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Research Article

Dynamical Modeling of Climate-Related Financial Risk and the Interplay of Natural Disasters, Migration, and Loan Defaults

Sunday Onos Edeki[1,2,3]*, Ozioma Ogoegbulem[1], Ini Adinya[4], Imekela Donaldson Ezekiel[5], Chaudry Masood Khalique[6]

[1] Department of Mathematics, Dennis Osadebay University, Asaba, Delta State, 320242, Nigeria
[2] Department of Science and Engineering, Faculty of Science, Novel Global Community Educational Foundation, New South Wales 2770, Australia
[3] Covenant Applied Informatics and Communications-African Centre of Excellence, Covenant University, Ota, Ogun State, 112104, Nigeria
[4] Department of Mathematics, Faculty of Science, University of Ibadan, Ibadan, Oyo State, 200005, Nigeria
[5] Department of Mathematics and Statistics, School of Pure And Applied Sciences, Federal Polytechnic Ilaro, Ilaro, Ogun State 234102, Nigeria
[6] Material Science, Innovation and Modelling Research Focus Area, Department of Mathematical Sciences, North-West University, Mafikeng Campus, Private Bag X2046, Mmabatho 2735, Republic of South Africa
* Corresponding author: sunday.edeki@dou.edu.ng

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ABSTRACT

The global financial system is at risk of experiencing systemic crises due to climate change and the combined impacts of higher natural disaster-related losses, migration pressures, and deterioration in loan default rates. A deterministic dynamical systems model is developed in this study to analyze the factors of climate change-related loss, people migration dynamics, credit default behavior, and financial sector strength. The model, based on a set of nonlinear ordinary differential equations aligned with the principles of economic and ecological dynamics, made it possible to see how the financial system might be influenced by environmental interventions in the long run. The qualitative study confirmed that the model possesses certain very critical qualities, such as positivity, boundedness, and local stability of equilibria. Consequently, a semi-analytical decomposition solution for the same was obtained using the Adomian Decomposition Method. Numerical simulations are presented as a means to demonstrate how the system dynamics respond to variations in the critical parameters and are also employed in situations that are significant for policymaking. The results show the nonlinearity and interconnectedness of climate-induced financial risk, thereby indicating the necessity for maintaining financial flexibility through adaptive policy frameworks that cater to the changing climate conditions.

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1. INTRODUCTION

Climate change poses significant risks to the global financial system by increasing exposure to systemic vulnerabilities. Natural disasters are not only more frequent but also more intense, and thereby human migration, economic losses, and default on loans become more likely (D'Orazio & Thole, 2022). The interaction between financial resilience and environmental risk means that they are provided with the corresponding strategies to deal with them, which are progressive measures. The role played by climate change in the resilience and governance of the world's economy is increasingly being valued. The increased incidence of natural disasters, coupled with population migration triggered by migration, poses serious risks to international financial systems. The complex interdependence of environmental and socio-economic processes enhances the governance of climate change financial risk (Vermeulen et al., 2021; Zürn et al., 2021). Towards this, risk management and mitigation in financial institutions deserve the necessary perspective on the interconnectedness of natural disasters, migration, and loan default. Over and above physical destruction, natural disasters in the form of hurricanes, floods, bushfires, and drought affect economies through infrastructure, productivity, and livelihood. Migration affects demographic processes strongly and socio-economic processes reflected in consumer purchasing behavior, labor markets, and loan repayment. Political instability, economic opportunity, or environmental stress may induce migration. Banks, however, are under the stress of default on loans, to which population movement and economic shocks give further momentum. This stress affects the liquidity, solvency, and shock-absorbing ability of the banks (Baldauf et al., 2020).

