these exercises illustrate that observed heterogeneity in empirical credit-risk estimates may reflect differences in supervisory models and recovery regimes as much as genuine differences in underlying credit quality, a consideration that complicates the interpretation of cross-country climate risk studies.

Identification and endogeneity. Establishing causal estimates of the effect of climate-related exposures on credit risk is methodologically challenging, and several distinct forms of endogeneity complicate the interpretation of the evidence.

Reverse causality and simultaneity arise when banks' credit conditions themselves influence firms' environmental behaviour or adaptation choices. For example, if banks charge higher interest rates to carbon-intensive borrowers, some firms may respond by reducing emissions or investing in green assets—meaning that observed climate exposures partially reflect prior credit conditions, not exogenous environmental characteristics. This creates a simultaneity problem in which both credit risk and climate exposure are jointly determined.

Endogenous portfolio reallocation is a related concern. As documented by Meisenzahl (2023), banks began reallocating portfolios away from high-climate-risk regions following the 2014 UN Climate Summit, meaning that observed lending patterns already embody anticipatory behavioural responses to perceived climate risks. Cross-sectional comparisons of bank exposure at a given point in time may therefore capture equilibrium outcomes shaped by prior adaptation rather than the causal effect of climate shocks on credit quality.

Endogenous firm adaptation presents a symmetric problem on the borrower side. Firms that anticipate stricter climate regulation may invest in abatement or transition early, reducing their transition-risk exposure. If such adaptive behaviour is correlated with unobserved firm characteristics such as management quality, financial resilience, or access to green finance, then measures of climate exposure will be confounded with these omitted determinants of credit risk.

Measurement error in climate-risk exposure is an additional source of bias. Many studies rely on imperfect proxies—carbon emission intensities, flood-zone classifications, geographic coordinates—that capture climate exposure with error. Classical measurement error in the key regressor attenuates coefficient estimates toward zero, while non-classical error can produce bias of either sign. Moreover, the observed exposure of a firm or bank may already embody the results of risk management, hedging, or insurance, so that the measured exposure understates the true underlying vulnerability.

Taken together, these sources of endogeneity imply that naive OLS or fixed effects estimates of climate-risk effects on credit outcomes should be interpreted with caution, as they may conflate causal effects with selection, adaptation, and measurement artefacts.

Several identification strategies have been explored in the literature, though none completely resolves the identification problem. Plausibly exogenous physical climate shocks—such as sudden flooding events or extreme temperature realisations—can serve as natural experiments if their timing and geographic incidence are unpredictable, as in the study by Bellia et al. (2025). Regulatory or policy discontinuities, such as the announcement of the Paris Agreement or national carbon pricing legislation, provide event-study windows exploited by Ginglinger and Moreau (2023) and Meisenzahl (2023). Difference-in-Differences designs compare changes in credit outcomes for more- versus less-exposed firms before and after a climate event or policy change, as in the study by Aslan et al. (2022). Predetermined geographic exposure—such as a firm's location in a flood plain or coastal zone—is sometimes used as an instrument on the grounds that it predates the firm's credit history. Carefully constructed instrumental variables such as historical temperature anomalies or exogenous variation in regulatory stringency have been used by Cevik and Jalles (2023), who validate their instruments using Kleibergen–Paap and Hansen tests.

It should be noted, however, that the validity of each of these strategies depends on strong assumptions that may not hold universally. Physical shock instruments may be correlated with local economic conditions or infrastructure quality. Policy discontinuity instruments may be anticipated. Geographic exposure instruments may be related to adaptive behaviour, institutional characteristics, or other channels affecting credit risk independently of climate exposure. IV validity is particularly at risk when the instrument affects the outcome through multiple pathways, and standard overidentification tests may have limited power in this setting. A further concern, especially relevant for regulatory-

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stringency instruments, is weak-instrument bias: when the instrument has limited first-stage explanatory power, two-stage estimates can be severely biased toward OLS, and first-stage strength should be reported alongside overidentification tests. No single strategy definitively resolves the identification problem, and a degree of interpretive caution is warranted throughout this review.

Time horizon and dynamic effects. Most studies capture the immediate impact of climate shocks or policy changes, while longer-term adjustments—such as firm adaptation, technological change, and regulatory learning—remain largely unmodelled. Aiello and Angelico (2023) note that autoregressive models capture short-term dynamics but overlook longer-term macroeconomic consequences. This temporal dimension is particularly relevant for transition risks, whose effects may materialise gradually over years or decades rather than in response to discrete events.

These tensions underscore the need for methodological frameworks that can accommodate heterogeneous data structures, address identification challenges, and support credible inference in the presence of rare default events and sparse sectoral observations—motivations that are developed further in Sections 4 and 5.

3.2. A Quantitative Analysis

This subsection provides a descriptive quantitative characterisation of the 70 core academic and institutional sources retained through the review protocol described in Section 2. Of these, approximately 56% provide empirical evidence drawn from real-world data, while the remaining 44% are predominantly theoretical or institutional in orientation.

Table 1 classifies the reviewed studies by geographic focus, estimation method, and climate-risk type, and Table 2 maps climate-risk types to credit-risk outcomes and dominant empirical approaches.

A full summary of the empirical works included in the literature review is provided in Table 3 below. The geographic distribution of the 39 empirical studies is as follows: approximately 33% cover multiple geographic areas or adopt a worldwide sample, 23% focus on the United States, 10% on China, and 5% each on Germany, Poland, and European countries in aggregate. The remaining studies cover individual countries, including Italy, Hungary, Turkey, Africa, South Korea, and Canada, each accounting for approximately 3% of the sample. Note that these percentages are computed on the 39 empirical studies included in the empirical-study overview reported later in this paper and are rounded to the nearest integer; due to rounding, they need not sum exactly to 100%.

A diverse range of empirical methods have been applied. Fixed effects panel regression accounts for about 25% of applications. OLS regression and binary choice models such as logit and probit each appear in around 15% of the papers. IV approaches (2SLS and GMM) and simulation-based methods each represent roughly 13%. Other techniques include stress testing (10%), DiD (5%), random effects and quantile regression (5% each), and machine learning (3%). Note that some studies employ multiple empirical approaches, so these percentages may sum to more than 100%. These methods and their limitations are examined in the following section.

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Table 1. Distribution of reviewed studies by geographic focus, estimation method, and type of climate risk.

Dimension	Distribution
Geographic focus (39 empirical studies)	
Worldwide or multiple countries	33%
United States	23%
China	10%
Germany and Poland	5% each
European countries (aggregate)	5%
US and Europe combined	≈3%
Italy, Hungary, Turkey, Africa, South Korea, and Canada	≈3% each
Estimation methods used (non-mutually exclusive)	
Fixed effects panel regression	25%
OLS regression	15%
Binary choice models (logit/probit)	15%
IV approaches (2SLS, GMM, and SYS-GMM)	13%
Simulation-based methods	13%
Stress testing	10%
Difference in Differences	5%
Random effects/quantile regression	5% each
Machine learning	3%
Type of climate risk examined	
Physical risk only	38%
Transition risk only	25%
Both physical and transition risk	22%
General climate risk index	15%

Note: Geographic percentages are computed on the 39 empirical studies included in the empirical-study overview and rounded to the nearest integer; due to rounding, they need not sum exactly to 100%. Percentages for estimation methods may sum to more than 100% because some studies employ multiple empirical approaches.

