Topic: Using Graph Neural Networks and Network based climate stress testing to improve SME lending decisions

Abstract

1. Introduction

Increasingly, climate change is being recognised as a financial risk in global economies, particularly in emerging markets where Small and Medium Scale Enterprises (SMEs) contribute significantly to economic activity [1].

In Ghana, SMEs play a critical role in economic output and employment but remain highly vulnerable to climate-related hazards such as floods, droughts, coastal risks, and extreme heat [7].

These risks extend beyond individual firms and propagate through economic linkages including supply chains, geographic clustering, and sectoral dependencies, reinforcing the systemic nature of climate risk recognised in financial regulatory frameworks [3].

However, traditional credit risk models assume borrower independence and fail to capture correlated defaults and portfolio vulnerabilities arising from climate shocks.

This study develops a network-based climate stress testing framework using Graph Neural Networks (GNNs) to enhance credit risk assessment and lending decision-making. SMEs are modelled as nodes within a graph, with edges representing economic relationships, while node features integrate financial and climate exposure variables.

Using GraphSAGE and Graph Attention Networks, the model learns risk propagation patterns across interconnected firms [5].

A climate scenario simulation engine translates hazards into shocks affecting Probability of Default (PD), Exposure at Default (EAD), and Loss Given Default (LGD), with portfolio risk assessed using the Expected Loss framework.

Results show that the GNN-based model outperforms traditional approaches in predictive accuracy and effectively captures network-driven risk amplification, revealing significant increases in Expected Credit Loss under climate stress conditions.

Keywords

Graph Neural Networks, Climate Risk, Climate Stress Testing, MSME Credit Risk, Financial Networks

2. Methods

2.1 Graph Representation of SMEs

In this study, SMEs are modelled as nodes within a graph structure, where edges represent economic relationships.

These relationships are defined based on shared sector classification, geographic proximity, and value chain linkages, allowing the model to capture interdependencies across firms.

2.2 Feature Integration

Node features integrate both financial and climate-related variables. Financial indicators include loan characteristics and repayment behaviour, while climate exposure variables capture flood risk, drought indices, temperature anomalies, and other hazard indicators relevant to the Ghanaian context.

2.3 Graph Neural Network Architecture

Graph Neural Network architectures, specifically GraphSAGE and Graph Attention Networks (GAT), are employed to learn patterns of risk propagation across the SME network. GraphSAGE enables neighbourhood-based feature aggregation, while GAT assigns attention weights to neighbouring nodes, allowing the model to prioritise more influential relationships in the network [5].

2.4 Climate Scenario Simulation

A climate scenario simulation engine is developed using key climate hazards relevant to Ghana, including flooding, drought, extreme heat, coastal surge, and compound events [7]. These scenarios are translated into financial shocks affecting, Probability of Default (PD), Exposure at Default (EAD) and Loss Given Default (LGD)

2.5 Risk Quantification

Portfolio risk is quantified using the Expected Loss framework, where expected credit loss is estimated as a function of PD, LGD, and EAD under different climate stress scenarios [16].

3. Results

The results show that the GNN-based model outperforms traditional credit risk models such as logistic regression and gradient boosting in both predictive accuracy and calibration. The model effectively captures network-driven risk propagation, demonstrating that climate shocks lead to amplified and concentrated credit risk within interconnected SME clusters.

The findings reveal that SMEs operating within highly connected networks exhibit significantly higher vulnerability under climate stress scenarios due to contagion effects. Scenario analysis further demonstrates that portfolio-level Expected Credit Loss increases substantially under climate stress conditions, with measurable spillover effects driven by network dependencies.

4. Discussion and Conclusion

The findings of this study highlight the importance of incorporating network structures into credit risk modelling, particularly in climate-vulnerable economies.

By capturing interconnected risks and propagation dynamics, the GNN-based framework provides a more realistic representation of SME credit risk under climate stress conditions.

This has important implications for financial institutions, particularly in enhancing risk-based pricing, improving portfolio resilience, and integrating climate risk into credit decision-making processes, in line with emerging regulatory expectations on climate-related financial risks [3].

The ability to identify clusters of vulnerability also supports targeted interventions and more effective risk mitigation strategies.

However, the study is subject to limitations, including data availability constraints and assumptions in the construction of network relationships and climate scenarios. Future research can extend this work by incorporating real-time climate data, refining network structures, and exploring integration with regulatory frameworks and climate risk disclosure standards.

Overall, this study demonstrates that Graph Neural Networks provide a powerful approach for modelling climate-related financial risks and offer a robust framework for advancing climate-aware credit risk assessment in emerging markets such as Ghana.

References

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