Dynamic modeling makes it straightforward to simulate and study the most complicated interactions over time. The impact of the ecosystem can be depicted to enter the financial systems through differential equations that obey the ecological and economic rules, which are decipherable by the researchers. In their research, Bender et al. (2010) and Bordalo et al. (2020) refer to these models as demonstrating the nonlinear aspects of climate risk, where even small initial modifications can cause great impacts on the system and thus lead to either instability or resilience. By using a sequence of dynamical models, this research attempts to elucidate the above dynamics and outline how different natural disaster circumstances, patterns of migration, and government policies affect economic resilience. Our research attempts to provide evidence-based intervention approaches for improving adaptive capacity, improving the risk management practices, and promoting sustainable economic development in a climate-affected world by integrating theoretical results and mathematical models (Dell et al., 2014). The motivation behind this study is to develop an integrated model that would be able to estimate climate change financial risks and provide feedback on effective risk management for financial institutions (Shabir et al., 2023). This implies the will and need to understand and manage complex interactions between climate and financial risk factors (Engle et al., 2020). Global warming, among other things, has been the issue of the century, and it will last for many years, interfering with the planet's ecosystems, the global economy, and human civilizations (Nang, 2019; Ashaari et al., 2020). Natural calamities are becoming more and more common, and the Earth is so depleted of resources that people are changing their places of residence, which not only is a financial risk but also a worldwide decisive one. These interacting dynamics multiply the weaknesses of financial institutions, which also affect their resilience, stability, and their capability to support economic growth in the regions of environmental uncertainty (Field et al., 2012; Gensini & Brooks, 2018).

The natural movement of people adds another level of difficulty when it is motivated by the need for resources, environmental destruction, or conflicts that climate change has triggered. The areas where people migrate or choose not to migrate have an impact on the disaster's community resilience, the labor market, and consumption patterns. It could further influence the financial services needed and the borrower's capacity to repay the loan. This is the reason why the migration patterns that lead to financial risk, which is one of the main reasons for having strong adaptable strategies that assure economic safety, social integration, and even cross-development, depend on our comprehension (Beine & Parsons, 2015). The increasing number of defaults that are happening due to environmental uncertainties is another sign of the vulnerability of financial systems. Similarly, climate change events not only result in economic shocks but also lead to a situation where the rates of defaults are so high that they pose a threat to the financial stability of the system and call for risk management that is efficient and of high quality. The goal of the current study is to build dynamic models that include factors such as environmental stressors, which would then be able to show us how the networks of financial systems are influenced by the movement of such stressors. The aim is to make available empirical data that would be of help in policy-making and regulatory actions (Giglio et al., 2021; Giglio et al., 2015).

The study's ultimate goal is to connect the academic theoretical knowledge of climate finance with the practical application. The plan is to give the policymakers, the financial sector and the stakeholders the necessary tools to enhance the adaptive capacity, increase the sustainable economic growth and make the people and the infrastructure more resilient against the threat of the changing climate through examining the natural disaster dynamics, migration patterns and loan defaults from the financial perspective (Auffhammer & Vincent 2012). The last few years have seen a considerable interest in climate-related financial risks in the literature, mainly due to the fact that they could have a very destructive impact on the prices of investments, credit risk profiles, and the entire financial system (Battiston et al., 2021). A great deal of the research has pointed out that it is an absolute necessity to incorporate the considerations of climate risks into the traditional financial risk management paradigms. The studies indicate the complexity of climate-related risks, covering both extremes of the spectrum: the physical dangers linked to climate change and the transition risks from the switch to a low-carbon economy (Krueger et al., 2020). The physical risks can be felt in terms of the direct damage caused to assets and infrastructure by like hurricanes, floods, wildfires, and droughts. Such natural disasters can create a huge financial loss, not only hitting the price of assets but also causing the disruption of business operations across various industry sectors (Faiella et al., 2022).

Transformations in policy, technological advancements, and changing consumer behavior to mitigate climate change all contribute to the generation of transition risks (Ahmed et al., 2024). These changes may have an impact on the industries producing carbon, those activities that consume a lot of carbon, and the ones that are most susceptible to changes in regulations and market shocks (Baranzini et al., 2017). The transition already has the consequent risks of assets being frozen, demand fluctuations in markets, and costs of having to comply with regulations, all of which in turn affect the creditworthiness and financial stability indirectly. The greatest part of the research supports the view that the merging of climate risk analysis into the decision-making process in the finance sector will make the whole system more resilient and, at the same time, limit the amount of expected losses (Krueger et al., 2020). The integration is equivalent to the quantification of the investment portfolios' exposure to climate risks, incorporation of climate scenarios in stress testing and scenario analysis, as well as formulation of policies for climate risk avoidance and adaptation. Besides, initiatives such as the Task Force on Climate-related Financial Disclosures have led the way in disclosing and making climate risks and opportunities known (Stern et al., 2022; Lamperti et al., 2021). Such guidelines aim to prompt banks to become more transparent with regard to the disclosure, analysis, and management of climate-related risks, to become more responsive to the marketplace, and to facilitate more informed lending and investment decisions (Arian & Sands, 2024). Even with such developments, there is still a knowledge gap regarding integrated models that enhance understanding of interdependent relations between natural disaster losses, migration, and loan defaults in financial systems (Faiella et al., 2022). To close the gap is vital to informing effective risk management policy that takes into account the systemic impacts of climate change on financial system stability and economic resilience. Along this line, the present research seeks to contribute by building a hybrid differential equation model that is able to capture interdependencies of environmental stressors and financial risks. With the same, it seeks to provide insights that can be helpful in informing policy interventions and adaptation measures in the course of building the financial resilience of a climate-scarred world (Krueger et al., 2020; Griffin & Sun, 2024).