Table 2. Mapping of climate-risk type, credit-risk outcome, and dominant empirical approaches.

Climate-Risk Type	Credit-Risk Outcomes	Dominant Empirical Approaches
Physical risk	Non-performing loans, loan loss provisions, mortgage pricing, bank stability, and distance to default	Fixed effects panel regression, DiD, stress testing, and simulation
Transition risk	Probability of default, distance to default, loan spreads, bond spreads, and bank profitability	Logit/probit, OLS, IV (2SLS), GMM, and autoregressive models
Both physical and transition risk	Bank stability, systemic risk, lending growth, and credit quality	Panel FE, SYS-GMM, scenario analysis, and stress testing
General climate risk index	Sovereign credit ratings, cost of capital, and collateral values	OLS, quantile regression, IV, and descriptive analysis

Note: Assignments reflect the primary focus of each study as reviewed in Section 3. Some studies span multiple rows.

Table 3. Overview of the empirical studies.

Title	Author(s) and Year	Research Questions	Country	Empirical Methods	Results
Corporate environmental management and credit risk	Bauer and Hann (2010)	Examine corporate environmental management and its implications for bond investors	U.S.	OLS; probit	Significant relationship between environmental performance and the borrowing firm's cost of debt and credit ratings; higher emissions are correlated with higher borrowing costs and lower credit ratings.
A climate stress test of the financial system	Battiston et al. (2017)	How climate risk policies spread in the financial system	European and U.S.	Stress test	Banks are significantly exposed to climate-policy-affected sectors through equity holdings and loan portfolios; the timing of climate policies is crucial.
Carbon disclosure, emission levels, and the cost of debt	Kleimeier and Viehs (2018)	How voluntary carbon emission disclosure affects the cost of debt	Worldwide	OLS	Firms disclosing carbon emissions voluntarily receive lower interest rates; higher emissions drive up loan costs through environmental risk perceptions.
Finance and carbon emissions	De Haas and Popov (2023)	Relationship between financial systems and carbon emissions	Worldwide	IV (2SLS)	Economies with stronger stock market financing have lower per-capita carbon emissions, controlling for economic development and environmental regulation.
Climate change and credit risk	Capasso et al. (2020)	How firm-level climate exposure affects credit default risk	Worldwide	OLS regression	Firms with higher carbon emissions and carbon intensity exhibit lower distance to default, indicating greater perceived default risk.
The effect of environmental sustainability on credit risk	Höck et al. (2020)	Whether environmental sustainability affects European firms' credit risk	Europe	Random effects panel regression	More environmentally sustainable companies with high creditworthiness face lower credit-risk costs.
Risks of climate change and credit institution stress tests	Boros (2020)	How to evaluate climate change risk for commercial banks	Hungary	Stress test	Climate–economic linkages are complex; Hungarian commercial banks should incorporate stress testing and updated risk models.
The importance of climate risks for institutional investors	Krueger et al. (2020)	How investors consider climate risks in their strategies	Worldwide	Descriptive statistics; logit; probit; OLS	Many investors consider climate-risk materials; the industry is in early phases of integrating them.
The impact of climate change on credit risk of rural financial institutions	Ma et al. (2024)	How climate change and agricultural insurance affect rural banks' credit risk	China	Fixed effects panel regression	Climate change negatively affects rural banks; agricultural insurance mitigates the effects only above a coverage threshold.
Climate change and credit risk: carbon tax on Italian banks	Aiello and Angelico (2023)	Impact of different carbon taxes on bank credit risk	Italy	Autoregressive regression model	A carbon tax of €50–200/tCO_2 has minimal short-term impact; €800/tCO_2 has a more significant but still manageable effect.
Does climate change affect sovereign credit risk?	Naifar (2023)	Link between climate change and sovereign credit risk	Worldwide	Quantile regression (panel)	Climate preparedness decreases sovereign CDS spreads; vulnerability increases them.
How climate change shapes bank lending	Meisenzahl (2023)	How banks adjust lending in response to climate change	U.S.	Fixed effects panel regression	After the 2014 UN Climate Summit, banks reallocated portfolios away from high-climate-risk regions.
Climate risk and capital structure	Ginglinger and Moreau (2023)	How climate risk affects capital structure	Worldwide	IV (2SLS with FE); DiD	Firms with higher climate risks have become less leveraged since the Paris Agreement; lenders charge higher rates to riskier firms.

Table 3. *Cont.*

Title	Author(s) and Year	Research Questions	Country	Empirical Methods	Results
Feeling the heat: Climate shocks and credit ratings	Cevik and Jalles (2023)	Impact of climate change on sovereign credit ratings	Worldwide	Fixed effects panel regression; IV (2SLS); logit; probit	Climate change negatively affects credit ratings; resilient countries achieve higher ratings; developing economies are the most affected.
Climate policy relevant sectors and credit risk	Borsuk (2023)	How climate risk affects the Polish banking sector	Poland	–	Banks closely tied to carbon-intensive sectors face greater environmental and credit risks.
The impact of climate change on banking systemic risk	Wu et al. (2023)	How climate change affects systemic risk in Chinese banking	China	Quantile regression; random effects panel regression	Climate change increases banking systemic vulnerability in China; non-state-owned commercial banks are more affected than state-owned banks.
Climate-change scenarios require volatility effects	Aguais and Forest (2023)	How climate change-induced volatility affects credit losses	U.S.	Simulation	Climate change significantly affects credit losses through increased volatility; financial institutions need to integrate climate risk.
How environmental performance affects firms' access to credit	Zhang (2021)	Effect of environmental performance on bank lending decisions	Europe	Logit	Firms with higher environmental performance are more likely to obtain loan approval and face fewer collateral requirements.
Carbon emissions and default risk	Kabir et al. (2021)	How carbon emissions impact firms' default risk	Worldwide	IV (2SLS)	Carbon emissions negatively impact firms' distance to default.
The impact of climate change on the cost of bank loans	Javadi and Masum (2021)	Whether banks consider climate change in loan contracts	U.S.	Fixed effects panel regression	Climate risk affects firms' cost of capital; banks should factor it into loan pricing.
A case study of climate change on agricultural credit risk	Kaur Brar et al. (2021)	Best agricultural lending portfolios for climate scenarios	Canada	Simulation	Climate change significantly impacts agricultural loan repayments; climate factors must be integrated into agricultural risk management.
Climate risk and credit-risk assessment: Poland	Nehrebecka (2021)	How climate risk influences credit-risk assessment in Poland	Poland	Stress test; logit	A direct carbon tax raises the PD for CO_2-emitting firms from 3.6% to 6.31–10.12% depending on the scenario.
What do you think about climate finance?	Stroebel and Wurgler (2021)	Investor views on climate risks	Worldwide	Descriptive statistics	Regulatory risk is the most important near-term climate threat; physical risk is the main long-term concern; assets undervalue climate risks.
Climate change news risk and corporate bond returns	Huynh and Xia (2021)	How climate news risk affects corporate bond returns	U.S.	Fixed effects panel regression	Bonds sensitive to climate news have lower future returns; investors favour bonds from high-environmental-performance issuers.
The impact of climate risk on corporate credit risk	Bell and van Vuuren (2022)	How climate risks affect corporate credit risk	African countries	Simulation	Climate events significantly affect corporate default probabilities and asset volatility.
Does climate change affect bank lending behavior?	Aslan et al. (2022)	How banks in high-climate-risk regions adjust credit supply	Turkey	Fixed effects panel regression	Banks reduced lending in higher-pollution areas after the Paris Agreement.
Climate change commitment, credit risk and environmental performance	Birindelli et al. (2022)	Relationship between banks' climate commitment and credit risk	Worldwide	SYS-GMM	Banks with higher climate commitment have lower credit risk, especially in high-environmental-performance countries.

