Journal of
Risk and Financial Management

MDPI

Review

Climate-Related Operational Risk in Banking: A Critical Review and Methodological Roadmap

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, Piazza Vincenzo Arbarello, 8, 10122 Turin, Italy
[3] Centre Emile Bernheim de Recherche Interdisciplinaire en Gestion, Université Libre de Bruxelles, 1050 Brussels, Belgium
[4] LABORatorio Riccardo Revelli, Piazza Vincenzo Arbarello, 8, 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

Physical climate hazards—floods, storms, heatwaves, and wildfires—are increasingly disrupting banking operations and generating growing litigation and legal-risk exposures, yet operational risk remains one of the least studied channels through which climate change may affect financial institutions. This paper provides a critical review of the emerging literature on climate-related operational risk in banking, covering both physical disruptions and the legal risk dimension explicitly recognised within the Basel operational risk framework. We map the empirical evidence, critically evaluate the methodological toolkit—event studies, fixed-effects regressions, difference-in-differences, dynamic panel estimators, and logit models—and assess their suitability for a domain characterised by data scarcity, rare events, and non-linearity. Building on this assessment, we outline a conceptual methodological roadmap intended to guide future research, organised around three stages: (i) machine learning-based variable selection and anomaly detection applied to operational loss and climate databases; (ii) econometric modelling of climate-related operational events with explicit identification strategies; and (iii) agent-based modelling to simulate system-wide propagation of climate shocks. Each stage can be conceptually related to elements of the Basel operational risk framework, offering a structured research programme for academics and a diagnostic toolkit for supervisors and risk managers.

Keywords: operational risk; climate risk; non-financial risk; bank regulation; climate finance; financial stability; ESG risk; operational risk capital; machine learning; agent-based modelling

Academic Editors: Klaus Schäfer, Huong Dang and Andreas Höfer

Received: 26 May 2026
Revised: 17 June 2026
Accepted: 27 June 2026
Published: 7 July 2026

1. Key Policy Insights

- Physical climate hazards are already generating measurable operational losses for banks through infrastructure damage, service interruptions, and forced reliance on costly contingency arrangements.
- Legal and litigation risk—a component of operational risk with direct implications for regulatory capital under the Basel operational risk framework—is a rapidly growing but under-studied exposure for financial institutions facing climate-related lawsuits.
- Existing empirical methods capture some dimensions of climate-related operational risk but each has blind spots; no single approach can resolve the sparse-data, rare-event, and non-linear challenges simultaneously.

- The integration of machine learning for anomaly and pattern detection, rigorous econometric identification strategies, and agent-based modelling for systemic simulation may constitute a viable and complementary research programme to fill current gaps.
- Supervisors and risk managers need a clearer taxonomy linking climate event types to Basel operational risk event categories, enabling more systematic capital allocation and stress-testing under existing frameworks.

2. Introduction

Climate change poses growing threats to financial stability through multiple channels. Among them, climate-related operational risk represents a rapidly evolving category of non-financial risk, increasingly relevant for both microprudential supervision and enterprise risk management frameworks. One important channel is the familiar credit and market risk nexus—climate shocks erode borrower creditworthiness, impair collateral values, and reprice assets (Basel Committee on Banking Supervision, 2021b; Network for Greening the Financial System, 2020). The second channel, far less studied, operates through operational risk: the direct disruption of banks' own processes, systems, people, and infrastructure by physical climate hazards. Floods inundate branches and data centres; heatwaves degrade hardware and force staff absences; storms sever communications and power supplies; wildfires destroy physical assets and prevent employees from reaching facilities. Beyond these physical disruptions, the transition to a lower-carbon economy introduces a fast-growing legal risk exposure as banks face climate-related litigation over alleged greenwashing, inadequate climate disclosure, and financing of high-emission activities. Legal risk—explicitly included in the Basel definition of operational risk and distinct from reputational risk in that it carries direct capital requirement implications (Basel Committee on Banking Supervision, 2006)—is attracting increasing attention from supervisors (European Banking Authority, 2025; European Central Bank, 2021; Network for Greening the Financial System, 2023c) and from climate litigation scholars (Smołeńska et al., 2025). It is important to note that climate-related litigation constitutes operational risk only insofar as it generates actual legal losses; broader reputational consequences of litigation exposure fall outside the Basel operational risk perimeter.

A terminological clarification is warranted at the outset. Following the Basel framework (Basel Committee on Banking Supervision, 2006), this paper distinguishes between two related but conceptually distinct dimensions. *Operational risk of the bank* refers to losses arising from the failure of a bank's own internal processes, people, and systems—for example, IT outages caused by extreme heat overloading data centre cooling capacity, or staff absences due to flood-related mobility constraints. *Climate risk transmitted through operations*, by contrast, refers to external climate shocks that propagate through the bank's operational environment, including physical infrastructure damage, supply chain disruptions from third-party providers, and litigation losses generated by the bank's financing of high-emission activities. Both dimensions fall within the Basel operational risk perimeter, but they differ in their transmission mechanisms and require different analytical approaches.

The scale of the problem is not hypothetical. In 2024 alone, natural disasters generated an estimated USD 417 billion in direct global economic losses, of which 63% were uninsured—meaning the residual fell directly on businesses, households, and financial systems (EY, 2025). Hurricane Katrina (2005), the Western European floods of 2021, and the Los Angeles wildfires of early 2025, which produced estimated property losses of between USD 76 billion and USD 131 billion (UCLA Anderson Forecast, 2025), all caused severe and lasting disruptions to regional banking networks. Recent international reports indicate that global temperatures in 2023 and 2024 reached record highs, with successive years setting new benchmarks for extreme heat (World Economic Forum, 2024)—suggesting that such events are becoming increasingly recurrent rather than exceptional.

Regulatory pressure is accelerating. The Basel Committee on Banking Supervision (BCBS) has clarified that climate-related events can generate losses across every Basel risk category—including operational risk—and has called on banks to identify and flag climate-related losses in their operational loss databases (Basel Committee on Banking Supervision, 2021c, 2023). The European Central Bank (ECB) and the European Banking Authority (EBA) have set binding supervisory deadlines requiring banks to integrate climate risks into their risk management frameworks, stress tests, and internal capital adequacy assessment processes (European Central Bank, 2025). Yet, as Toma and Stefanelli (2022) show, many banks remain insufficiently prepared to integrate climate risks into their risk management frameworks, and operational risk remains one of the least studied channels through which climate change may affect financial institutions.

The academic literature on climate-related operational risk in banking is still nascent. Existing studies are geographically scattered, methodologically heterogeneous, and often limited to reputational or market-value effects of operational loss announcements rather than the direct, primary operational impacts of climate hazards. There is no comprehensive review that maps the field, critically evaluates its methodological toolkit, and outlines a coherent programme for future research.

This paper contributes to addressing this gap by providing a structured review of the literature and outlining directions for future research. Our contribution is threefold. First, we provide a comprehensive and up-to-date review of the empirical literature, mapping evidence across geographies, event types, and methodological approaches (Section 3). Second, we critically evaluate the methodological toolkit deployed in existing studies, assessing strengths, limitations, and suitability to the specific challenges of this domain—including the rare-event and data-scarcity problems that are particularly acute for operational risk (Section 4). Third, we outline a conceptual methodological roadmap structured around three complementary approaches—machine learning for variable selection and pattern recognition, econometric modelling for causal identification, and agent-based modelling for systemic simulation—and discuss how each can be conceptually related to the Basel framework for operational risk capital (Section 5). Importantly, this paper does not aim to propose a fully operational model but rather to clarify the structure of the problem and organise future research directions in a coherent analytical framework.

Our review is designed as a narrative literature review (Baumeister & Leary, 1997) with explicit methodological assessment, positioned between a purely qualitative narrative and a systematic meta-analysis. This format is well suited to a field that is still at an early and heterogeneous stage of development, where the primary need is conceptual mapping and identification of research priorities rather than meta-analytic aggregation.

To help the reader navigate the paper's combined scope, it is useful to clarify upfront how the three main analytical components relate to one another. Section 3 is a literature review: it maps what is already known empirically about climate-related operational risk, identifies geographic and thematic gaps, and provides the evidentiary foundation for the subsequent analysis. Section 4 is a methodological critique: it assesses the tools used in existing studies—not as a textbook introduction but as a targeted evaluation of their suitability and limitations for this specific research problem. Section 5 is a forward-looking research agenda: it builds directly on the gaps and limitations identified in the preceding sections to propose a coherent programme of future research. The Discussion (Section 6) then addresses cross-cutting issues that span all three components. This layered structure is intentional: each section informs the next, and together they are designed to bridge the gap between what is currently known and what needs to be done.

3. Empirical Literature Review

3.1. Literature Search Protocol

This review follows a structured narrative approach (Baumeister & Leary, 1997). The literature search was conducted primarily through Google Scholar, supplemented by targeted searches of the institutional repositories of the Bank for International Settlements (BIS), the European Central Bank (ECB), the European Banking Authority (EBA), and the Network for Greening the Financial System (NGFS). To ensure a comprehensive and targeted coverage, we used a wide range of keywords reflecting both the financial and climate dimensions of the research. Keywords related to the financial sector and operational vulnerabilities included “Operational risk”, “Banking system”, “Bank operational risk”, and “Operational loss events”. To capture climate-related aspects, we integrated terms such as “Climate change”, “Climate disasters”, “Storm”, “Hurricane”, “Tornadoes”, and “Severe thunderstorms”. The scope was further broadened with additional terms including “Reputational risk”, “Operational losses”, “Financial companies”, “Event study”, and “Bank damage”, which helped identify studies exploring the reputational and financial impacts of climate change on banking institutions. The search covered publications up to June 2026.