Models of differential equations have been widely applied in finance to facilitate a proper basis to describe and analyze dynamic processes like asset prices, risk management, and economic growth. The models provide a proper technique for the temporal analysis of financial variables and quantifying the influence of affecting agents on financial markets (Chenet et al., 2021). Differential equation modeling has become the geometric ground for the Black-Scholes option pricing model and similar underpricing models in asset pricing in finance. Equation models apply stochastic differential equations to explain the time dynamics of the asset prices driven by inputs like volatility, interest rates, and market conditions. As a result, the models allow financial analysts and investors to dominate risk projection and fair value calculation of financial derivatives in the disordered market conditions (Akinci & Olmstead-Rumsey, 2018; Goldsmith-Pinkham et al., 2019). By the differential equation models, financial risk management is being ramped up. The models can yield simulations and various scenarios for risks like market risk, credit risk, and operational risk. Through analyzing risk factor behavioral patterns and association, the financial institutions can measure their loss-bearing capacity and risk (Jackson et al., 2025). In addition to that, the differential equation models illustrate the economy of economic growth, macroeconomic variables. The extensions and the Solow-Swan model have taken to differential equations for the dissecting of the determinants such as technological change, capital accumulation, and labor supply in the long-run economic growth rates. The models help policymakers to come up with the economic policies that will not only keep the stability slate but also invite sustainable growth (Castro et al., 2025).

One of the main hurdles for the financial application, even though it has its advantages, is parameter estimation, calibration, and the handling of nonlinearities and uncertainty. At the same time, progress in computational power and numerical techniques such as Monte Carlo and finite difference methods has broadened the range of the models' application and provided them with a firmer ground for being used in finance (Broeders et al., 2023). Besides, the differential equation models in the context of climate finance risk considerations have not only created more complexities in financial modeling but also have given a new dimension to model building by making environmental factors an integral part of the model simulation. The implemented models, which take into account the interrelations among disaster losses, migration, and loan defaults, will help the researchers to get a clearer picture of the financial stability and resiliency challenge areas from the climate change aspect. The present study tries to connect with the new literature on differential equations that deals with the intricate dynamics of climate finance risk for the purpose of influencing policymaking knowledgeably and optimizing adaptation initiatives amid a changing climate (Olper et al., 2021).

Current climate-related financial risk modeling frameworks address separate parts like credit risk, asset prices, or economic loss from natural disasters independently of one another (Aysan et al., 2025). Coupled models that simulate interdependent dynamics between natural disaster loss, migration, and financial default are in urgent need (Parikh et al., 2023). They are still pertinent since they concentrate on the systemic risks and complexities of financial institutions in the case of a changing environment (Scott et al., 2024). While some models include such details as the economic cost of the extreme weather strike or migration, few combine them in one framework (Beheshti & Eilam, 2025). It reduces the potential to see in an integrated way how environmental shocks are transmitted through economic sectors, affect market structures, and impact financial stability in the long term (Ozili & Lorember, 2024; Didenko & Kulik, 2018). Moreover, current models do not have the specific dynamical formulation to incorporate the new interactions and couplings between those variables under the situation of changing environmental conditions (Dai & Zhang, 2023). The significant gap mentioned in the literature will be bridged by this research through the creation of a coupled differential equation model. The model tries to cover the whole range of climate-related financial risks by including the losses from natural disasters as a reason for economic dislocation, migration as an adaptation to environmental stress, and loan defaults as a proxy for financial exposure. The study uses empirical research and precise numeric modeling to consider policy intervention and environmental state transition impact on financial systems' resilience (Menghistu et al., 2020). The coupled model will provide not only predictability but also scenario analysis in studying policy interventions and adaptation strategies. The project, which links theory to practice, is predicted to make it easier for stakeholders, policymakers, and financial institutions to take preventive measures against climate risks, to promote sustainable economic development, and to create resilience in a world that is constantly changing (Davlasheridze & Miao, 2021).