Table 3. *Cont.*

Title	Author(s) and Year	Research Questions	Country	Empirical Methods	Results
Firm climate risk, risk management, and bank loan financing	Huang et al. (2022)	How firm climate risk affects bank loan conditions	U.S.	OLS; Poisson; logit	Firms with higher climate risk receive unfavourable loan terms; high climate risk is associated with higher PD and stricter conditions.
No need to worry? German banking and transition risks	D'Orazio et al. (2024)	Exposure of the German banking sector to climate transition risks	Germany	Simulation	German banks face direct transition risks; large private banks are at higher risk.
Predicting corporate carbon footprints	Nguyen et al. (2021)	How to improve corporate carbon emission prediction	Worldwide	Machine learning	Machine learning can predict corporate carbon emissions from observable financial and operational data.
Climate change risk and the cost of mortgage credit	Nguyen et al. (2022)	How lenders price sea-level rise risk in mortgages	U.S.	OLS	Higher interest rates on mortgages for SLR-exposed properties; mortgage lenders treat SLR as a forward-looking credit risk.
Local banks and flood risk: Germany	Bellia et al. (2025)	Impact of river flooding on regional German banks	Germany	Simulation; stress test	Climate risk has greater effects during financial crises; a 3 °C rise could cause banking losses of up to 1% of total assets.
Climate risk and financial stability: syndicated lending	Conlon et al. (2024)	How unexpected climate shocks affect banks' systemic risk	U.S.	Fixed effects panel regression (WLS)	Exposure to climate risk through cross-state lending has a statistically and economically significant impact on bank risk.
Climate risk and the systemic risk of banks: A global perspective	Wu et al. (2024)	Global implications of climate risk for banking systemic stability	Worldwide	Fixed effects panel regression	Climate risk significantly increases banks' systemic risk; profitability and capital adequacy buffer the effect.
Climate risks, financial performance and lending growth	Chalabi-Jabado and Ziane (2024)	How physical and transition risks affect bank performance and lending	Worldwide	GMM	Transition risks positively affect bank performance and lending; physical risks have negative effects driven by extreme weather unpredictability.
Climate change fueling non-performing loans in China	Fan et al. (2024)	Relationship between climate change and NPL ratios in China	China	SYS-GMM	Temperature fluctuations significantly increase NPL ratios; precipitation changes have a less significant effect.
Climate change shocks and credit risk in Chinese banks	Liu et al. (2024)	How temperature fluctuations affect NPL ratios in Chinese banks	China	Fixed effects panel regression; GMM; IV	A 1 °C rise in average temperature is associated with a 0.1107 percentage point increase in the NPL ratio; smaller and rural banks are the most sensitive.
Does disaster risk relate to banks' loan loss provisions?	Dal Maso et al. (2024)	How banks adjust loan loss provisions in response to disaster risk	U.S.	DiD; panel regression	A positive link between disaster risk and loan loss provisions; a 1 SD increase in disaster risk raises LLP by 5.4–7.0%.
Climate change transition risk and bank profitability: South Korea	Kim and Moh (2025)	How transition risk affects bank profitability in South Korea	South Korea	Fixed effects panel regression	Transition risk lowers bank profitability; strong climate performance improves it; large loan exposure reduces the positive climate impact.

4. A Methodological Review

The review of empirical studies shows that researchers have applied a wide range of analytical methods, each with specific strengths and limitations in the context of climate-related credit risk.

OLS and fixed effects models. OLS regression is widely used for its simplicity and interpretability, but its assumptions of homoscedasticity and no autocorrelation may not hold in climate-finance settings. Nguyen et al. (2022) employed OLS to examine mortgage pricing under sea-level rise risk, noting that backward-looking models may overlook the evolving nature of climate risks. Bauer and Hann (2010) used OLS to study how environmental performance affects banks' lending conditions. Fixed effects specifications control for time-invariant unobserved heterogeneity (Huynh and Xia 2021) and are common in this body of literature—for example, Aslan et al. (2022) use them to examine credit supply responses to climate exposure—but cannot identify effects of time-invariant variables such as a bank's baseline geographic exposure.

Binary choice models. When the dependent variable is binary, logit and probit models are more appropriate. Zhang (2021) applied a logit model to examine how environmental performance influences banks' lending decisions. Bauer and Hann (2010) used an ordered probit to account for the ordinal nature of credit ratings. These models are well suited to estimating PD as a function of climate and financial covariates, though coefficient interpretation can be challenging, particularly for ordered outcomes.

IV and GMM approaches. The IV approach (typically 2SLS) addresses endogeneity and reverse causality (Ginglinger and Moreau 2023). De Haas and Popov (2023) used 2SLS to examine financial development and carbon emissions, introducing exogenous shocks to financial sector composition. Cevik and Jalles (2023) validated their instruments with Kleibergen–Paap and Hansen tests. Birindelli et al. (2022) employed SYS-GMM to address endogeneity in panel data, though instrument proliferation can distort estimates in smaller samples (Alsagr and van Hemmen 2021). Chalabi-Jabado and Ziane (2024) highlighted the usefulness of SYS-GMM for unbalanced panels and its robustness to autocorrelation and heteroskedasticity.

Quantile regression and autoregressive models. Wu et al. (2023) applied quantile regression to capture heterogeneous climate effects across the risk distribution—offering richer insights than mean-based approaches, though requiring large samples for stable estimates (Naifar 2023). Aiello and Angelico (2023) applied an autoregressive model to carbon tax scenarios, capturing short-term dynamics but at the cost of overlooking longer-term macroeconomic adjustments. Höck et al. (2020) used random effects with time-clustered White standard errors to examine environmental sustainability and credit risk.

Machine learning. Nguyen et al. (2021) compare OLS with machine learning algorithms for predicting carbon emissions. Barboza et al. (2017) show that machine learning models can improve predictive performance relative to conventional statistical models in some bankruptcy-prediction settings, although the magnitude of the gain is model- and data-dependent. The interpretability trade-off remains a key limitation for regulatory and risk-management applications.