Inclusion criteria were: (i) the study addresses operational risk—broadly defined—in financial institutions; (ii) the study considers climate-related or weather-related factors as drivers or analogues; (iii) the study employs a quantitative, qualitative, or mixed-methods empirical or conceptual approach. Studies were excluded if they addressed only credit or market risk without any operational risk component, or if they were purely descriptive policy documents without analytical content. In total, 55 sources were retained, comprising peer-reviewed journal articles, working papers from central banks and international organisations, and regulatory guidance documents. The final selection of 15 empirical studies included in Table 1 represents those that most directly examine the relationship between climate events and operational risk or closely analogous outcomes in financial institutions.

3.2. Conceptual Framework

Operational risk, as defined by the BCBS, encompasses losses resulting from “inadequate or failed internal processes, people and systems, or from external events”, explicitly including legal risk (Basel Committee on Banking Supervision, 2006). Physical climate hazards sit squarely in the “external events” category. The BCBS has further specified that climate-related events can generate losses across multiple operational risk event-type categories: business disruption and system failures (e.g., power cuts following storms), damage to physical assets (e.g., flooding of branches), and clients, products, and business practices (e.g., litigation arising from greenwashing allegations) (Basel Committee on Banking Supervision, 2021c). Table 2 summarises the main Basel risk categories and highlights the channels through which climate-related drivers can affect them, with particular attention to the operational and legal risk dimensions discussed in this paper.

The empirical literature addressing these linkages has developed along three distinct lines: studies of market-based responses to operational loss announcements (reputational spillovers), studies of the direct financial impact of climate events on bank performance and lending, and more recent work explicitly linking extreme weather to operational loss data.

Table 1. Overview of empirical studies on climate-related operational risk in banking.

Title	Author(s) and Year	Research Question	Country or Region	Empirical Method	Main Findings
The market value impact of operational loss events for U.S. banks and insurers	Cummins et al. (2006)	Impact of operational loss events on market valuation of U.S. banks and insurers	Worldwide (U.S. focus)	Event study; OLS regression	Negative stock price reactions to operational loss announcements; larger market value declines for insurers than banks.
Measuring reputational risk: The market reaction to operational loss announcements	Perry and de Fontnouvelle (2005)	Stock price response to operational loss event announcements	Worldwide (North America, Europe, Japan, Oceania)	Event study; OLS regression	Market value reacts negatively; external event losses generate proportional reactions; internal fraud losses trigger disproportionately large market penalties.
Operational risk and reputation in the financial industry	Gillet et al. (2010)	Stock market reaction to operational loss announcements by financial institutions	Europe and U.S.	Event study; OLS regression	Negative market reactions on announcement date; elevated trading volumes; fraud-related losses trigger most severe responses.
Operational and reputational risk in the European banking industry	Sturm (2013)	Impact of operational losses on reputational standing of European financial firms	Europe	Event study; OLS regression	Firm characteristics (especially liability-to-asset ratio) matter more than loss event specifics in determining reputational damage.
The determinants of reputational risk in the banking sector	Fiordelisi et al. (2013)	Determinants of reputational damage following operational losses	Europe and U.S.	Event study; OLS; Logit regression	Larger, more profitable banks suffer greater reputational damage; higher capital and intangible assets buffer the effect; legal structure matters.
Reputational losses and operational risk in banking	Fiordelisi et al. (2014)	Impact of operational losses on reputations of financial institutions	Europe and U.S.	Event study; OLS regression	Financial firms experience reputational losses following operational loss announcements; losses in Europe are more severe than those in the U.S.
The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean	Brei et al. (2019)	Impact of hurricane strikes on the banking sector	Eastern Caribbean countries	Fixed-effects panel regression	Hurricane strikes trigger deposit withdrawals and adverse funding shocks; banks cut lending and raise holdings of liquid assets; effect driven by liability side, not loan impairments.
Business complexity and risk management: Evidence from operational risk events in U.S. BHCs	Chernobai et al. (2021)	Influence of business complexity on operational risk management	U.S.	Difference-in-differences regression	Higher business complexity increases both frequency and severity of operational risk events.
How climate change may impact operational risk	Grimwade (2022)	Effects of climate-related risks on banking operations	Worldwide	Network model; dynamic evolutionary macroeconomic model	Climate change induces operational risk through three interacting channels: behavioural shifts, physical disruptions, and macroeconomic impacts.
Climate risks in the U.S. banking sector: Evidence from operational losses and extreme storms	Berger et al. (2023)	Effects of climate change on operational losses of U.S. BHCs	U.S.	Event study; Fixed-effects regression	Extreme storms significantly increase BHC operational losses; prior storm experience reduces subsequent operational losses.

Table 1. *Cont.*

Title	Author(s) and Year	Research Question	Country or Region	Empirical Method	Main Findings
Bank reputation and operational risk: The impact of ESG	Galletta et al. (2023)	Relationship between ESG scores and operational risk in banks	Worldwide	System GMM panel regression	ESG factors significantly influence bank operational risk and reputational profiles; risk management aligned with ESG principles reduces operational risk.
What are the banks doing in managing climate risk?	Toma and Stefanelli (2022)	How banks manage climate risk; alignment with regulatory requirements	Italy	Cluster analysis	Many banks remain insufficiently prepared to manage climate risk; bank management often lacks familiarity with responsible practices.
Impact of tropical storms on the banking sector in the British Colonial Caribbean	Huesler (2024)	Impact of tropical storms on bank stability and lending	British Colonial Caribbean	Case study; OLS regression	Tropical storms increase overdraft levels (borrowing to absorb shocks) and raise savings deposits (precautionary behaviour).
Operational risk, climate change, and economic growth in Iran	Amani et al. (2023)	Impact of operational risk and climate change on economic growth	Iran	TVP-VAR dynamic regression	Mitigating operational risk positively affects economic growth; climate-related disruptions undermine long-term productivity.
Banks and climate litigation risk: Navigating the low-carbon transition	Smołeńska et al. (2025)	How banks manage climate litigation risk; implications for prudential capital	Europe	Document analysis; policy review	Banks tend to frame litigation exposure as reputational rather than operational risk, potentially under-capitalising; supervisory guidance increasingly requires operational risk treatment of climate litigation.

Table 2. Definitions of Basel risk types and potential effects of climate risk drivers.

Risk Type	Definition	Potential Effects of Climate Risk Drivers
Credit risk	"The potential that a bank borrower or the counterparty will fail to meet its obligations in accordance with agreed terms" (Basel Committee on Banking Supervision, 2000)	Credit risk increases if climate risk drivers reduce borrowers' ability to repay and service debt (income effect) or banks' ability to fully recover the value of a loan in the event of default (wealth effect) (Basel Committee on Banking Supervision, 2021b).
Market risk	"The risk of losses in on- and off-balance sheet positions arising from movements in market prices" (Committee on Payment and Settlement Systems, 2003)	Reduction in financial asset values; potential for large, sudden price adjustments where climate risk is not yet priced in; breakdown in asset correlations and market liquidity (Basel Committee on Banking Supervision, 2021b).
Liquidity risk	"The risk that a bank is unable to meet its obligations as they come due without incurring unacceptable losses" (Basel Committee on Banking Supervision, 2006)	Reduced access to stable funding; climate risk drivers may cause counterparties to draw down deposits and credit lines; operational disruptions may force emergency liquidity needs (Basel Committee on Banking Supervision, 2021b).
Operational risk	"The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" (Basel Committee on Banking Supervision, 2006)	Infrastructure damage from extreme weather (floods, storms, heatwaves); IT system failures; service interruptions; power outages; litigation arising from greenwashing or inadequate climate disclosure (Basel Committee on Banking Supervision, 2021c).
Reputational risk	"The risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators" (Basel Committee on Banking Supervision, 2017)	Changing market or consumer sentiment regarding banks' climate exposure, ESG performance, or climate risk governance; note that reputational risk, unlike operational risk, does not carry direct Basel capital requirements (Smołeńska et al., 2025).

3.3. Reputational Spillovers from Operational Loss Announcements

The earliest strand examines how operational loss announcements affect bank stock prices. It is important to note that this literature primarily captures reputational spillovers—market-value consequences of disclosed losses—rather than direct operational disruptions. The climate link is therefore indirect: to the extent that climate hazards trigger such announcements, this evidence implies a pathway from physical risks to reputational damage, while the primary operational losses may be larger and longer-lasting. Perry and de Fontnouvelle (2005) analysed a broad international sample and found that firms' market values react negatively to operational loss disclosures. Critically, losses from external events generate market responses proportional to the loss amount, while internal fraud events trigger disproportionately large reactions—a pattern consistent with investors penalising governance failures more severely than bad luck. Gillet et al. (2010) confirmed significant negative stock price reactions on announcement dates for European and U.S. financial institutions, accompanied by elevated trading volumes, with fraud-related losses triggering the most severe responses. Sturm (2013) extended this to European banks and found that firm-level characteristics—particularly the liability-to-asset ratio—matter more than loss event characteristics in determining the magnitude of reputational damage. Fiordelisi et al. (2013) showed that larger, more profitable banks suffer greater reputational damage, while higher capitalisation and intangible assets buffer the effect. Fiordelisi et al. (2014)

found that operational losses in Europe are generally more severe than those in the U.S., possibly reflecting differences in institutional and legal environments. Cummins et al. (2006) documented that insurers suffer larger market value declines than banks following operational loss announcements, a finding with implications for the financial contagion potential of climate events given banks' increasing reliance on insurance for operational risk transfer.

3.4. Direct Financial Impacts of Climate Events on Banks

A second strand directly examines how natural disasters affect bank balance sheets. Brei et al. (2019) used fixed-effects panel regressions on Eastern Caribbean banking data and found that hurricane strikes cause deposit withdrawals and adverse funding shocks, forcing banks to cut lending and increase holdings of liquid assets. Crucially, they show that the lending contraction is driven primarily by the liability side—deposit flight—rather than by loan impairments, with direct implications for liquidity risk management. Huesler (2024) studied the British Colonial Caribbean and found that tropical storms increase overdraft usage—evidence that households and firms borrow to absorb climate shocks—and raise savings deposits, suggesting precautionary buffer-building.