Thus, it is noteworthy to state that the novelty of this study lies in the formulation and rigorous analysis of a coupled nonlinear dynamical system that simultaneously captures climate-induced disaster losses, migration dynamics, loan/credit defaults, and banking-sector resilience. Unlike other existing approaches that address these channels in an isolated manner, the proposed framework is enabled to merge these operations within a united system of mathematical structure for stability analysis and policy-oriented settings.

2. METHODOLOGY

2.1. Variables and Parameters

Here, the coupled non-linear ODE modeling framework introduces the interactions between natural disaster losses, migration, loan defaults, and bank resilience over time, whereas migration and defaults follow with sensitivity parameters, while bank health decreases with the shocks but increases through recovery processes. In what follows, all the variables, parameters, and analytical operators are listed in Table 1 (nomenclature) and constitute the basis for the model development and intermaterial calculations.

Table 1. Model variables and parameters

Symbol	Description	Symbol	Description
$D(t)$	Loan defaults	γ_D	Impact of loan defaults on bank resilience
$L(t)$	Natural disaster losses	γ_L	Impact of disaster losses on bank resilience
$M(t)$	Migration (movement of people)	δ	Recovery or policy intervention strength
$R(t)$	Resilience of banks	K_L	Carrying capacity of disaster losses
t	Time parameter	r_D	Baseline loan default growth rate
α_L	Sensitivity of migration to disaster losses	r_L	Growth rate of natural disaster losses
β_L	Effect of disaster losses on loan defaults	r_M	Baseline migration growth rate
β_M	Effect of migration on loan defaults		

Consequently, the main factors and settings applied in the model are *L(t)* for Natural disaster losses, *M(t)* for Movement of people, *D(t)* for Loan defaults, *R(t)* for Resilience of banks, and *t* for Period of time. All variables are interdependent and governed by differential equations that illustrate their changes with time. Below is a step-by-step elaboration using the proto-compartmental approach.

Natural Disaster Losses (L): Natural disaster losses increase over time due to the increasing frequency and severity of climate events. We model this with a logistic growth function, where the growth rate slows as the losses approach a carrying capacity K_L:

$$\frac{dL}{dt} = r_L L\left(1 - \frac{L}{K_L}\right) \tag{1}$$

where L is the for amount of natural disaster losses, r_L for growth rate of natural disaster losses, and K_L for carrying capacity represents the maximum potential losses. Assumption: Natural disaster losses L grow logistically, where r_L is the growth rate, and K_L is the carrying capacity representing the maximum sustainable level of losses.

Migration (M): Migration is influenced by the rate of natural disasters. As natural disaster losses increase, more people are likely to migrate:

$$\frac{dM}{dt} = r_M M + \alpha_L L \tag{2}$$

where M implies the number of people migrating, r_M implies a natural growth rate of migration, and α_L implies sensitivity of migration to natural disaster losses. Assumption: Migration M increases with a constant rate r_M and is additionally influenced by natural disaster losses L through a coefficient α_L

Loan Defaults (D): Loan defaults are influenced by both natural disaster losses and migration. Higher losses and more migration can lead to more loan defaults:

$$\frac{dD}{dt} = r_D D + \beta_L L + \beta_M M \tag{3}$$

where D implies the number of loan defaults, r_D implies a natural growth rate of loan defaults, β_L implies the sensitivity of loan defaults to natural disaster losses, and β_M implies the sensitivity of loan defaults to migration. Assumption: Loan defaults D are governed by a default rate r_D, and are affected by natural disaster losses L (with coefficient β_L) and migration M (with coefficient β_M).

Bank Resilience (R): Bank resilience decreases due to the impacts of natural disaster losses and loan defaults, but can be mitigated by risk management strategies:

$$\frac{dR}{dt} = -\gamma_L L - \gamma_D D + \delta R \tag{4}$$

where R implies the level of bank resilience, γ_L implies the Impact of natural disaster losses on bank resilience, and γ_D implies the impact of loan defaults on bank resilience. The parameter (δ) implies the effectiveness of the bank's risk management strategies. Assumption: Bank resilience R changes based on the negative impacts of natural disaster losses L (with coefficient γ_L), loan defaults D (with coefficient γ_D), and is supported by a recovery mechanism δ. Combining these models, we get the system of differential equations:

$$\left.\begin{aligned}
\frac{dL}{dt} &= r_L L\left(1 - \frac{L}{K_L}\right), \\
\frac{dM}{dt} &= r_M M + \alpha_L L, \\
\frac{dD}{dt} &= r_D D + \beta_L L + \beta_M M, \\
\frac{dR}{dt} &= -\gamma_L L - \gamma_D D + \delta R
\end{aligned}\right\}. \tag{5}$$