Simulation-based approaches. Bell and van Vuuren (2022) combine Geometric Brownian Motion with a Merton-based structural model to estimate default probabilities under climate shocks—forward-looking but reliant on simplifying assumptions such as normally distributed returns. Kaur Brar et al. (2021) use a Conditional Value at Risk simulation to evaluate climate-related agricultural credit risk, though results depend heavily on simulated yield data. Bellia et al. (2025) combine a micro-simulation portfolio model with Monte Carlo procedures to assess systemic exposure to flooding events. Supervisory stress-testing exercises by national central banks have adopted similar top-down simulation approaches at a systemic level: Vermeulen et al. (2018) was among the first to develop a quantitative energy-transition-risk stress test for a national financial system, finding that losses for Dutch financial institutions in disruptive transition scenarios could be sizeable but manageable and illustrating how industry-specific PD adjustments can be derived from macroeconomic transition scenarios.

In summary, each method captures some dimensions of climate-related credit risk while leaving others inadequately addressed. These differences highlight the need for careful methodological choice in future research. The following section outlines analytical perspectives that may help address some of these shortcomings. Among the unresolved challenges identified in the literature, the treatment of sparse default events and heterogeneous climate exposures appears particularly important for firm-level credit-risk modelling.

5. Methodological Considerations for Future Research

In empirical analyses of bank credit risk under climate change, researchers often rely on binary-outcome data—whether a firm has defaulted or survived—which naturally calls for binary-response econometric models, most commonly logit regression or its extensions (Hosmer et al. 2013). Logit models are well suited to estimating the PD as a function of firm characteristics, sectoral attributes, and climate-related exposures (Nehrebecka 2021; Zhang 2021).

However, when the dataset contains many qualitative or sparse variables, the issue of (quasi-)complete separation often arises (Lesaffre and Albert 1989). This occurs when certain predictors almost perfectly divide defaulting from non-defaulting observations, causing standard maximum likelihood estimates to become unstable or undefined. Convergence failures and inflated coefficients are typical symptoms that undermine the interpretability and reliability of the model.

A promising direction is to consider a Bayesian reformulation of the logit model (Fontana et al. 2019). By introducing weakly or moderately informative priors, the estimation process can be regularised to yield more stable posterior estimates (Gelman et al. 2008). Prior information acts as a penalisation mechanism that may mitigate separation while allowing for coherent probabilistic inference. Hierarchical Bayesian logistic extensions can further accommodate unobserved heterogeneity across firms, regions, or sectors (Allenby and Rossi 2006; Congdon 2014; Fontana et al. 2019)—particularly useful when modelling climate-related credit exposures that depend on both firm-level and contextual factors. It should be noted that this discussion is conceptual in nature and does not constitute an empirical validation of these properties in the specific context of climate-related credit risk.

When the analytical goal is purely predictive—identifying firms at risk of failure without quantifying the marginal contribution of each determinant—the methodological focus shifts toward classification performance. In this setting, traditional econometric models (logit, multilevel logistic, and Bayesian logit) are considered alongside machine learning algorithms such as SVM, naive Bayes classifiers, and CIT (Guerzoni et al. 2021; James et al. 2013, 2023), as well as more recent deep learning architectures and survival analysis methods, evaluated using cross-validated metrics such as the AUC, accuracy, and Brier scores.

The methodological discussion is organised as follows: First, we present the logit and multilevel logistic model (MLM) frameworks and discuss the quasi-complete separation problem. Second, we outline the Bayesian reinterpretation of these models as a conceptual analytical perspective. Third, we consider classical machine learning classifiers, highlighting the trade-off between interpretability and predictive performance. Fourth, we discuss deep learning approaches and survival analysis methods. Finally, we provide a structured illustrative comparison of the alternative modelling approaches discussed, assessing their suitability under data conditions typical of climate-finance research. Figure 1 illustrates the main stages of the modelling discussion.

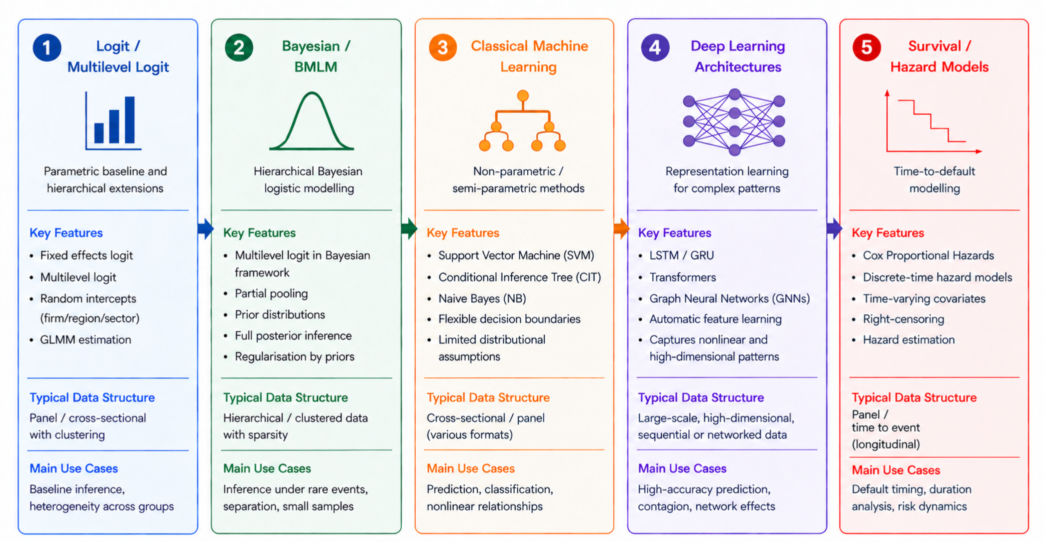

Figure 1. Methodological roadmap for climate-related credit-risk assessment.

5.1. *Logit and Multilevel Logistic Models*

Logit regression has become a standard choice for modelling firm-level credit risk. The model estimates the PD as a function of explanatory variables capturing firm characteristics, financial conditions, and climate-related exposures. Its main strength is the ability to assess multiple factors simultaneously, producing coefficients interpretable as changes in the odds of default. For these reasons, logit and related binary-response models are widely used in empirical analyses of credit risk (Klomp 2014; Zhang 2021).

We model the credit risk faced by a bank that has extended a loan to firm i ($i = 1, \ldots, n$) as a binary outcome: $Y_i = 1$ if the firm defaults and $Y_i = 0$ otherwise. Following random utility theory (Train 2003), the probability that firm i defaults, derived from the logit model (Luce and Suppes 1965; McFadden 1974), is:

$$\pi_i = \mathrm{P}(Y_i = 1 \mid \mathbf{x}_i) = \frac{\exp(\mathbf{x}_i'\boldsymbol{\beta})}{1 + \exp(\mathbf{x}_i'\boldsymbol{\beta})}, \tag{1}$$

where $\mathbf{x}_i$ is the vector of explanatory variables—financial indicators (e.g., leverage and liquidity), sectoral characteristics, and climate-related exposures—and $\boldsymbol{\beta}$ is the corresponding parameter vector. The logistic specification is consistent with random utility models based on extreme-value errors and provides a tractable framework for binary default modelling.