In the U.S. context, Berger et al. (2023) provide the most direct evidence linking extreme weather to operational loss events. Using event study and fixed-effects regression applied to Federal Reserve data on bank holding company (BHC) operational losses, they show that extreme storms significantly increase operational loss amounts, and that BHCs that have previously experienced storm exposure develop greater resilience, reducing subsequent operational losses. The Federal Reserve's own 2023 climate scenario analysis exercise, in which large banks were asked to estimate operational loss impacts under extreme physical risk scenarios calibrated to 2050 climate conditions, confirmed that storm events constitute a major operational risk channel (Federal Reserve Board, 2023). Chernobai et al. (2021) demonstrated that operational risk events increase in both frequency and severity with business complexity—a finding relevant to large, diversified banks that also tend to have the widest geographic exposure to climate hazards.

These findings need to be understood against the background of the substantial baseline scale of operational losses in banking. Berger et al. (2023) documented that operational losses already exceeded 25% of net income for large U.S. bank holding companies between 2001 and 2016, with operational risk accounting for approximately 30% of average regulatory capital for these institutions. Against this backdrop, even a modest climate-driven increase in loss frequency or tail severity could represent a material "tipping point" for capital adequacy, particularly if losses are correlated across banks exposed to the same regional climate event. The spatial dimension of this risk is critical: Pagliari (2023) showed that matching the exact location of bank branches with high-resolution flood data reveals that a one-percentage-point reduction in lending caused by an adverse climate event reduces the return on assets of territorially concentrated small banks by approximately 3.1%, with potentially half of all territorial banks reporting below-average profitability if fully exposed to high-risk areas. These quantitative benchmarks underscore why climate-related operational risk—even if marginal in absolute terms today—warrants urgent analytical and regulatory attention.

At the macroeconomic level, Amani et al. (2023) analysed Iran using a time-varying parameter vector autoregression (TVP-VAR) model and found that mitigating operational risk positively affects economic growth, with climate-related disruptions undermining long-term productivity. Colacito et al. (2019) showed that higher summer temperatures reduce U.S. state GDP growth, tracing a pathway from physical climate change to the broader economic environment in which banks operate. Recent evidence from Europe confirms that physical climate shocks also pose significant risks within the European financial system (Bos et al., 2022; Chabot & Bertrand, 2023), with cooperative and locally oriented banks particularly exposed due to their inability to diversify geographic risk (Caselli & Migliorelli, 2024). The geographic scope of the evidence base, however, remains limited. Research on Asian banking systems—particularly in South and Southeast Asia, where tropical cyclone and monsoon flood exposure is high—is sparse, with most available evidence focusing on macroeconomic impacts rather than bank-level operational losses (Banholzer et al., 2014). In Africa and Latin America, where adaptive capacity is often lowest and financial systems are less diversified, the absence of systematic operational loss data makes quantitative assessment particularly difficult. This geographic gap is itself a research priority: the countries facing the highest physical climate exposure are precisely those for which the least bank-level operational risk evidence exists.

3.5. Legal Risk and Climate Litigation

A rapidly emerging dimension of climate-related operational risk concerns legal and litigation risk. This dimension is increasingly relevant from a prudential perspective: under the Basel framework, legal risk is explicitly included in the operational risk definition (Basel Committee on Banking Supervision, 2006), and high exposure to legal risk is expected to translate into higher own-fund requirements under the Standardised Approach (Smoleńska et al., 2025). Recent empirical evidence confirms the financial materiality of this channel: Beyer and Nobile (2025) find that a one-percent increase in climate-related litigation faced by firms is associated with a 6.6 basis-point increase in the cost of bank loans, suggesting that lenders already price climate legal risk into credit conditions.

A key distinction is warranted here between legal risk and reputational risk, as the two are often conflated in both practitioner and academic discourse despite having fundamentally different capital implications. Legal risk—a component of operational risk under Basel—generates direct, quantifiable financial losses: litigation settlement payments, court awards, regulatory fines, and legal defence costs. These are actual cash outflows that flow into the Internal Loss Multiplier calculation and affect regulatory capital. Reputational risk, by contrast, refers to losses arising from negative perception and is explicitly excluded from the Basel operational risk perimeter (Basel Committee on Banking Supervision, 2006, 2017); it carries no direct capital requirement. Concretely: when a bank pays a settlement in a greenwashing lawsuit, that is operational (legal) risk. When the same lawsuit causes customers to withdraw deposits or investors to demand a higher risk premium, those are reputational consequences—real but outside the Basel capital framework. Smoleńska et al. (2025) documented that banks frequently misclassify climate litigation exposure as reputational rather than operational risk in their disclosures, a practice that may lead to systematic under-capitalisation. The ECB's 2020 supervisory guide established an expectation that banks assess the extent to which their own activities expose them to litigation risk (European Central Bank, 2020), and the EBA's 2025 guidelines on ESG risk management explicitly reference climate litigation as an operational risk concern (European Banking Authority, 2025).

The empirical evidence on the financial consequences of climate litigation for banks is growing. Galletta et al. (2023) used System GMM panel estimation on a global sample to show that ESG scores—which capture, inter alia, climate-related governance—significantly influence banks' operational risk profiles and reputational standing. Banks perceived to misrepresent sustainability features of products or investments face litigation exposure under the "clients, products and business practices" event-type category of the Basel taxonomy (Basel Committee on Banking Supervision, 2021c). Smoleńska et al. (2025) provided a systematic review of bank disclosures on climate litigation risk and document a tendency for banks to frame litigation exposure as reputational risk—which carries no capital requirement implications—rather than as operational risk, creating a potential under-capitalisation concern.

Climate litigation has also become increasingly relevant in financial stability discussions within the Network for Greening the Financial System (NGFS), which has flagged litigation trends as a prominent source of legal risk for banks (Network for Greening the Financial System, 2023a, 2023b). The BCBS has acknowledged the need to ensure that litigation losses stemming from climate-related drivers are identifiable in operational loss databases (Basel Committee on Banking Supervision, 2021c; KPMG, 2024), a prerequisite for capital calculations under the Basel Standardised Approach.

3.6. The Role of Organisational and Governance Factors

Firm heterogeneity plays an important moderating role. Toma and Stefanelli (2022) analysed Italian banks using cluster analysis and found wide variation in climate risk management practices, with many institutions lacking adequate policies and strategies. This heterogeneity means that the operational risk impact of identical climate events will differ substantially across banks depending on their preparedness, digital resilience, geographic concentration, and governance quality. Grimwade (2022) argued that climate change induces operational risk through three interacting channels: behavioural shifts (e.g., changes in work patterns following extreme events), physical disruptions (direct damage to infrastructure), and broader macroeconomic impacts (e.g., reduced customer activity and revenue loss). Network and dynamic evolutionary models are required to capture these interactions, which linear regression approaches may miss.

3.7. Quantitative Characterisation of the Literature

Table 1 provides a systematic overview of the empirical studies reviewed in this paper. The literature shows significant geographic diversity: a substantial share of studies use multi-country or global data, others combine the U.S. and Europe, while the remaining contributions focus on individual countries including the U.S., Caribbean nations, Italy, and Iran. This distribution reflects the global relevance of the topic but also points to a relative under-representation of European, African, and Asian banking systems despite their potentially high exposure.

Methodologically, event study analysis remains the predominant approach (used in roughly half of the empirical papers), well suited to measuring immediate market reactions to loss announcements. Ordinary least squares (OLS) regression is the second most common technique, appearing in over one-third of papers. Fixed-effects panel regressions, System GMM dynamic estimators, TVP-VAR models, logit regressions, difference-in-differences (DiD), cluster analysis, and network-based approaches each appear in at least one study, indicating growing methodological diversity. However, no single paper yet combines identification strategies robust to endogeneity with granular climate event data and bank-level operational loss data—a gap that Section 5 addresses.

Despite the growing body of empirical evidence reviewed above, the literature remains fragmented across conceptual definitions, empirical strategies, and policy relevance. To clarify the main limitations and structure the contribution of this paper, Table 3 summarises the key gaps identified in the literature. The table highlights where current research falls short and outlines directions for future work. This synthesis provides a bridge between the empirical review and the methodological assessment that follows.

To further clarify the conceptual architecture of climate-related operational risk, Table 4 maps the principal physical and legal climate hazard types onto the seven Basel III operational risk event-type categories (Basel Committee on Banking Supervision, 2006, 2021c).

This mapping provides practitioners and researchers with a standardised reference for attributing climate-driven losses to the appropriate regulatory category—a prerequisite for the data labelling and climate-flagging exercises required under the BCBS guidance (Basel Committee on Banking Supervision, 2021c).

Table 3. Main gaps in the literature and research directions.

Literature Gap	Limitation in Existing Studies	Implications and Research Directions
Conceptual ambiguity	Operational, reputational, and legal risk are often conflated, leading to inconsistent definitions and measurement.	Future research should adopt clearer conceptual boundaries aligned with Basel definitions, distinguishing operational disruptions from reputational and legal spillovers.
Limited focus on operational risk	Most climate finance literature focuses on credit and market risk rather than operational disruptions.	Greater emphasis is needed on operational risk channels, especially those linked to physical climate hazards and legal exposure.
Data limitations	Operational loss data are incomplete, proprietary, and rarely linked directly to climate events.	Improved data collection, harmonised reporting, and the development of proxies for climate-related operational events are essential.
Fragmented empirical approaches	Different methods capture isolated dimensions of risk without integration.	Future research should combine econometric, machine learning, and simulation approaches within unified frameworks.
Short-term focus	Event studies capture immediate market reactions but miss longer-term operational impacts.	Dynamic and long-horizon approaches are needed to capture persistence, recovery, and adaptation dynamics.
Limited modelling of mechanisms	Many studies identify correlations without modelling transmission channels.	Research should explicitly model causal pathways linking climate hazards to operational disruptions.
Lack of system-level perspective	Most analyses focus on individual banks rather than interconnected systems.	Agent-based and network models should be used to capture systemic propagation of operational disruptions.
Weak integration with regulatory frameworks	Empirical work is often disconnected from Basel operational risk requirements.	Future models should link directly to supervisory frameworks, including capital requirements and stress testing.