The system described in (5) consists of multiple interconnected nonlinear ordinary differential equations (ODEs) that model the combined movements of environmental stress and financial stability factors. The differential system combines the dynamics of natural disaster losses (L), migration (M), loan defaults (D), and bank resilience (R) into a coherent framework. With reference to Table 2, existing literature on climate-finance, migration, and financial stability informs the parameter ranges, and where necessary, these ranges are supplemented by empirically reasonable hypothetical bounds that are commonly used in nonlinear dynamical system modeling.

Table 2. Parameter definitions, units, and empirically motivated plausible ranges for system (5)

Parameter	Description	Unit	Plausible Range	Justification
r_L	Growth rate of natural disaster losses	$year^{-1}$	0.01 – 0.30	Reflects increasing frequency and severity of climate events (Abatzoglou & Williams, 2016; Xhindole et al., 2025)
K_L	Carrying capacity of disaster losses	monetary units (USD)	50 – 500	Upper bound on cumulative or annualized climate-related losses (Baldauf et al., 2020; Svartzman et al., 2021)
r_M	Baseline migration growth rate	$year^{-1}$	0.005 – 0.10	Captures demographic and socio-economic migration trends (Berlemann & Steinhardt, 2017)
α_L	Sensitivity of migration to disaster losses	persons per monetary unit per year	0.001 – 0.10	Measures the responsiveness of population movement to environmental shocks (Backhaus et al., 2015)
r_D	Baseline loan default growth rate	$year^{-1}$	0.01 – 0.20	Consistent with observed credit deterioration during crises (Barrot & Sauvagnat, 2016; Giglio et al., 2021)
β_L	Effect of disaster losses on defaults	defaults per monetary unit per year	0.01 – 0.30	Physical damage and income shocks elevate default risk (Jackson et al., 2025; Arian & Sands, 2024)
β_M	Effect of migration on defaults	defaults per person per year	0.001 – 0.10	Migration disrupts borrower stability and repayment capacity (Cortes & Strahan, 2017)
γ_L	Impact of disaster losses on bank resilience	resilience units per monetary unit per year	0.01 – 0.40	Loss-driven erosion of bank capital and liquidity buffers (Borghei et al., 2024)
γ_D	Impact of loan defaults on bank resilience	resilience units per default per year	0.05 – 0.50	Defaults directly weaken balance sheets (Cao & Zhang, 2025)
δ	Recovery or policy intervention strength	resilience units per year	0.01 – 0.30	Captures the effectiveness of regulatory support, insurance, and risk management strategies (Campiglio et al., 2018; Svartzman et al., 2021)

2.2. Mathematical Analysis of the Model

The qualitative properties of the model, such as positivity, boundedness, and stability of the solutions, are considered in this section. An analysis conducted would clearly establish the well-posed nature of the system and serve as a theoretical basis for equilibrium behavior.

2.2.1. Positivity and Boundedness of Solutions

Theorem 2.1 (Positivity). For any initial condition, $(L(0), M(0), D(0), R(0)) \in R_+^4$, the solution of system (5) remains in R_+^4 for all t≥0.

Proof: Consider the boundary hyperplanes *L=0, M=0, D=0*, and *R=0*. On each boundary, the corresponding right-hand side of system (5) is nonnegative. In particular, the logistic equation governing L(t) preserves positivity for all t≥0. The remaining equations are linear in their respective state variables with nonnegative forcing terms. Consequently, no solution trajectory can cross into the negative orthant. Hence, R_+^4 is positively invariant under system (5). Q.E.D.

Theorem 2.2 (Boundedness). All solutions of system (5) are uniformly bounded for t≥0.

Proof: The logistic growth term implies $0 \le L(t) \le K_L$ for all $t \ge 0$.
Substituting this bound into the remaining equations yields linear differential equations with bounded coefficients and bounded forcing terms. Standard comparison principles for linear ODEs ensure that M(t), D(t), and R(t) remain bounded for all t≥0. Q.E.D.