A brief note on interpretation is warranted. The elements of $\boldsymbol{\beta}$ are on the log-odds scale: a unit increase in covariate x_j, holding all other variables constant, changes the log-odds of default by β_j, which corresponds to an odds ratio of $\exp(\beta_j)$. The implied effect on the predicted probability of default is, however, nonlinear and depends on the values of all covariates: $\partial \pi_i / \partial x_{ij} = \beta_j \pi_i (1 - \pi_i)$. When the substantive interest concerns changes in the probability of default—for instance, the increase in PD associated with a one-standard-deviation increase in a firm's carbon intensity—marginal effects or average marginal effects (AMEs), computed by averaging the derivative across the observed covariate distribution, provide a more directly interpretable summary than the raw log-odds coefficients.

To account for dependence among firms sharing a common context—region, industry, or lending institution—we extend the model to a multilevel logistic specification (Goldstein 2011; Snijders and Bosker 2012). Multilevel logistic models extend standard logit regression by introducing random effects that capture unobserved heterogeneity and within-cluster dependence (Nava et al. 2016). Let Y_{kr} denote the default status of firm r ($r = 1, \ldots, R_k$) within cluster k ($k = 1, \ldots, K$). We introduce a cluster-specific random intercept $u_k \sim \mathcal{N}(0, \sigma_u^2)$ capturing unobserved heterogeneity at the cluster level—such as regional macroeconomic conditions, climate-policy intensity, or bank-specific credit standards. The multilevel logistic PD is then:

$$\pi_{kr} = \Pr(Y_{kr} = 1 \mid \mathbf{x}_{kr}, u_k) = \frac{\exp(\mathbf{x}_{kr}'\boldsymbol{\beta} + u_k)}{1 + \exp(\mathbf{x}_{kr}'\boldsymbol{\beta} + u_k)}.$$

This hierarchical structure accounts for intra-cluster correlation and is particularly relevant when firms are nested within shared environments such as bank portfolios or regional climate-risk zones (Snijders and Bosker 2012).

(Quasi-)Complete Separation

Separation is a common problem in firm-level logit models: it arises when one or more explanatory variables—or their linear combinations—perfectly or near-perfectly predict the binary outcome (Hosmer et al. 2013). Under complete separation, outcome categories can be perfectly divided by one or more covariates; under quasi-complete separation, the division is nearly perfect with only a few exceptions. In both cases, maximum likelihood estimates diverge toward extremely large values with inflated standard errors (Amemiya 1985; Webb et al. 2004), rendering conventional inferential tools unreliable (Albert and Anderson 1984; Zorn 2005).

Separation arises when too many predictors are included relative to the sample size, when categorical variables contain sparse categories, or when strong multicollinearity exists among covariates (Zeng and Zeng 2021). The standard response of removing problematic variables can be counterproductive when those variables—such as indicators of climate exposure or sectoral vulnerability—are precisely the ones that genuinely distinguish defaulting from solvent firms.

The severity of rare-event and separation problems is, however, portfolio- and sample-dependent and should not be treated as a universal feature of climate-finance data. In portfolios of large corporate or high-credit-quality borrowers, annual default rates may be very low and sector-level cells may contain few or no observed defaults, making quasi-complete separation a potentially important concern. In contrast, SME portfolios typically contain larger borrower populations and higher observed default frequencies, so that rare-event bias and separation are less likely to be the binding constraint; in such settings, other modelling challenges such as unobserved heterogeneity, measurement error, and endogeneity may be more pressing. Analysts should therefore assess the severity of the separation problem in their specific sample before selecting a remedial approach.

Where separation is indeed a concern, two established approaches are available. Firth's penalised likelihood (Firth 1993) removes the first-order term in the bias of the maximum likelihood estimator by augmenting the score equations with a penalty proportional to the observed information. Firth's method has the practical advantage of not requiring explicit specification of a prior distribution, which makes it straightforward to apply without subjective choices about prior hyper-parameters; it has been widely validated in finite-sample settings and is particularly tractable for single-level models. Bayesian logit regularisation (Gelman et al. 2008) addresses separation by specifying weakly or moderately informative prior distributions on the coefficients, which constrain extreme estimates without requiring the data alone to identify them. Bayesian hierarchical models can additionally accommodate multilevel heterogeneity through partial pooling across clusters—an advantage in settings where firms are nested within banks or regions with systematically different climate exposures. Bayesian regularisation may therefore be particularly useful in sparse hierarchical settings but is not universally necessary, and method choice should depend on the empirical objective, the data structure, and the analyst's tolerance for prior specification. Neither approach completely eliminates identification problems when separation is extreme, and both should be applied with appropriate sensitivity checks. Rare-event logit corrections (King and Zeng 2001) provide an additional tool when the primary concern is small-sample bias in binary-outcome models.

5.2. Bayesian Multilevel Logistic Model

A Bayesian framework addresses the separation problem by introducing prior distributions $p(\boldsymbol{\beta})$ that regularise the estimation process. By specifying weakly or moderately informative priors—such as normal distributions centred around zero (Gelman et al. 2008)—the posterior distribution may remain proper even when the data are separable, yielding more stable coefficient estimates. In multilevel logistic specifications, Bayesian hierarchical modelling further stabilises estimation through partial pooling across clusters. The Bayesian approach may therefore help mitigate the inferential issues induced by separation, particularly in small or unbalanced samples—though empirical validation in climate-finance settings remains an important direction for future research.

In the Bayesian framework, parameters are treated as random variables assigned prior distributions. After observing the data, the prior is updated via the likelihood to form the posterior:

$$\pi(\boldsymbol{\theta}|\mathbf{Y}) \propto L(\mathbf{Y}|\boldsymbol{\theta})\,\pi(\boldsymbol{\theta}),$$

from which estimates are derived. This approach provides a full probabilistic characterisation of parameter uncertainty—particularly valuable in credit-risk models affected by separation or limited data.

Under this perspective, we model the PD for firm i in bank k's portfolio as:

$$\operatorname{logit}(\pi_{ik}) = \alpha + \boldsymbol{f}'\boldsymbol{\beta}^{f} + \boldsymbol{s}'\boldsymbol{\beta}^{s} + \boldsymbol{c}'\boldsymbol{\beta}^{c} + u_k, \tag{2}$$

where $\boldsymbol{f}$, $\boldsymbol{s}$, and $\boldsymbol{c}$ represent, respectively, firm-level financial indicators (e.g., leverage and profitability), sectoral or macroeconomic characteristics, and climate-related exposures such as carbon intensity or vulnerability to physical risks. The bank-specific random intercept $u_k \sim \mathcal{N}(0, \sigma_u^2)$ captures unobserved heterogeneity in lending practices and credit standards.