Table 4. Mapping of climate hazard types onto Basel III operational risk event-type categories.

Climate Hazard	Primary Operational Impact	Basel Event Category	Examples of Operational Losses
Flood	Branch/data centre inundation; system downtime; staff displacement	Business Disruption and System Failures; Damage to Physical Assets	IT system outages; branch closure costs; asset write-downs; revenue loss
Storm/Hurricane	Power and communications outages; infrastructure damage; supply chain disruption	Business Disruption and System Failures; Damage to Physical Assets	Emergency recovery costs; data loss; outsourced service failure

Table 4. *Cont.*

Climate Hazard	Primary Operational Impact	Basel Event Category	Examples of Operational Losses
Heatwave	Hardware degradation; staff absence; cooling system failure	Business Disruption and System Failures	IT cooling failures; reduced operational capacity; welfare costs
Wildfire	Destruction of physical assets; evacuation of staff; road/communication severed	Damage to Physical Assets; Business Disruption and System Failures	Asset write-offs; business interruption losses; relocation costs
Sea-level rise/Chronic flooding	Long-term branch viability; stranded real estate collateral	Damage to Physical Assets	Progressive asset impairment; insurance premium increases
Climate litigation (greenwashing)	Legal fees; court awards; regulatory fines	Clients, Products and Business Practices; Execution, Delivery and Process Management	Settlement costs; restitution; regulatory penalties
Climate disclosure failure	Regulatory sanctions; supervisory action	Clients, Products and Business Practices	Fines; legal costs; supervisory remediation requirements
Third-party/ supply chain disruption	Outsourced service failure (IT, utilities) due to climate event	Business Disruption and System Failures; Execution, Delivery and Process Management	Contingency arrangement costs; SLA breach penalties

Note: Basel event-type categories follow Basel Committee on Banking Supervision (2006). Climate hazard definitions follow Network for Greening the Financial System (2020). This mapping is indicative; a single climate event may generate losses across multiple event-type categories simultaneously.

4. Methodological Review

The methodological toolkit deployed in the literature encompasses a spectrum from financial econometrics to network modelling. Each approach captures some dimensions of climate-related operational risk while leaving others inadequately addressed. We assess each in turn, with explicit attention to suitability for the distinctive features of this problem: rare events, data scarcity, non-linearity, endogeneity, and regulatory context.

The purpose of this section is not to provide a general textbook introduction to these methods but to conduct a targeted critical assessment of their strengths and limitations for the specific problem of climate-related operational risk in banking. Each limitation identified here directly motivates a design choice in the three-stage roadmap of Section 5. The equations are reproduced from the cited literature and are not original contributions of the present paper.

4.1. Event Study Analysis

The event study methodology identifies the financial market impact of a specific event by measuring abnormal returns around the event date. The equations presented in this and subsequent subsections follow standard formulations as established and applied in the operational risk literature (Cummins et al., 2006; Fiordelisi et al., 2013; Perry & de Fontnouvelle, 2005); they are not original contributions of the present paper but are reproduced here to allow a critical assessment of their assumptions and limitations in the climate risk context. The approach defines an event date t_0, an event window $[t_1, t_2]$, and an estimation window $[t_{-T}, t_{-1}]$ (typically 120 to 250 trading days) used to fit a market model:

$$\mathrm{E}(R_{it}) = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

where R_{it} is the return of bank i at time t, R_{mt} is the market return, and $\mathrm{E}(R_{it})$ is the expected return. Abnormal returns (ARs), cumulative abnormal returns (CARs), and cumulative average abnormal returns (CAARs) are then computed as

$$\mathrm{AR}_{it} = R_{it} - \mathrm{E}(R_{it}), \quad \mathrm{CAR}_i = \sum_{t=t_1}^{t_2} \mathrm{AR}_{it}, \quad \mathrm{CAAR} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{CAR}_i \tag{2}$$

with significance assessed via t-tests.

Strengths. Event studies are effective at capturing the immediate reputational and market-value consequences of climate-related operational loss announcements—a first-order policy concern since market discipline is an important complement to supervisory oversight (Fiordelisi et al., 2013; Gillet et al., 2010; Perry & de Fontnouvelle, 2005).

Limitations. Four limitations are particularly acute for climate-related operational risk. First, event studies require publicly traded firms, excluding the vast majority of cooperative, savings, and community banks that are most geographically concentrated and therefore most exposed to localised climate hazards (Caselli & Migliorelli, 2024). Second, climate events often unfold over days or weeks, making it difficult to identify a precise event date; the gradual onset of a flood, for example, may be poorly approximated by a single t_0. Third, the short time horizon of standard event windows (often $[-1, +1]$ or $[-5, +5]$ trading days) systematically misses longer-term operational costs such as infrastructure rebuilding, regulatory remediation, and sustained revenue loss from customer attrition. Fourth, concurrent macroeconomic conditions during major climate events (e.g., government disaster declarations and monetary policy responses) introduce confounders that are difficult to isolate from event windows.

4.2. OLS and Pooled Regression

OLS regression relates an outcome variable Y_i (such as reputational loss magnitude or operational loss frequency) to a set of explanatory variables (following standard econometric practice as applied in this literature by Fiordelisi et al. (2013) and Cummins et al. (2006), among others):

$$Y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i \tag{3}$$

Fiordelisi et al. (2013) used this approach to identify determinants of reputational damage following operational loss events, while Cummins et al. (2006) and Perry and de Fontnouvelle (2005) combined event studies with OLS to explain cross-sectional variation in abnormal returns.

Strengths. OLS is transparent, computationally tractable, and well suited to detecting linear relationships and testing hypotheses about bank-level characteristics that moderate operational risk impacts.

Limitations. OLS is vulnerable to endogeneity arising from omitted variables, reverse causality, and measurement error. In the climate-operational risk context, a bank's exposure to climate events may be correlated with its size, geographic strategy, and risk appetite—all of which also affect operational losses independently. Climate event occurrence is exogenous but the selection of which banks operate in high-exposure regions is not. Standard OLS also imposes linearity, which may be inappropriate for rare, large-loss events that characterise the tail of the operational risk loss distribution.

4.3. Fixed-Effects Panel Models

Fixed-effects (FE) models control for time-invariant unobserved heterogeneity by within-transforming the data:

$$Y_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j X_{ijt} + \varepsilon_{it} \quad (4)$$

where α_i captures bank-specific fixed effects. Brei et al. (2019) deployed this approach to assess hurricane impacts on Caribbean banks, and Berger et al. (2023) combined FE with event study to study U.S. BHCs.

Strengths. FE models eliminate bias from time-invariant unobservables—bank culture, location, charter type—and are well suited to panel datasets where banks differ systematically in ways not fully observed. They are appropriate when the treatment (e.g., storm incidence) varies over time within the panel.

Limitations. FE models cannot estimate the effect of time-invariant variables (such as a bank's baseline geographic exposure to flood risk). They also remain susceptible to bias from time-varying unobservables—for example, changes in macroeconomic conditions during storm periods that affect bank performance independently of the storm. Pre-trends tests and event-study-style robustness checks are advisable but rarely deployed in this literature.

4.4. Difference-in-Differences

DiD compares outcome changes in exposed banks relative to unexposed banks before and after a climate event:

$$\Delta Y = (Y_{T,\text{post}} - Y_{T,\text{pre}}) - (Y_{C,\text{post}} - Y_{C,\text{pre}}) \quad (5)$$

where T and C denote treated and control groups. Chernobai et al. (2021) used DiD to examine the operational risk consequences of increases in business complexity, a closely related methodological approach.

Strengths. DiD addresses time-invariant heterogeneity and, under the parallel trends assumption, provides a credible estimate of the causal effect of a climate event on treated banks. It is well suited to discrete, geographically bounded events, such as a flood or hurricane, that affects some banks but not others.

Limitations. The parallel trends assumption requires that, in the absence of the climate event, treated and control banks would have followed similar outcome trajectories—an assumption that may be violated if the banks most exposed to climate events are systematically different along other dimensions (e.g., concentrated in economically weaker regions). Recent advances in staggered DiD estimators (Callaway & Sant'Anna, 2021; Sun & Abraham, 2021) address concerns about heterogeneous treatment effects over time and should be incorporated in future work.

4.5. Dynamic Panel Models and System GMM

Dynamic panel models include lagged dependent variables and address endogeneity through instrumental variable strategies, most commonly the System GMM estimator developed by Arellano and Bover (1995), which uses lagged levels and differences as instruments:

$$Y_{it} = \beta Y_{it-1} + \sum_{j=1}^{k} \gamma_j X_{ijt} + \eta_i + \varepsilon_{it} \quad (6)$$

Galletta et al. (2023) used System GMM to examine the relationship between ESG scores and bank operational risk, instrumenting for potential reverse causality between bank performance and ESG ratings.

Strengths. System GMM is appropriate when the dependent variable is persistent (as operational risk frequency often is), when regressors are endogenous, and when fixed effects are correlated with regressors. Instrument validity can be tested via the Hansen J-test and Arellano-Bond autocorrelation tests.