Theorem 2.3 (Existence and Uniqueness of Solutions-Well-posedness). System (5) admits a unique global solution for any initial condition in R_+^4.

Proof: The right-hand side of system (5) consists of polynomial and linear terms in the state variables (L, M, D, R). Hence, it is continuously differentiable and locally Lipschitz on R_+^4. By the Picard-Lindelöf theorem, a unique local solution exists for any admissible initial condition (Edeki & Azu-Nwosu, 2024). The boundedness established in Theorem 2.2 guarantees that solutions do not blow up in finite time, allowing extension to a unique global solution for all t≥0. Q.E.D.

2.2.2. Equilibrium Point and Stability Analysis

Setting all time derivatives in system (5) to zero yields a unique interior equilibrium $E^* = (L^*, M^*, D^*, R^*)$, where

$$\left. L^* = K, \quad M^* = \frac{\beta K}{\alpha}, \quad D^* = \frac{\theta K + \eta M^*}{\gamma}, \quad R^* = \frac{\mu K + \nu D^*}{\delta}. \right\} \tag{6}$$

The Jacobian matrix of system (5) is given by

$$J = \begin{pmatrix} r_L\left(1 - \dfrac{2L}{K_L}\right) & 0 & 0 & 0 \\ \alpha_L & r_M & 0 & 0 \\ \beta_L & \beta_M & r_D & 0 \\ -\gamma_L & 0 & -\gamma_D & \delta \end{pmatrix}. \tag{7}$$

Evaluating at the equilibrium point E^* gives

$$J\left(E^*\right) = \begin{pmatrix} -r_L & 0 & 0 & 0 \\ \alpha_L & r_M & 0 & 0 \\ \beta_L & \beta_M & r_D & 0 \\ -\gamma_L & 0 & -\gamma_D & \delta \end{pmatrix}. \tag{8}$$

Theorem 2.4 (Local Asymptotic Stability). The equilibrium point E^* is locally asymptotically stable if $r_L > 0, \quad \alpha_L > 0, \quad \gamma_L > 0, \quad \gamma_D > 0, \quad \delta > 0.$

Proof: The Jacobian matrix $J(E^*)$ is lower triangular, and its eigenvalues are given by the diagonal entries: $\lambda_1 = -r_L, \quad \lambda_2 = \alpha, \quad \lambda_3 = \gamma, \quad \lambda_4 = \delta.$ Under the stated parameter conditions, all eigenvalues have strictly negative real parts. Therefore, the equilibrium point E^* is locally asymptotically stable by linearization theory. Q.E.D.

3. RESULTS AND DISCUSSION

3.1. System Dynamics

Considering the dynamics of the system, it is deduced that the system exhibits interdependencies where natural disaster losses drive migration patterns, which in turn influence loan defaults. Bank resilience, influenced negatively by both natural disaster losses and loan defaults, represents the overall capacity of financial institutions to withstand shocks (*interdependencies*). In addition, the nonlinear terms such as $L\left(1 - \frac{L}{K_L}\right)$, ensure interactions between variables (for instance, $\alpha_L L$ in the migration equation, and negative feedback mechanisms (for instance, $-\gamma_D D$ in the resilience equation), introduce complexities and feedback loops within the system (*nonlinearities*). Analysis of stability will involve examining how the parameter values affect the system's equilibrium points and stability conditions.

3.1.1. The Phase Plane Analysis of the Dynamics

Phase plane analysis is a useful method employed in the study of the qualitative behaviors of systems of differential equations. It involves plotting variable trajectories against each other in the phase space defined by the variables. This helps in visualizing how the system behaves over time and gives insight into how equilibrium points are stable or unstable and their dynamic nature. Any Trajectory Representation (TR) creates a particular curve, which illustrates how two variables (let's say, V and P) vary together over time. Furthermore, each point on the curve represents the real system state at a particular moment with coordinates (V(t), P(t)), and the nature and orientation of the curve illustrate how the system is going to transform in time. For example, a curve in the phase space plane (V, P) gives an idea of how bank resilience R varies as natural disaster losses L vary, hence illustrating a mutual interaction between variables. Thus, for the natural disaster losses differential equations system of migration and migration (M), loan defaults (D), bank resilience (R), and natural disaster losses (L) as represented by (5), we made the phase plane analysis by plotting trajectories within the (M, D), (L, M), (L, D), (L, R), (M, R), and (D, R) planes. This helps us to understand the role played by natural disaster losses in affecting migration and loan defaults, and vice versa.