The Bayesian multilevel logistic model (BMLM) considered here (Goldstein 2011; Nava et al. 2016) places independent weakly informative normal priors on the fixed effects coefficients $\boldsymbol{\beta}$ (Gelman et al. 2008). For the scalar random-intercept variance σ_u^2, a proper weakly informative scale prior—such as a half-normal or half-t prior—is preferred over diffuse or improper alternatives, as it regularises the variance estimate while remaining dominated by the data in typical sample sizes (Gelman 2006; Gelman et al. 2008). Weakly informative proper priors regularise coefficient estimates while allowing the likelihood to remain influential; sensitivity to alternative prior specifications should be assessed explicitly when applying this framework. Since the posterior lacks a closed form, approximation can be conducted using Markov chain Monte Carlo methods, including Gibbs or Metropolis-based algorithms, or modern Hamiltonian Monte Carlo implementations. In practice, convergence of the Markov chains should be monitored using standard diagnostics such as the potential scale reduction factor ($\hat{R}$) and effective sample size; satisfactory convergence is a prerequisite for drawing reliable inferences from the posterior. Bayesian model assessment may rely on posterior predictive checks and predictive information criteria where appropriate.

The Bayesian formulation offers several potential advantages over its classical counterpart: greater flexibility in handling complex hierarchical structures, stability under milder regularity conditions, and—most relevantly for this context—the capacity to address quasi-complete separation. Bayesian multilevel logistic models are well established within the broader hierarchical-modelling literature and provide a natural framework for binary outcomes observed within clustered or nested data structures (Congdon 2014; Goldstein 2011; Snijders and Bosker 2012). The BMLM may be well suited to modelling firm-level credit risk in the presence of climate-related exposures, providing a conceptually coherent structure for analysing both systematic and idiosyncratic components of credit risk. Empirical validation in climate-finance applications remains an important direction for future research.

5.3. Classical Machine Learning Classifiers

When the analytical goal is prediction rather than inference—identifying firms at risk without quantifying the marginal contribution of each determinant—the methodological focus shifts to classification performance. This is particularly relevant in climate-related credit risk, where environmental shock transmission is complex and often nonlinear. Banks and researchers increasingly rely on machine learning models to anticipate defaults and assess portfolio resilience in different climate scenarios (Yu et al. 2022).

Three classical machine learning classifiers are particularly relevant in this context. SVM identifies the hyperplane that best separates defaulting from non-defaulting firms by maximising the margin between classes (Noble 2006). Kernel functions extend this to nonlinear boundaries, making SVM well suited to integrating financial and environmental indicators in high-dimensional settings (Khan et al. 2021). Barboza et al. (2017) show that machine learning models including SVM can outperform traditional statistical approaches in bankruptcy prediction when applied to large panel datasets. The naive Bayes (NB) classifier computes default probabilities using Bayes' theorem under a conditional independence assumption and can provide a simple probabilistic benchmark for classification tasks (Berrar 2018). The conditional inference tree (CIT) recursively partitions the data into homogeneous subgroups using statistical tests to identify the most informative splits (Hothorn et al. 2006), capturing nonlinear relationships and variable interactions without imposing parametric assumptions.

Across these methods, the emphasis shifts from inference on a prespecified parametric relationship toward flexible out-of-sample prediction. Performance is optimised through cross-validation and assessed using ROC curves and AUC statistics (Fawcett 2006; Marzban 2004; Thompson and Zucchini 1989)—providing an objective basis for comparing models that incorporate both financial and environmental variables as early warning tools for credit-risk management (Battiston et al. 2021).

5.4. Deep Learning Approaches

Beyond classical machine learning, a growing body of literature has explored deep learning architectures for credit-risk prediction. These models can capture complex temporal dependencies, relational structures among borrowers, and nonlinear interactions between financial and climate-related variables that may be beyond the reach of shallow machine learning methods.

Recurrent neural networks (RNNs) and their variants—long short-term memory (LSTM) and gated recurrent unit (GRU) networks—are particularly suited to sequential credit data, where default risk evolves over time as a firm's financial conditions and climate exposures change. Kriebel and Stitz (2022) demonstrate that deep learning architectures can improve default prediction in peer-to-peer lending using user-generated text data, outperforming shallower models in out-of-sample AUC. LSTM networks, in particular, have been applied to capture the temporal dynamics of credit deterioration (Gunnarsson et al. 2021), making them potentially useful in climate-finance contexts where physical and transition risks unfold over extended time horizons.

Transformer models adapt the self-attention mechanism originally developed for natural language processing to financial time series and tabular data. By weighting the relative importance of different time steps or features dynamically, transformers can in principle capture long-range dependencies between a firm's historical financial trajectory and its evolving climate exposure—a feature that is difficult to model with fixed-lag specifications. While applications in credit risk remain relatively nascent compared with natural language tasks, the architecture offers potential for integrating heterogeneous data streams (financial ratios, climate scores, and sectoral indicators) into a unified default prediction framework.

Graph Neural Networks (GNNs) model firms and financial institutions as nodes in a graph, with edges capturing relationships such as interbank exposures, supply-chain linkages, or shared sectoral membership. Wang et al. (2021) propose a temporal-aware GNN framework for credit-risk prediction that jointly models structural dependencies and temporal dynamics. In climate-finance applications, GNNs may be particularly useful for representing systemic contagion and network-based transmission mechanisms—for example, how a climate shock affecting a carbon-intensive sector propagates through supply-chain networks to downstream lenders. By encoding both firm-level features and network topology, GNNs can represent network dependencies more directly than conventional static regression specifications.

Despite their predictive power, deep learning methods share important limitations in credit-risk applications: they typically require large labelled datasets, are computationally intensive, and—crucially—produce opaque predictions that are difficult to explain to regulators and risk managers (Gunnarsson et al. 2021). The interpretability constraint is especially binding in climate-finance contexts, where the causal pathway from climate exposure to credit loss must be communicable to supervisors and policymakers. Research on explainable AI (XAI) techniques—such as SHAP values and attention visualisation—is actively working to address this gap, but the trade-off between predictive accuracy and interpretability remains a key challenge for the deployment of deep learning in regulatory credit-risk assessment.

5.5. Survival Analysis and Hazard Models

Survival analysis models the time to default rather than the binary occurrence of default within a fixed observation window and complements both logit-based and machine learning approaches. This distinction is particularly relevant in climate-related credit risk, where the timing of default—not just whether a firm defaults—carries important information about the nature and severity of climate shocks.

The Cox proportional hazards (CPH) model (Bellotti and Crook 2009) is the most widely used survival approach in credit-risk modelling. The hazard function takes the form:

$$h(t \mid \mathbf{x}_i) = h_0(t)\exp(\mathbf{x}_i'\boldsymbol{\beta}), \tag{3}$$

where $h_0(t)$ is a baseline hazard function, $\mathbf{x}_i$ is the vector of covariates for firm i, and $\boldsymbol{\beta}$ denotes the estimated coefficients. The key advantage of the CPH model over logit regression is its ability to handle right-censored observations—firms that have not yet defaulted by the end of the observation window—without discarding them from the analysis. This is important in climate-finance datasets, where the realisation of climate risks may be delayed or incomplete during the observation period.