Limitations. System GMM performs poorly with short panels and many instruments, a "too many instruments" problem that is common in banking panel datasets. Instrument relevance and validity require careful validation. In the climate risk context, finding valid instruments for climate exposure is non-trivial since geographic exposure is often correlated with bank size and business model.

4.6. Binary Outcome and Count Models

When the outcome of interest is binary (e.g., whether a climate event leads to a branch closure or a service interruption) or a count (e.g., number of operational loss events in a period), logit/probit and Poisson/negative binomial models are appropriate:

$$\Pr(Y_i = 1 \mid X_i) = \frac{e^{\beta_0 + \sum_j \beta_j X_{ij}}}{1 + e^{\beta_0 + \sum_j \beta_j X_{ij}}} \tag{7}$$

Fiordelisi et al. (2013) incorporated logit regressions alongside OLS to model the probability of reputational damage.

Strengths. These models are well suited to discrete outcomes and can accommodate rare events through appropriate correction (e.g., rare-events logit). They can be combined with survival analysis to model the time until an operational failure occurs following a climate event (Miller, 2011).

Limitations. Fixed effects in non-linear panel models suffer from the incidental parameters problem, making standard within-group estimation inconsistent in short panels. Conditional logit circumvents this for binary outcomes but cannot accommodate certain covariate patterns. Accounting for time-varying unobserved shocks remains difficult.

4.7. Network and Dynamic Models

Grimwade (2022) used network and dynamic evolutionary macroeconomic models to trace how climate change generates operational risk through interdependent behavioural, physical, and macroeconomic channels. This approach captures feedback loops that regression-based methods miss—for example, how staff absences due to a heatwave interact with IT system fragility and customer behaviour to amplify a local disruption into a systemic service failure.

Strengths. Network models capture propagation dynamics and second-order effects, essential for understanding how climate shocks spread through interconnected banking systems (Battiston et al., 2017; Campiglio et al., 2018).

Limitations. Network models require high-quality data on inter-bank exposures and operational interdependencies that are rarely publicly available. They are computationally demanding and difficult to validate against historical outcomes, particularly for rare climate events.

4.8. Summary Assessment

No single method adequately addresses all dimensions of climate-related operational risk: event studies miss physical disruptions and non-listed banks; OLS and FE regressions struggle with rare events and endogeneity; dynamic GMM requires valid instruments that are difficult to construct; network models require unavailable data. The roadmap in Section 5 is designed to address these limitations in combination.

5. A Methodological Roadmap

This roadmap is conceptual and does not aim to provide a fully operational or empirically validated model but rather to organise future research directions in a coherent framework. The three stages are designed to be complementary and sequentially informative: the outputs of Stage 1 inform Stage 2, and the estimated relationships from Stage 2 calibrate Stage 3. Each stage addresses specific challenges identified in Section 4 and can be conceptually related to the Basel operational risk framework. Figure 1 provides a schematic overview of the framework.

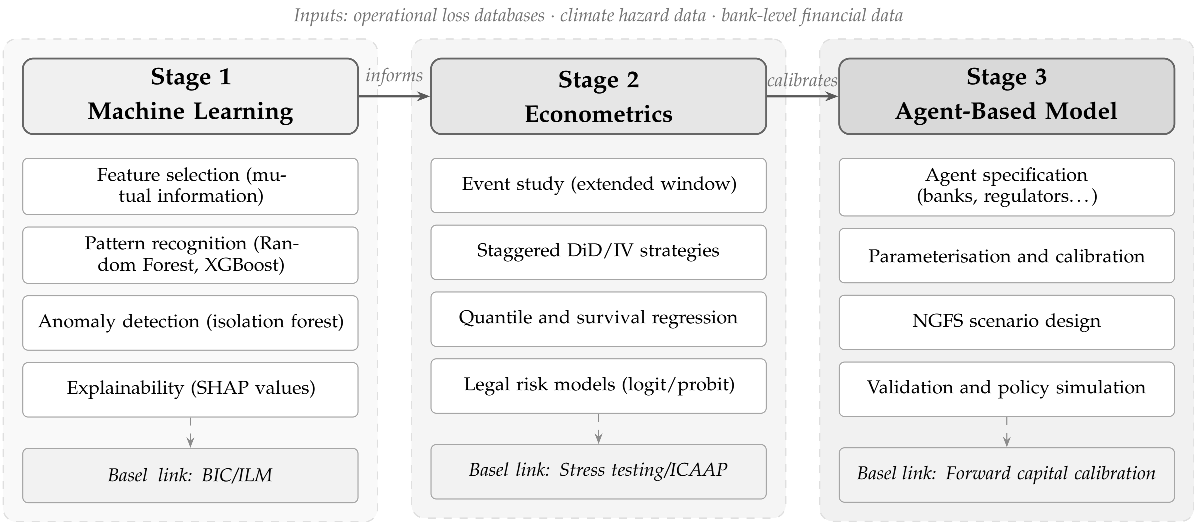

Figure 1. The three-stage methodological roadmap. Stages are sequentially informative: outputs of Stage 1 (machine learning) inform Stage 2 (econometrics), whose estimates calibrate Stage 3 (agent-based modelling). The bottom row shows the connection of each stage to elements of the Basel Standardised Approach for operational risk capital. BIC = Business Indicator Component; ILM = Internal Loss Multiplier; ICAAP = Internal Capital Adequacy Assessment Process.

5.1. Stage 1: Machine Learning for Variable Selection and Pattern Recognition

Rationale. A fundamental challenge for empirical research on climate-related operational risk is the high-dimensional, heterogeneous nature of both climate data and operational loss data. Operational loss databases (such as those required under the Basel framework) record events across seven event-type categories, five business line categories, multiple geographies, and varying time horizons. Climate data likewise encompass numerous hazard types (floods, storms, heatwaves, droughts, and wildfires), intensities, durations, and spatial resolutions. Naive variable selection—including all potentially relevant climate and bank-level variables—leads to overfitting, multicollinearity, and unstable estimates.

Approach. We recommend a two-step machine learning strategy. In the first step, mutual information-based feature selection methods (Peng et al., 2005) are applied to identify which climate variables (hazard types, intensities, and spatial proximity to bank infrastructure) and bank-level variables (size, geographic concentration, capitalisation, IT infrastructure age, and business complexity) are most informative about operational loss outcomes. This approach minimises redundancy while preserving explanatory power, reducing multicollinearity and improving out-of-sample predictive performance.

In the second step, supervised and unsupervised machine learning techniques are applied to detect patterns and anomalies in historical operational loss data that may signal climate attribution. Random forests (Breiman, 2001) can capture non-linear interactions between climate variables and bank characteristics in predicting loss frequency and severity, providing variable importance rankings that guide subsequent econometric analysis. Gradient boosting methods (e.g., XGBoost and LightGBM) offer similar capabilities with better performance on sparse data. Anomaly detection algorithms—such as isolation forests or autoencoders—can flag unusual loss episodes in operational databases that coincide with climate events but may not be explicitly labelled as climate-related, addressing a key data limitation identified by the BCBS (Basel Committee on Banking Supervision, 2021c).

Explainability tools such as SHAP (SHapley Additive exPlanations) values (Lundberg & Lee, 2017) should accompany all machine learning models to ensure that variable importance rankings are interpretable to risk managers and regulators—a prerequisite for regulatory acceptance of ML-based risk models. The use of interpretable ML in climate risk identification is increasingly advocated in the climate science literature (Wei et al., 2025) and is beginning to diffuse into financial applications.

To ground this stage concretely, Table A1 (see Appendix A) provides an illustrative set of input variables for the ML models, organised by category. Climate input variables include: daily precipitation anomalies and peak wind speeds at the location of bank branches and data centres (from ERA5 reanalysis at 0.25° resolution); flood inundation depth and duration (from EFAS or FEMA); heat stress index (wet-bulb globe temperature) aggregated at the postcode level; and wildfire perimeter data (from FIRMS/MODIS). Bank-level variables include: number of branches and data centres per flood zone and heat risk zone (from GIS matching); IT infrastructure age (from annual reports or supervisory data); share of outsourced critical services; capitalisation (CET1 ratio); and business complexity score (Chernobai et al., 2021). Outcome variables include: quarterly operational loss amounts by Basel event-type category; number of loss events above a materiality threshold; and indicators of service interruption duration. These variables are available at quarterly or annual frequency for most large banks; higher-frequency (daily or weekly) data are available from supervisory sources but typically require data-sharing agreements.

Data sources and spatial preparation. This stage combines operational loss data (from supervisory repositories or consortium databases such as ORX), climate hazard data (EM-DAT, ERA5 reanalysis, and catastrophe model outputs), and bank-level financial data (BankFocus, Federal Reserve Y-9C reports, and ECB supervisory data).

GIS integration. A critical data preparation step that the roadmap explicitly requires is the integration of Geographic Information Systems (GIS) to map a bank's physical infrastructure—branches, data centres, processing facilities—against high-resolution hazard maps (flood zones, wildfire risk areas, heat stress indices). Pagliari (2023) demonstrated the value of this approach for small European banks, constructing a unique database matching branch locations with river flood frequency and severity data; the resulting spatial matching reveals heterogeneity in climate exposure that aggregate national data would obscure. GIS-based geolocalisation is therefore not merely a data enhancement but a prerequisite for credible spatial identification in subsequent econometric stages. Practically, branch geocoordinates can be overlaid with publicly available hazard databases such as EFAS (EU), the FEMA National Flood Hazard Layer (U.S.), or the DRMKC natural hazard database.

