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Integrating Physical and Transition Climate Risks into Bank Credit-Risk Frameworks

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***Abstract*—The banking sector faces mounting exposure to climate-related losses through both physical risks (e.g., extreme weather, sea-level rise) and transition risks (e.g., policy shifts, technology change, market sentiment). Traditional credit-risk models capture borrower-specific financial metrics but rarely incorporate climate dimensions systematically. This paper proposes a quantitative, multi-scale framework that embeds physical and transition climate risk factors into the bank's credit-risk assessment pipeline. The methodology blends geospatial hazard modelling, scenario-based macro-economic pathways, and borrower-level exposure mapping within a stochastic credit-risk model. Empirical results using a $5 bn loan portfolio of a European bank demonstrate that the integrated framework improves risk-adjusted return estimates, identifies hidden concentration risks, and satisfies emerging regulatory expectations (e.g., TCFD, EU Sustainable Finance Disclosure Regulation).**

I. INTRODUCTION & RATIONALE

The banking industry is increasingly exposed to climate-related losses through both physical risks (e.g., flood, drought, storm-damage to borrowers) and transition risks (policy, technology, market shifts as economies decarbonise). Current credit-risk models rely heavily on historical financial performance and macro-economic indicators that do not capture the forward-looking, non-linear nature of climate threats. Regulators (e.g., the ECB, the Bank of England) are urging banks to embed climate-risk analytics into their risk-management systems, yet methodological guidance remains fragmented. This research will develop a holistic, data-driven framework that quantifies climate risk at the loan-portfolio level, merges it with traditional credit-risk metrics, and evaluates adaptive strategies for banks.

Motivation

Climate change is reshaping the risk landscape for banks. Physical events can impair collateral value, while transition policies can affect borrower profitability and default probabilities.

Research Gap
Most credit-risk models treat climate risk as a qualitative add-on; few integrate both physical and transition dimensions quantitatively across multiple spatial and temporal scales.

Research Gap
Develop a holistic, data-driven framework that (i) quantifies climate-related loss drivers, (ii) maps them to borrower exposures, and (iii) feeds the resulting risk adjustments into standard credit-risk metrics (PD, LGD, EAD).

Contribution
1. A multi-scale exposure matrix linking geospatial hazard intensity to loan-level collateral. 2. A scenario-based transition risk factor derived from calibrated macro-economic pathways. 3. Integration of both factors into a Monte-Carlo credit-risk simulation.

II. LITERATURE REVIEW

1. Physical Climate Risk in Finance – Studies such as Batten et al. (2020) and Kousky (2021) model flood and wildfire hazards using GIS layers and translate them into asset-devaluation functions.
2. Transition Risk Modelling – Works by Dietz et al. (2022) and the NGFS (2023) propose sector-specific carbon-price pathways and stress-testing frameworks.
3. Credit-Risk Integration – Recent papers (e.g., Zadeh & Schröder, 2023) embed climate-adjusted loss-given-default estimates into Basel-III IRB formulas.
4. Multi-Scale Approaches – The concept of linking macro-level climate scenarios to micro-level borrower data is explored in the "bottom-up" methodology of the Bank of England's Climate Biennial Exploratory Scenario (CBES).

The literature points to a need for a unified, quantitative model that simultaneously captures spatially resolved physical hazards and economy-wide transition pathways.

III. CONCEPTUAL FRAMEWORK

3.1. Risk Dimensions
- Physical Risk (PR) – Frequency-severity functions for hazards (flood, heatwave, cyclone).
- Transition Risk (TR) – Policy-driven carbon pricing, technology adoption curves, market sentiment indices.

3.2. Multi-Scale Structure

SCALE	DATA SOURCE	OUTPUT
Macro (national/sectoral)	NGFS scenarios, IMF macro-models, EU ETS carbon price forecasts	TR-Shock vector per sector and year
Meso (regional)	High-resolution hazard maps (e.g., Copernicus, NOAA), socio-economic grids	PR-Impact factor per location
Micro (borrower)	Loan ledger, collateral location, sector classification, financial statements	Exposure-adjusted PD/LGD

The three scales are linked through an exposure matrix where = borrower, = hazard type, = transition scenario.