Discrete-time hazard models (Shumway 2001) offer an alternative formulation that links survival analysis to standard logit regression, making them straightforward to estimate and interpret while retaining the ability to accommodate time-varying covariates such as evolving climate risk scores, carbon price trajectories, or cumulative exposure to physical climate events. Bellotti and Crook (2009) demonstrate that including macroeconomic variables within a survival framework improves out-of-sample default prediction relative to static logit models. Dirick et al. (2017) provide a benchmark comparison of survival models for credit scoring, finding that spline-based extensions of the CPH model and mixture cure models—which distinguish firms that will eventually default from those that will not—perform well across multiple evaluation criteria.

In the context of climate-related credit risk, survival analysis offers several conceptual advantages. First, it naturally accommodates the time-varying nature of climate exposures: firms' carbon intensity, regulatory burden, and physical vulnerability change over time, and these dynamics can be incorporated as time-varying covariates in the hazard function. Second, survival models provide duration-specific risk estimates—when a default is likely to occur, not just whether it will—which is more informative for banks' provisioning decisions and stress-testing exercises. Third, mixture cure models are particularly useful in climate-finance settings where not all firms are expected to eventually default: some will successfully adapt to climate regulation or reduce their carbon exposure over time, meaning that the population is heterogeneous in its long-run default propensity.

5.6. Illustrative Comparison of Modelling Approaches

Given that this paper is designed as a critical methodological review rather than an original empirical contribution, we do not estimate a new model. A single empirical application would necessarily be limited to one dataset, country, and institutional context. Instead, we provide a structured methodological comparison designed to clarify under which data conditions each modelling approach is the most appropriate.

Table 4 presents an illustrative comparison of seven modelling approaches discussed in this paper—standard logit, multilevel logistic model (MLM), Bayesian logit, Bayesian multilevel logistic model (BMLM), classical machine learning classifiers (SVM, CIT, and NB), deep learning (LSTM/GRU, Transformer, and GNNs), and survival/hazard models—evaluated against eight dimensions that are particularly relevant for climate-related credit-risk modelling. The comparison is based on theoretical properties established in the methodological literature cited throughout this section, rather than on original empirical estimation. It is intended as a structured analytical guide for researchers and practitioners selecting a methodology among these approaches.

The evaluation dimensions are: (1) the handling of quasi-complete separation; (2) accommodation of unobserved heterogeneity across clusters (banks and regions); (3) performance under rare-event data structures typical of credit-risk datasets (King and Zeng 2001); (4) interpretability of parameter estimates for regulatory and policy purposes; (5) predictive accuracy in out-of-sample settings; (6) ability to model time to default rather than binary default; (7) computational tractability; and (8) suitability for small or unbalanced samples with sparse sector coverage.

The comparison in Table 4 highlights several patterns. Standard logit is the most computationally tractable and interpretable approach but performs poorly under quasi-complete separation and does not accommodate hierarchical data structures or temporal dynamics. MLM and BMLM improve on this by incorporating cluster-level random effects. The Bayesian specifications may improve estimation stability under sparse data conditions when appropriate priors are specified, though this is conditional on prior choice and sample structure. Classical machine learning classifiers can offer strong predictive performance and flexibility but sacrifice interpretability. Deep learning architectures can offer high predictive potential when sufficiently large and informative training datasets are available but require substantial computational resources, are sensitive to architecture and hyper-parameter choices, and produce opaque outputs that are difficult to communicate to regulators. Survival and hazard models fill a distinct niche: they model when default occurs, accommodate time-varying covariates, and handle right-censored observations—advantages that are particularly relevant for climate-finance applications with long-horizon risk dynamics.

Table 4. Illustrative comparison of modelling approaches for climate-related credit risk.

Criterion	Standard Logit	Multilevel Logistic (MLM)	Bayesian Logit	Bayesian Multilevel Logistic (BMLM)	ML Classifiers (SVM, CIT, and NB)	Deep Learning (LSTM, GRU, Transformer, and GNNs)	Survival/Hazard Models
Handles quasi-complete separation	✗	✗	✓ *	✓ *	N/A	N/A	✗
Accommodates cluster heterogeneity	✗	✓	✗	✓	✗	Partial †	Partial; yes with frailty/multilevel extensions
Robust to rare events	Limited	Limited	Potentially suitable *	Potentially suitable *	Depends on class balance ‡	Depends on class balance ‡	Depends on event count/specification
Interpretability of parameters	High	High	High	High	Low	Very Low	High
Out-of-sample predictive accuracy	Moderate	Moderate	Moderate	Moderate	High	High, data-dependent ‡	Moderate
Models time to default	✗	✗	✗	✗	✗	Partial	✓
Computational tractability	High	Moderate	Moderate	Low	Moderate–High	Low	Moderate
Suitable for small/unbalanced samples	Limited	Limited	Depends on sample structure *	Depends on sample structure *	Limited	✗	Limited

Note: ✓ = suitable; ✗ = not suitable or limited; N/A = not directly applicable. ML = machine learning; SVM = support vector machine; CIT = conditional inference tree; NB = naive Bayes; LSTM = long short-term memory; GRU = gated recurrent unit; GNN = graph neural network. * Bayesian models mitigate quasi-complete separation and may be suitable for small/unbalanced samples when weakly or moderately informative priors are specified; assessments are therefore conditional on appropriate prior choice and sample structure (Gelman et al. 2008). † GNNs can accommodate heterogeneity through graph structure (e.g., supply-chain or interbank networks) but do not model hierarchical clustering in the same sense as multilevel logistic specifications. ‡ Performance of ML and deep learning classifiers under rare events depends on class imbalance, sample size, resampling or weighting strategy, architecture choice, and hyper-parameter tuning; "High, data-dependent" indicates potential rather than guaranteed performance (Barboza et al. 2017; Gunnarsson et al. 2021). Assessments are based on theoretical properties established in the methodological literature (Albert and Anderson 1984; Bellotti and Crook 2009; Dirick et al. 2017; Gunnarsson et al. 2021; Hosmer et al. 2013; Hothorn et al. 2006; King and Zeng 2001; Noble 2006; Snijders and Bosker 2012; Train 2003). They are intended as a structured conceptual guide and do not reflect original empirical estimation.

Three illustrative cases help clarify when each approach may be most appropriate.

Illustrative Case A (rare events and sparse sectors). Consider a dataset of 1000 firms across 15 industry sectors, with an overall default rate of 3% and no defaults observed in two carbon-intensive sectors. This case is the most relevant for large corporate or high-credit-quality portfolios; SME datasets with higher base default rates are less likely to encounter the same degree of separation. Standard logit is likely to encounter complete or quasi-complete separation for the corresponding sector indicator variables, producing unstable or undefined coefficient estimates (Albert and Anderson 1984). Both Firth's penalised likelihood (Firth 1993) and Bayesian logit regularisation (Gelman et al. 2008) are established remedies. Firth's method has the advantage of not requiring explicit prior specification and is straightforward to apply in single-level settings. Bayesian regularisation with weakly informative priors constrains extreme coefficient estimates in a probabilistic framework; when the data are also hierarchically structured—for instance, if firms are nested within bank portfolios—Bayesian hierarchical specifications can additionally accommodate partial pooling across clusters, which Firth's method does not naturally provide. Method choice between these two approaches should depend on the data structure and the analyst's modelling objectives.