NLP and unstructured data for early warning. Stage 1 should also incorporate Natural Language Processing (NLP) applied to unstructured data sources—news articles, regulatory filings, earnings call transcripts, and social media—to provide an early warning system for emerging transition and legal risks before they crystallise into operational losses. Research applying discourse network analysis to nearly 5000 news articles documents a marked post-2020 shift in which ESG became the dominant framing in banking discourse, with media attention to climate risk often peaking months before major policy milestones

(Naysary et al., 2026). This anticipatory quality means that NLP-based sentiment tracking can serve as a leading indicator for litigation risk—one of the fastest-growing components of climate-related operational risk—complementing the retrospective anomaly detection applied to internal loss databases. Practically, this can be implemented using transformer-based language models (e.g., FinBERT, BERT fine-tuned on financial corpora) applied to aggregated news and filing databases.

Connection to Basel framework. The BCBS has called on banks to identify and flag losses driven by climate-related factors in their loss databases (Basel Committee on Banking Supervision, 2021c). ML anomaly detection provides a scalable method for retrospective climate attribution, enabling banks to calibrate the Business Indicator Component (BIC) and Internal Loss Multiplier (ILM) of the Standardised Approach with climate-relevant data.

5.2. Stage 2: Econometric Modelling of Climate-Related Operational Risk

Rationale. Machine learning provides predictive patterns but does not deliver causal identification. Understanding whether climate events causally increase operational losses—and how the relationship is moderated by bank characteristics, regulatory environment, and preparedness—requires econometric frameworks with credible identification strategies.

Approaches. We advocate for a suite of complementary econometric strategies, chosen based on data availability and the specific research question.

High-frequency event studies with extended windows. Building on Berger et al. (2023), future work should extend the event window beyond the standard $[-5, +5]$ day horizon to capture medium-term operational consequences (e.g., $[-1, +90]$ days), and use daily operational loss data rather than quarterly aggregates where available. Cross-sectional regressions of CAR on bank preparedness indicators (backup power capacity, data centre geographic diversification, remote work capability, and cyber resilience scores) would identify the operational determinants of climate resilience.

Staggered DiD with robust estimators. For geographically bounded climate events (storms, floods) that affect some banks but not others, staggered DiD designs using recent advances (Callaway & Sant'Anna, 2021; Sun & Abraham, 2021) can credibly estimate average treatment effects while allowing for treatment effect heterogeneity across time and bank type. Instrumental variable strategies using climate variables (e.g., sea surface temperature anomalies as instruments for hurricane intensity (Berger et al., 2023)) can address concerns about endogenous adaptation behaviour.

Quantile regression and tail analysis. Given the heavy-tailed distribution of operational losses (Moscadelli, 2004), quantile regression—rather than mean regression—is the appropriate tool for analysing large loss events. This is particularly relevant for rare but severe climate events (a once-in-a-century flood) where the policy concern is with tail risk rather than average losses. An important refinement suggested by the operational risk literature is to test explicitly whether climate events alter the *thickness* of the tail of the operational loss distribution, rather than merely shifting its mean or median. If climate shocks increase the tail index parameter of a generalised Pareto distribution fit to the loss data, this would imply that climate risk disproportionately inflates extreme losses—precisely the losses that drive capital requirements under Value-at-Risk based regulatory frameworks. This test can be implemented by comparing tail index estimates for periods of high versus low climate event incidence, or by including a climate hazard intensity variable in an extreme value regression (Moscadelli, 2004).

Survival analysis for operational disruptions. The time until an operational failure occurs—e.g., a data centre failing under heat stress, or a payment system going down following storm damage—is naturally analysed using survival or duration models (Miller, 2011).

These models can incorporate time-varying climate covariates (temperature trends and precipitation anomalies) and bank-level resilience indicators to predict failure probability over time.

Legal risk modelling. Climate litigation risk calls for dedicated econometric analysis. Panel data models linking banks' climate-related legal exposures (measured from litigation databases such as the Sabin Center Climate Litigation database) to operational risk capital requirements can examine whether current prudential treatment adequately reflects litigation trends (Network for Greening the Financial System, 2023a; Smoleńska et al., 2025). Logit or probit models can estimate the probability of climate litigation across banks as a function of governance, disclosure quality, and ESG performance.

Connection to Basel framework. Econometric estimates of the frequency and severity of climate-related operational events can directly inform scenario design for climate stress testing, as required by Basel III and the ECB supervisory framework. Quantile regression estimates of tail losses can calibrate the stress scenarios used in Internal Capital Adequacy Assessment Processes (ICAAPs). Survival analysis can inform Business Continuity Planning (BCP) requirements by providing empirical estimates of failure probabilities under different climate intensities.

5.3. Stage 3: Agent-Based Modelling for Systemic Simulation

Rationale. Econometric methods estimate average or tail effects of climate events conditional on historical data. They are less suited to simulating the forward-looking propagation of climate shocks through interconnected banking systems, the feedback effects of bank adaptation strategies, or the system-wide consequences of regulatory interventions. Agent-based modelling (ABM) addresses these limitations by simulating heterogeneous agents—banks, employees, customers, regulators, infrastructure operators—interacting under user-specified climate scenarios (Poledna et al., 2023; Tesfatsion & Judd, 2006).

ABM is particularly well suited to climate risk analysis because climate events are characterised by non-linearity (small changes in hazard intensity can trigger disproportionate system responses), heterogeneity (different banks face very different exposures), and feedback (bank adaptation strategies—such as relocating data centres or adopting remote work protocols—change the system's risk profile). The macroeconomic ABM framework developed by Poledna et al. (2023) for the Austrian economy has already been applied to simulate the cascading economic impacts of flood events (Bachner et al., 2024), demonstrating the feasibility and policy relevance of this approach for financial institutions.

Agent specification. The agent population draws on established practice in financial ABMs (Poledna et al., 2023; Tesfatsion & Judd, 2006). Six agent types are specified as a transparent baseline designed to preserve the distinct transmission channels of climate-related operational risk identified in the review. A more parsimonious specification may be possible, but collapsing functionally distinct roles could obscure important mechanisms: for example, merging infrastructure operators with banks would prevent the simulation of cascading failures across institutions. The six types are:

1. Banks: Heterogeneous in size, geographic exposure, IT infrastructure quality, capitalisation, and climate preparedness. Their decision rules govern liquidity management, infrastructure investment, remote work deployment, and outsourcing strategies.
2. Regulators: Set capital requirements, enforce disclosure obligations, and update supervisory expectations in response to observed climate events and bank behaviour.
3. Employees: Subject to mobility constraints during extreme weather events (heatwaves and floods). Their availability affects banks' operational capacity—a channel documented empirically in the context of hurricane strikes (Brei et al., 2019).

4. Infrastructure operators: Provide power, communications, and IT services to banks. Infrastructure failures cascade to bank operations and can generate correlated losses across multiple institutions sharing the same utilities.
5. Third-party providers: IT vendors, cloud service providers, outsourced processing centres. Their geographic concentration may create correlated failure risks during regional climate events, constituting a systemic concentration risk that individual bank-level analysis would miss.
6. Customers: Both retail (households) and corporate. Their behaviour—including deposit withdrawals, increased borrowing, and payment delays—following climate events affects bank liquidity and credit risk as documented by Brei et al. (2019) and Huesler (2024).

Parameterisation and calibration. Agent attributes and decision rules should be calibrated using the econometric estimates from Stage 2 and the pattern identification from Stage 1: specifically, the probability of operational disruption as a function of climate hazard intensity (from survival analysis), the magnitude of deposit outflows following climate events (from DiD or FE estimates), the probability of litigation (from logit models), and the cross-bank correlation of infrastructure failures under regional climate events (from network analysis). Bayesian networks can model probabilistic dependencies among agent states, and Markov chain models can describe transitions between operational states (normal, degraded, and failed) under varying climate intensities.

Scenario design. Simulation scenarios should cover the full range of NGFS climate scenarios (Network for Greening the Financial System, 2023c), from an orderly transition to a disorderly transition and a "hot house world", each implying different physical risk trajectories. Within each scenario, specific acute event simulations—a once-in-fifty-year flood, an extended heatwave, a Category 4 hurricane—should be run to generate probability distributions of operational loss outcomes across the banking system. Sensitivity analyses on key parameters (e.g., the fraction of banks with offsite data backups, and the degree of IT infrastructure geographic concentration) identify the most important leverage points for systemic resilience.

Validation. Model validation is critical for establishing the credibility of ABM outputs for regulatory use. We recommend a multi-layered validation strategy following best practice in computational economics (Tesfatsion & Judd, 2006). Historical back-testing involves running the model on historical climate events—the 2021 Western European floods, Hurricane Katrina (2005), the 2011 Thailand floods—and comparing simulated aggregate operational loss distributions and recovery trajectories against observed data. Goodness-of-fit can be assessed using distributional tests (Kolmogorov–Smirnov and Anderson–Darling) on simulated vs. observed loss amounts. Sensitivity analysis involves systematically varying key parameters—climate hazard intensity, fraction of banks with offsite data backups, geographic concentration of IT infrastructure—and verifying that model outputs respond in the expected direction and magnitude. Parameters to which outputs are most sensitive should receive the most careful empirical calibration from Stage 2 estimates. Scenario stress testing involves running the model under NGFS-aligned forward scenarios (orderly transition, disorderly transition, hot house world at $+3^{\circ}$C) and comparing outputs to ECB climate stress test benchmarks (European Central Bank, 2021) as an external plausibility check. Cross-validation involves splitting the historical data into training and test periods—calibrating the model on pre-2015 events and validating on 2015–2025 events—to assess out-of-sample performance. Monte Carlo methods provide confidence bounds on all simulation outputs, and results should be reported as probability distributions rather than point estimates.

Connection to Basel framework. ABM outputs—specifically, the frequency and severity distributions of operational loss events under different climate scenarios—can inform the Standardised Approach for operational risk capital by providing forward-looking supplements to the historical loss data on which the Business Indicator Component is currently based. The BCBS has acknowledged that historical data may underestimate future climate-related operational losses as climate conditions shift (Basel Committee on Banking Supervision, 2021c); ABM scenarios provide a principled method for forward adjustment. ABM can also simulate the system-wide effects of different regulatory interventions—such as requiring minimum standards for data centre geographic diversification or mandatory remote work capability—enabling evidence-based regulatory design.