3.1.2. Remarks on the Phase Plane Dynamics and Equilibrium Attraction

The phase plane diagrams presented in Figure 1 further support the stability analysis. Trajectories in the (L, M), (L, D), and (D, R) planes spiral or move monotonically toward equilibrium points, indicating dissipative dynamics. These geometric features are consistent with the eigenvalue structure of the Jacobian matrix at E^*. Negative real parts of all eigenvalues imply that the equilibrium acts as an attractor, a property clearly reflected in the Adomian Decomposition Method (ADM)-based phase portraits.

3.1.3. Results of the Adomian Decomposition Method on the System (5)

For the approximations of analytical solutions in (5). We apply the ADM. This method is applicable to strongly nonlinearly coupled systems and can provide rapidly converging series solutions referred to as an ADM solution, or an Adomian series, under certain good convergence conditions given in Theorems 2.1-2.3. Each state variable is expressed as an infinite series:

$$\left.L(t)=\sum_{n=0}^{\infty}L_n(t),\quad M(t)=\sum_{n=0}^{\infty}M_n(t),\quad D(t)=\sum_{n=0}^{\infty}D_n(t),\quad R(t)=\sum_{n=0}^{\infty}R_n(t).\right\} \tag{9}$$

The nonlinear terms, including the logistic component $L(1-L/K)$ and the coupling terms $\alpha L,\ \beta_L L,\ \beta_M M,\ \gamma_L L$, and $\gamma_D D$, are decomposed using Adomian polynomials. The zeroth components are chosen to satisfy the initial conditions:

$$L_0(0)=L(0),\quad M_0(0)=M(0),\quad D_0(0)=D(0),\quad R_0(0)=R(0).$$

Successive components are obtained recursively by integrating the linear parts of system (5) and incorporating the Adomian polynomials associated with the nonlinear interactions.

3.1.4. Truncated ADM Solutions for Simulation

For numerical implementation, the ADM series-polynomials are truncated after a finite number of terms N, yielding the approximate solutions:

$$\left.\begin{array}{l} L^{(N)}(t)=\sum_{n=0}^{N}L_n(t),\quad M^{(N)}(t)=\sum_{n=0}^{N}M_n(t),\\ D^{(N)}(t)=\sum_{n=0}^{N}D_n(t),\quad R^{(N)}(t)=\sum_{n=0}^{N}R_n(t). \end{array}\right\} \tag{10}$$

The boundedness result in Theorem 2.2 ensures that these truncated solutions remain finite and physically meaningful, while Theorem 2.3 guarantees convergence toward the unique solution of system (5). When parameters satisfy the stability conditions in Theorem 2.4, the truncated ADM trajectories initialized near equilibrium converge toward the interior equilibrium point E^*. These truncated ADM expressions form the basis for all numerical simulations presented in the work, in line with the solution via the phase plane analysis. Thus, the following figures are referred.

3.1.5. Findings from Phase Plane Analysis Insights

The phase plane setup in Figure 1 elucidates how equilibrium points and trajectories instigate the interactions among its main variables. For natural disaster losses and migration, an equilibrium will tend to stability, with migration initially responding to disaster shocks, before stabilizing. The interdependence of natural disaster losses with loan defaults exhibits some stabilizing mechanisms, as defaults would initially rise before evening out for some time, and then either stabilize if the hardship caused over time stops or escalate further. The relationship between migration and defaults gets settled upon equilibrium, showing the succession of dynamics between migration and defaults. In the combination of losses from natural disasters and bank resilience, the system tends toward stabilization; resilience adjusts and recovers with each after a shock. Migration and bank resilience also have stable equilibria, showing the ever-present evolving effects migration has on resilience. Finally, defaults and bank resilience come to settle their equilibrium cases, with their respective trajectory showing the change associated with increasing defaults.