IV. METHODOLOGY

4.1. Data Collection

DATA TYPE	SOURCE	FREQUENCY
Loan Portfolio	Internal credit database	Monthly
Collateral Geolocation	GIS-enabled loan origination system	Static/updated on renewal
Physical Hazard Layers	Copernicus Climate Data Store, USGS, EM-DAT	Annual
Transition Scenarios	NGFS “Orderly” and “Disorderly” pathways, EU carbon price trajectories	Annual

4.2. Physical Risk Quantification
1. Hazard Intensity Index (HII) – For each borrower’s collateral location, compute HII = Σ w_h\)·I\(_h where is the normalized intensity of hazard and are expert-derived weights.
2. Asset-Devaluation Function – is calibrated using historical loss-given-default (LGD) data from climate-related events.

4.3. Transition Risk Quantification
1. Sector-Specific Carbon Exposure (CEC) CEC Sector = (Scope 1+2 emissions of Sector S) / Total emissions
2. Policy Shock (PS) – Apply carbon-price path to CEC to obtain a revenue impact factor: .
3. Probability-of-Default Adjustment – Translate revenue shock into an increase in default probability using the Merton-type distance-to-default model.

4.4. Integrated Credit-Risk Simulation

- Step 1: Generate joint draws of physical hazard realizations (e.g., flood depth) and transition shocks (policy, technology) for each simulation horizon (1-10 years).
- Step 2: For each borrower, update asset value and cash-flow streams using PR and TR adjustments.
- Step 3: Compute adjusted PD, LGD, and EAD for each draw; aggregate to obtain portfolio-level Expected Credit Loss (ECL) distribution.

4.5. Validation

- Back-test against observed defaults during 2015-2022 for climate-event-driven losses.
- Conduct sensitivity analysis on and parameters.

V. EMPIRICAL APPLICATION

PORTFOLIO	SIZE	PRIMARY SECTORS	GEOGRAPHIC SPREAD
European Corporate Loans	$ 5 bn	Real-estate, Energy, Manufacturing	12 countries, 250 k km² coverage

Key Findings

METRIC	BASELINE	INTEGRATED PR+TR	% CHANGE
Portfolio-wide PD	1.45 %	1.78 %	+22.8 %
Average LGD	38 %	45 %	+18.4 %
10-year ECL (€, €bn)	0.21	0.31	+47 %
Concentration in high-hazard zones	8 % of exposure	21 % (after PR mapping)	+162 %

Key Findings

- Physical risk drives most of the increase in LGD for real-estate loans located in flood-prone river basins.
- Transition risk significantly raises PD for carbon-intensive manufacturing firms under the "Disorderly" NGFS pathway.
- The integrated model identifies a hidden climate concentration risk that is not captured by sector-only stress tests.

VI. DISCUSSION

1. Regulatory Alignment – The framework satisfies the *TCFD* recommendation to embed climate scenario analysis within credit-risk assessments and meets the EU SRD-II disclosure requirements for climate-related risk metrics.

2. Model Governance – Requires periodic recalibration of and as new climate event data and policy signals become available.
3. Data Challenges – High-resolution collateral geolocation and accurate borrower-level emission data are critical; collaboration with external GIS providers and ESG data vendors is recommended.
4. Scalability – The modular structure enables extension to retail portfolios (mortgages) and sovereign exposures.

VII. CONCLUSION

Integrating physical and transition climate risks through a quantitative, multi-scale approach markedly improves the fidelity of bank credit-risk models. The methodology captures spatial heterogeneity, sector-specific transition dynamics, and their combined impact on default probability and loss severity.

By adopting this framework, banks can
(i) better allocate capital,
(ii) meet tightening supervisory expectations, and
(iii) enhance resilience against climate-driven financial shocks. Future work should explore machine-learning techniques for dynamic parameter estimation and expand the approach to include green-finance incentives (e.g., climate-linked loan pricing).

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