Implementation platforms. The ABM can be implemented using open-source platforms such as NetLogo, Repast Simphony, or Mesa (Python-based); AnyLogic offers a commercial alternative. Cloud-based infrastructure makes large-scale simulations increasingly accessible.

6. Discussion

The roadmap proposed in Section 5 raises several broader questions that merit explicit discussion.

Data availability and the chicken-and-egg problem. A recurring theme across all three stages is data scarcity. Operational loss databases at the bank level are typically confidential supervisory data; climate hazard data at the spatial resolution of individual branches are improving but remain imperfect; and litigation databases are fragmented. The BCBS call for explicit climate flagging in loss databases (Basel Committee on Banking Supervision, 2021c) is a necessary first step, but implementation is uneven. Academic researchers can partially circumvent data scarcity by using natural disasters as exogenous shocks in quasi-experimental designs, by combining public financial data with publicly available climate databases (EM-DAT, NatCatSERVICE, and IBTrACS for tropical cyclones), and by exploiting geographic variation in climate exposure at the county or zip-code level. Supervisory researchers with access to confidential data have a particular comparative advantage in Stage 2 econometric work.

The legal risk gap. The review reveals a significant asymmetry: physical disruption risk has received more empirical attention than legal and litigation risk, despite the latter's direct capital implications under Basel. This is partly because litigation data are sparse and fragmented, and partly because the academic literature has not yet systematically engaged with the Basel taxonomy in this dimension. Future research should prioritise building harmonised climate litigation databases (building on the Sabin Center and Grantham Research Institute datasets) and linking them to bank-level operational risk capital data.

Regional asymmetries in risk perception and reporting. A practical challenge for the roadmap is that the perception, measurement, and reporting of climate-related operational risk varies substantially across jurisdictions. Media attention to climate risk in banking is not geographically neutral: research on discourse networks connecting banks and regulators finds that U.S.-led news coverage tends to emphasise certain risk framings—particularly transition and reputational dimensions—more than others, with systematic differences in how ESG themes are framed before and after major regulatory milestones (Naysary et al., 2026). These regional asymmetries in discourse imply that the NLP component of Stage 1 must be calibrated separately for different jurisdictions, and that the interpretation of sentiment signals as early warning indicators of litigation risk may require region-specific thresholds. The econometric and ABM stages similarly need to account for cross-country heterogeneity in regulatory frameworks, litigation environments, and physical hazard profiles—arguing for international data-sharing agreements among supervisors as a priority for advancing this research programme.

Transition risk interactions. Our focus throughout is on physical climate risk as the primary driver of operational disruptions. However, transition risk—regulatory changes, carbon pricing, and shifts in consumer preferences—can also generate operational risk through compliance costs, litigation arising from greenwashing allegations, and stranded asset write-downs. The interaction between physical and transition risks may be non-linear: for example, banks facing high transition risk (due to fossil fuel portfolio concentration) may simultaneously be reluctant to invest in climate adaptation for their physical infrastructure, creating correlated exposure. Future ABM work should incorporate transition risk channels alongside physical risk.

Geographic heterogeneity. The empirical literature is dominated by U.S. and Caribbean evidence. Despite high physical climate exposure in Asia, Africa, and Latin America, bank-level operational risk data from these regions are largely absent—precisely the gap identified in Section 3. International data-sharing agreements among supervisors would significantly accelerate progress.

The Basel operational risk capital nexus. A distinctive feature of the roadmap outlined here is its explicit connection to the Basel Standardised Approach. Under the Basel III finalised framework for operational risk, capital requirements are determined by the Business Indicator (BI)—a measure of bank scale—and an internal loss multiplier for large banks with significant historical loss experience (Basel Committee on Banking Supervision, 2021a). Climate-related operational losses, if properly identified and flagged in loss databases, would flow directly into the Internal Loss Multiplier calculation, potentially requiring additional capital buffers. Our ABM framework provides a principled method for forward-looking capital calibration that complements the historical data used in the current approach.

7. Conclusions

Climate-related operational risk in banking is a field in rapid but uneven development. The empirical evidence is fragmented across geographies, methodologies, and risk dimensions, and one increasingly consequential channel—legal and litigation risk—remains under-theorised despite its direct capital implications. This paper has provided a critical review of the field, a detailed methodological assessment, and a structured roadmap for future research.

Three core messages emerge from our analysis. It should be recalled that the roadmap proposed here is conceptual in nature and does not constitute a fully operational model; its value lies in organising future research directions within a coherent analytical structure.

First, the methodological toolkit of the existing literature is individually inadequate to the distinctive challenges of this domain. Event studies (Berger et al., 2023; Perry & de Fontnouvelle, 2005) capture immediate market reactions but miss longer-term operational costs and exclude non-listed banks. Fixed-effects regressions (Brei et al., 2019) control for unobserved heterogeneity but cannot identify time-varying confounders. Network models (Grimwade, 2022) capture propagation dynamics but require unavailable data. No single method simultaneously addresses data scarcity, rare-event structure, non-linearity, endogeneity, and regulatory relevance. The three-stage framework proposed here—combining machine learning (Breiman, 2001; Peng et al., 2005), robust econometric identification (Callaway & Sant'Anna, 2021; Sun & Abraham, 2021), and agent-based simulation (Poledna et al., 2023)—is designed as a set of complements, where each stage addresses the limitations of the others.

Second, the legal risk dimension of climate-related operational risk must be elevated in research priority. The BCBS (Basel Committee on Banking Supervision, 2021c), ECB (European Central Bank, 2020), and NGFS (Network for Greening the Financial System, 2023a) have all flagged climate litigation as a growing prudential concern, and the Basel framework explicitly includes legal risk within the operational risk perimeter (Basel Committee on Banking Supervision, 2006). Yet Smołeńska et al. (2025) documented that banks systematically mis-classify litigation exposure as reputational rather than operational risk—a practice that may lead to under-capitalisation. Empirical research has barely begun to quantify the magnitude of this exposure or its capital implications under the Standardised Approach (Basel Committee on Banking Supervision, 2021a).

Third, the connection between academic research and the Basel operational risk framework must be strengthened. The empirical benchmarks documented by Berger et al. (2023)—operational losses exceeding 25% of net income for large U.S. BHCs—illustrate that even a modest climate-driven increase in loss frequency or tail severity could represent a material tipping point for capital adequacy. Empirical estimates of loss frequencies and severities under different climate scenarios can directly inform the Standardised Approach (Basel Committee on Banking Supervision, 2021a), enabling a more forward-looking and climate-responsive regulatory framework. ABM scenarios (Bachner et al., 2024; Poledna et al., 2023) offer a principled method for forward calibration, going beyond the historical loss data on which the current Business Indicator Component is based.

Limitations of our approach include the inherent model uncertainty of ABMs, whose parameterisation depends on the quality of econometric estimates in Stage 2, and the risk that historical data underestimate future climate-related operational losses as climate conditions shift beyond historical ranges—a problem common to all backward-looking risk models. Future work should develop validation strategies based on multiple historical climate events and stress-testing exercises calibrated to forward-looking climate pathways.

The overarching goal is to equip both financial institutions and their supervisors with the analytical tools needed to assess, price, and mitigate operational risks in an increasingly volatile climate. The academic research programme outlined here, if pursued, can make a material contribution to that goal.

Author Contributions: Conceptualization, E.G., P.M. and C.R.N.; methodology, E.G. and P.M.; writing—original draft preparation, E.G., P.M. and C.R.N.; writing—review and editing, E.G., P.M. and C.R.N.; supervision, E.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the European Union-Next Generation EU-PRIN 2022-code 2022KKHAF3.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Acknowledgments: The authors thank the participants of seminars and workshops where earlier versions of this work were presented for their valuable comments and suggestions.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-Based Model
BCP	Business Continuity Planning
BCBS	Basel Committee on Banking Supervision
BHC	Bank Holding Company
BIC	Business Indicator Component

CAR	Cumulative Abnormal Return
CAAR	Cumulative Average Abnormal Return
DiD	Difference-in-Differences
EBA	European Banking Authority
ECB	European Central Bank
ESG	Environmental, Social, and Governance
FE	Fixed Effects
ICAAP	Internal Capital Adequacy Assessment Process
ILM	Internal Loss Multiplier
ML	Machine Learning
NGFS	Network for Greening the Financial System
OLS	Ordinary Least Squares
ORX	Operational Riskdata eXchange Association
SHAP	SHapley Additive exPlanations
TVP-VAR	Time-Varying Parameter Vector Autoregression

Appendix A. Illustrative Input Variables for Stage 1 Machine Learning Models

Table A1. Illustrative input variables for Stage 1 machine learning models.

Variable Category	Variable	Source/Frequency
Climate hazard (spatial)	Daily precipitation anomaly at branch/data centre location	ERA5 reanalysis, 0.25°/daily
	Peak wind speed during storm events	ERA5/event-based
	Flood inundation depth and duration	EFAS (EU), FEMA (U.S.)/event-based
	Heat stress index (wet-bulb globe temperature)	ERA5/daily
	Wildfire perimeter proximity	FIRMS/MODIS/daily
Bank physical exposure	Number of branches per flood zone category	GIS matching/annual
	Data centres in high heat-stress zones	GIS matching/annual
	Share of outsourced critical IT services	Annual reports/annual
	IT infrastructure age (proxy: capex trend)	Supervisory data/annual
	Geographic concentration index of operations	Annual reports/annual
Bank financial	CET1 ratio	Supervisory data/quarterly
	Business complexity score (Chernobai et al., 2021)	Annual reports/annual
	Net income and operational loss ratio	Supervisory data/quarterly
	Insurance coverage for operational risk	Annual reports/annual
Outcome variables	Operational loss amount by Basel event-type category	Internal loss databases/quarterly
	Number of loss events above materiality threshold	Internal loss databases/quarterly
	Service interruption duration (hours)	Operational records/event-based
	Legal claim filings and settlement amounts	Litigation databases/event-based

Note: This list is illustrative and not exhaustive. Actual variable selection should follow the mutual information-based feature selection procedure described in Stage 1 (Peng et al., 2005). Availability varies by jurisdiction and bank size; supervisory databases typically provide richer coverage than public sources.