Illustrative Case B (hierarchical structure with bank heterogeneity). Consider a panel of firms nested within 30 bank portfolios, where banks differ in their credit standards, regional exposure to climate risk, and sectoral concentration. A standard logit model ignoring the bank-level clustering may understate uncertainty and produce overly precise inference when within-cluster dependence is ignored (Snijders and Bosker 2012). The MLM and BMLM explicitly model the bank-level random intercept, enabling the separation of firm-level from portfolio-level risk drivers and recovering appropriate uncertainty quantification.

Illustrative Case C (predictive screening for early warning). Consider a supervisory context in which the goal is to flag firms at elevated risk of default in the next quarter, using a large dataset combining financial ratios, sectoral affiliations, climate risk scores, and time series of past financial performance. When out-of-sample predictive performance is the primary objective, SVM and CIT classifiers may be attractive candidates, as they do not impose parametric assumptions and can capture nonlinear relationships between climate indicators and default. LSTM or GRU networks may offer additional flexibility in capturing temporal trajectories of climate exposure—for instance, when a firm's carbon intensity has been rising over several quarters—though their advantage over classical classifiers depends on data availability and architecture choices. For supervisory applications where model transparency is required, Bayesian logit offers an alternative probabilistic classifier with coefficient-level interpretability that may be valuable in supervisory applications. When the relevant outcome is time to default rather than binary default, discrete-time hazard models or the CPH model provide a natural framework.

These illustrative cases show that the choice of modelling approach should be driven by the specific analytical objective, the data structure, and the institutional context. No single approach dominates across all dimensions. The contribution of this comparison is therefore not to rank modelling families unconditionally but to clarify the empirical settings in which their respective strengths become most relevant. A hybrid strategy—using BMLM for inferential analysis, machine learning or deep learning for predictive screening, and survival models for duration-specific risk assessment—may offer a useful framework for applied climate-related credit-risk assessment.

6. Conclusions

This paper has reviewed the literature on climate-related credit risk and its implications for the banking sector. The evidence consistently shows that bank exposure to climate hazards can substantially affect credit quality, lending conditions, and overall financial stability. Scholars have applied various empirical and analytical approaches to study the connection between climate change and credit risk, and while these methods have contributed valuable insights, they each face challenges related to robustness, interpretability, and predictive accuracy.

The critical synthesis in Section 3.1 highlights several unresolved tensions in the literature: the estimated magnitudes of climate effects on credit risk vary substantially across studies; the effects of physical and transition risks appear to operate through distinct channels; cross-country comparability is limited by the absence of harmonised risk taxonomies; identification of causal effects remains challenging due to endogeneity concerns;

and the temporal dimension of climate risk transmission is inadequately modelled in most studies. These observations underscore the need for greater methodological rigour and transparency in future empirical work.

Building on the existing literature, this paper outlines a methodological framework for analysing firm-level credit risk in the context of climate-related exposures. The approach starts from the classical logit model, extends it into a multilevel logistic model (MLM) to account for unobserved heterogeneity and within-cluster dependence, and then considers a Bayesian reformulation, yielding the Bayesian multilevel logistic model (BMLM). The BMLM specification may help address empirical challenges such as quasi-complete separation and instability in small samples, producing more stable posterior estimates even when explanatory variables are sparse or highly correlated. The inclusion of random effects allows the model to capture unobserved variation across banks, industries, and regions—a relevant capability for assessing the uneven effects of physical and transition climate risks.

This paper also discusses deep learning approaches—including LSTM, GRU, Transformer, and GNN architectures—which offer the potential to capture complex temporal dependencies and relational structures in credit-risk data, at the cost of interpretability and data requirements. For applications where the timing of default is the primary outcome of interest, survival analysis methods including the Cox proportional hazards model and discrete-time hazard models provide a natural complement to the binary-outcome framework, accommodating time-varying climate exposures and right-censored observations.

The structured comparison in Section 5.6 shows that the appropriate modelling approach depends on the analytical objective and data structure. No single method dominates across all settings. BMLM specifications may be particularly attractive when inferential interpretability and stability under sparse hierarchical data conditions are the primary concern and where explicit prior specification is feasible; machine learning and deep learning classifiers may offer strong predictive performance in applications with large, well-balanced datasets, though their accuracy is data-, architecture-, and tuning-dependent; and survival models provide the most natural framework when duration-specific risk assessment is required. The appropriate choice ultimately depends on the trade-offs among inference versus prediction, hierarchical structure, sparsity, interpretability requirements, temporal dynamics, and data availability. The principal methodological contribution of this review is therefore a structured mapping of research objectives, data characteristics, and modelling choices, with BMLM representing one particularly relevant option for sparse hierarchical settings rather than a universally preferred specification. In all cases, the absence of original empirical validation in this paper means that any performance claims remain conceptual and should be understood as hypotheses to be tested in future applied work.

From a policy standpoint, the methodological perspectives outlined here suggest several potential directions. Bayesian multilevel logistic specifications, by accounting for unobserved heterogeneity and stabilising estimates in sparse datasets, may improve the reliability of firm-level credit-risk assessments—relevant for regulatory stress testing and macroprudential oversight. The integration of Bayesian inference with predictive machine learning and deep learning classifiers may enable a hybrid approach that balances interpretability with predictive accuracy, supporting more adaptive credit policies and capital allocation strategies. Survival analysis methods may strengthen the temporal dimension of climate risk assessment, informing banks' provisioning decisions under long-horizon climate scenarios. More broadly, these analytical perspectives may help address common data challenges in climate-finance research, including sparsity, measurement error, and uneven sectoral coverage.

Overall, the methodological perspectives outlined in this paper may contribute to the development of more forward-looking approaches to climate-related credit-risk assessment. It should be noted that this paper does not provide an empirical implementation of the discussed framework; the Bayesian multilevel logistic approach should therefore be interpreted as a conceptual and methodological contribution rather than a fully validated model. Future research is encouraged to apply and empirically evaluate these approaches using firm-level climate-finance datasets.

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Abbreviations

The following abbreviations are used in this manuscript:

2SLS	Two-Stage Least Squares
AUC	Area Under the Curve
CIT	Conditional Inference Tree
CPH	Cox Proportional Hazards
DiD	Difference in Differences
ESG	Environmental, Social, and Governance
GHG	Greenhouse Gas
GMM	Generalised Method of Moments
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
IV	Instrumental Variable
LSTM	Long Short-Term Memory
BMLM	Bayesian Multilevel Logistic Model
MLM	Multilevel Logistic Model
NB	Naive Bayes
OLS	Ordinary Least Squares
PD	Probability of Default
ROC	Receiver Operating Characteristic
RNN	Recurrent Neural Network
SLR	Sea-Level Rise
SVM	Support Vector Machine
SYS-GMM	System Generalised Method of Moments
WLS	Weighted Least Squares
XAI	Explainable Artificial Intelligence

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