References

Amani, R., Ahmadzade, K., & Habibi, F. (2023). Operational risk, climate change, and economic growth in Iran. *International Journal of New Political Economy*, *4*(2), 301–338.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. [CrossRef]

Bachner, G., Knittel, N., Poledna, S., Hochrainer-Stigler, S., & Reiter, K. (2024). Revealing indirect risks in complex socioeconomic systems: A highly detailed multi-model analysis of flood events in Austria. *Risk Analysis*, *44*(1), 229–243. [PubMed]

Banholzer, S., Kossin, J., & Donner, S. (2014). The impact of climate change on natural disasters. In *Reducing disaster: Early warning systems for climate change* (pp. 21–49). Springer.

Basel Committee on Banking Supervision. (2000). *Principles for the management of credit risk* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2006). *International convergence of capital measurement and capital standards: A revised framework* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2017). *Guidelines: Pillar 2 supervisory review process* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2021a). *Basel III: Finalising post-crisis reforms* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2021b). *Climate-related financial risks—Measurement methodologies* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2021c). *Frequently asked questions on climate-related financial risks* (Technical Report). Bank for International Settlements.

Basel Committee on Banking Supervision. (2023). *Consultative document: Pillar 3 disclosure requirements—Climate-related financial risks* (Technical Report). Bank for International Settlements.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, *7*, 283–288. [CrossRef]

Baumeister, R. F., & Leary, M. R. (1997). Writing narrative literature reviews. *Review of General Psychology*, *1*(3), 311–320. [CrossRef]

Berger, A., Curti, F., Lazaryan, N., Mihov, A., & Roman, R. A. (2023). *Climate risks in the U.S. banking sector: Evidence from operational losses and extreme storms* (Working Paper No. 23-31). Federal Reserve Bank of Philadelphia.

Beyer, A., & Nobile, L. (2025). *The impact of climate litigation risk on firms' cost of bank loans* (Working Paper Series No. 3087). European Central Bank.

Bos, J. W. B., Li, R., & Sanders, M. W. J. L. (2022). Hazardous lending: The impact of natural disasters on bank asset portfolio. *Economic Modelling*, *108*, 105760. [CrossRef]

Brei, M., Mohan, P., & Strobl, E. (2019). The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. *The Quarterly Review of Economics and Finance*, *72*, 232–239. [CrossRef]

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. [CrossRef]

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. [CrossRef]

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., & Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, *8*, 462–468. [CrossRef]

Caselli, S., & Migliorelli, M. (2024). *Physical risk from climate change and local banks' lending: What lies ahead?* (Policy Note No. 339). SUERF.

Chabot, M., & Bertrand, J.-L. (2023). Climate risks and financial stability: Evidence from the European financial system. *Journal of Financial Stability*, *69*, 101190. [CrossRef]

Chernobai, A., Ozdagli, A., & Wang, J. (2021). Business complexity and risk management: Evidence from operational risk events in U.S. bank holding companies. *Journal of Monetary Economics*, *117*, 418–440. [CrossRef]

Colacito, R., Hoffmann, B., & Phan, T. (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking*, *51*(2–3), 313–368.

Committee on Payment and Settlement Systems. (2003). *A glossary of terms used in payments and settlement systems* (Technical Report). Bank for International Settlements.

Cummins, J. D., Lewis, C. M., & Wei, R. (2006). The market value impact of operational loss events for U.S. banks and insurers. *Journal of Banking & Finance*, *30*(10), 2605–2634. [CrossRef]

European Banking Authority. (2025). *Guidelines on the management of environmental, social and governance (ESG) risks* (Technical Report). European Banking Authority.

European Central Bank. (2020). *Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure* (Technical Report). European Central Bank.

European Central Bank. (2021). *Climate-related risk and financial stability* (Technical Report). European Central Bank.

European Central Bank. (2025, July 11). *Banks have made good progress in managing climate and nature risks—And must continue*. ECB Supervisory Blog. Available online: https://www.ecb.europa.eu/press/blog/date/2025/html/ecb.blog20250711~f5c6a0259f.en.html (accessed on 25 May 2026).

EY. (2025, May 22). *Impact of climate risk on banks and expected credit losses*. EY Insights. Available online: https://www.ey.com/en_gl/insights/ifrs/impact-of-climate-risk-on-banks-and-ecl (accessed on 11 June 2026).

Federal Reserve Board. (2023). *Pilot climate scenario analysis exercise: Participant instructions* (Technical Report). Federal Reserve Board.

Fiordelisi, F., Soana, M. G., & Schwizer, P. (2013). The determinants of reputational risk in the banking sector. *Journal of Banking & Finance*, *37*(5), 1359–1371. [CrossRef]

Fiordelisi, F., Soana, M. G., & Schwizer, P. (2014). Reputational losses and operational risk in banking. *European Journal of Finance*, *20*(2), 105–124.

Galletta, S., Goodell, J. W., Mazzú, S., & Paltrinieri, A. (2023). Bank reputation and operational risk: The impact of ESG. *Finance Research Letters*, *51*, 103494. [CrossRef]

Gillet, R., Hübner, G., & Plunus, S. (2010). Operational risk and reputation in the financial industry. *Journal of Banking & Finance*, *34*(1), 224–235. [CrossRef]

Grimwade, G. (2022). How climate change may impact operational risk. *Journal of Operational Risk*, *17*(4), 1–30. [CrossRef]

Huesler, J. (2024). Impact of tropical storms on the banking sector in the British Colonial Caribbean. *Cliometrica*, *18*(3), 653–690. [CrossRef]

KPMG. (2024). *Capturing climate-related financial risks in the Basel framework* (Technical Report). KPMG.

Lundberg, S. M., & Lee, S.-I. (2017, December 4–9). *A unified approach to interpreting model predictions*. Advances in Neural Information Processing Systems 30, Annual Conference on Neural Information Processing Systems 2017, Long Beach, CA, USA.

Miller, R. G. (2011). *Survival analysis*. Wiley.

Moscadelli, M. (2004). *The modelling of operational risk: Experience with the analysis of the data collected by the Basel Committee* (Working Paper No. 517). Bank of Italy.

Naysary, B., Edisen, M., & Tarazi, A. (2026). Climate risk news and banking industry: A natural language processing approach. *Journal of Financial Stability*, *84*, 101549. [CrossRef]

Network for Greening the Financial System. (2020). *Guide for supervisors: Integrating climate-related and environmental risks into prudential supervision* (Technical Report). Network for Greening the Financial System.

Network for Greening the Financial System. (2023a). *Climate litigation and financial risk* (Technical Report). Network for Greening the Financial System.

Network for Greening the Financial System. (2023b). *Nature-related financial risks: A conceptual framework to guide action by central banks and supervisors* (Technical Report). Network for Greening the Financial System.

Network for Greening the Financial System. (2023c). *NGFS scenarios for central banks and supervisors* (Technical Report). Network for Greening the Financial System.

Pagliari, M. S. (2023). LSIs' exposures to climate-change-related risks: An approach to assess physical risks. *International Journal of Central Banking*, *19*(1), 3–53.

Peng, H., Long, F., & Ding, C. (2005). Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *27*(8), 1226–1238. [CrossRef] [PubMed]

Perry, J., & de Fontnouvelle, P. (2005). *Measuring reputational risk: The market reaction to operational loss announcements* (Working Paper). Federal Reserve Bank of Boston.

Poledna, S., Miess, M. G., Hommes, C., & Rabitsch, K. (2023). Economic forecasting with an agent-based model. *European Economic Review*, *151*, 104306. [CrossRef]

Smołeńska, A., Chan, T., Poensgen, I., & Higham, C. (2025). *Banks and climate litigation risk: Navigating the low-carbon transition* (CETEx Discussion Paper). Centre for Economic Transition Expertise.

Sturm, P. (2013). Operational and reputational risk in the European banking industry: The market reaction to operational risk events. *Journal of Economic Behavior & Organization*, *85*, 191–206. [CrossRef]

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. [CrossRef]

Tesfatsion, L., & Judd, K. L. (Eds.). (2006). *Handbook of computational economics: Agent-based computational economics* (Vol. 2). Elsevier.

Toma, P., & Stefanelli, V. (2022). What are the banks doing in managing climate risk? Empirical evidence from a position map. *Ecological Economics*, *200*, 107530. [CrossRef]

UCLA Anderson Forecast. (2025). *Economic impact of the Los Angeles wildfires.* UCLA Anderson School of Management. Available online: https://www.anderson.ucla.edu/about/centers/ucla-anderson-forecast/economic-impact-los-angeles-wildfires (accessed on 11 June 2026).

Wei, J., Bora, A., Oommen, V., Dong, C., Yang, J., Adie, J., Chen, C., See, S., Karniadakis, G. E., & Mengaldo, G. (2025). XAI4Extremes: An interpretable machine learning framework for understanding extreme-weather precursors under climate change. *arXiv* [CrossRef]

World Economic Forum. (2024, July 5). *Navigating climate risks: 3 Strategies for building resilient financial institutions.* World Economic Forum. Available online: https://www.weforum.org/stories/2024/07/navigating-climate-risks-key-strategies-for-resilient-financial-institutions/ (accessed on 11 June 2026).