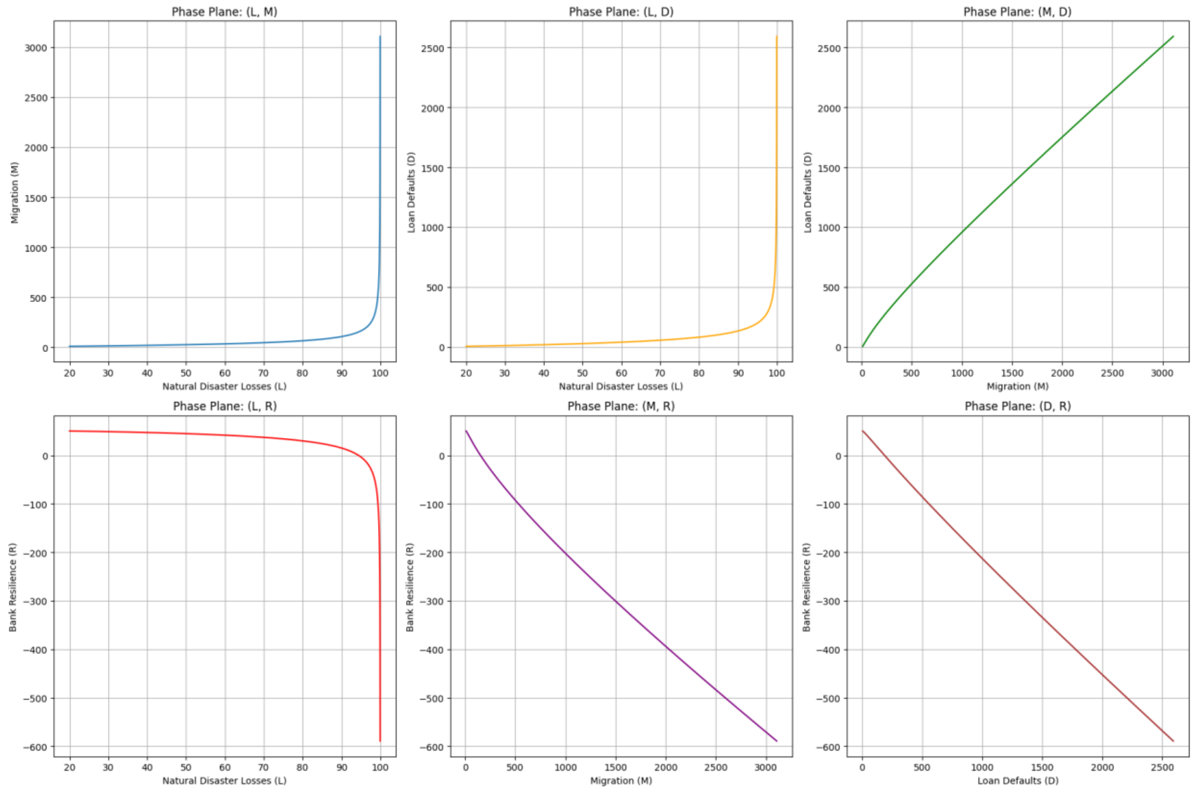

Figure 1. Phase plane trajectories of system (5) showing interactions among L, M, D, and R and convergence to equilibrium

3.1.6. Financial Implications from the Phase Plane Analysis

The stable equilibrium points revealed by this study not only advance the financial resilience against the impact of natural disasters but also indicate the tolerance limits that are important for the implementation of risk reduction measures. Moreover, the research indicates how the trends of migration have an impact on the demand for services and the credit market, which means that financial services need to evolve, credit risk modeling should be improved, and the default risks on loans should be reduced accordingly. The results from the policy and strategic point of view stress the need for the establishment of all-encompassing risk management frameworks and the holding of sufficient liquidity reserves. In this way, the analysis of the phase plane brings to light the interaction between the losses due to natural disasters, migration, defaults on loans, and the financial system's stability. Financial institutions that have a good grasp of these interactions will be able to upgrade their risk management, develop the right insurance and financial products, meet regulatory requirements, and contribute to the Sustainable Development goal, thus making the financial system more stable and resilient against the effects of climate change.

For central banks and regulators, the local stability condition in Theorem 2.4 provides a quantitative tool for identifying instability regions. Parameters like γL and γD may guide climate stress testing and countercyclical capital buffer adjustments. For commercial banks, the sensitivity parameters βL and βM indicate how disaster losses and migration affect default risk. These can inform climate-adjusted credit scoring, portfolio reallocation, and liquidity planning. For policymakers, reducing the disaster growth parameter through mitigation policies and strengthening the recovery parameter δ via fiscal and insurance mechanisms could enhance long-term financial resilience. For researchers, the coupled nonlinear framework provides a basis for stochastic extensions, spatial modeling, and empirical calibration. These results show that the proposed model presents practical insights for regulation, bank practice, and policy making.

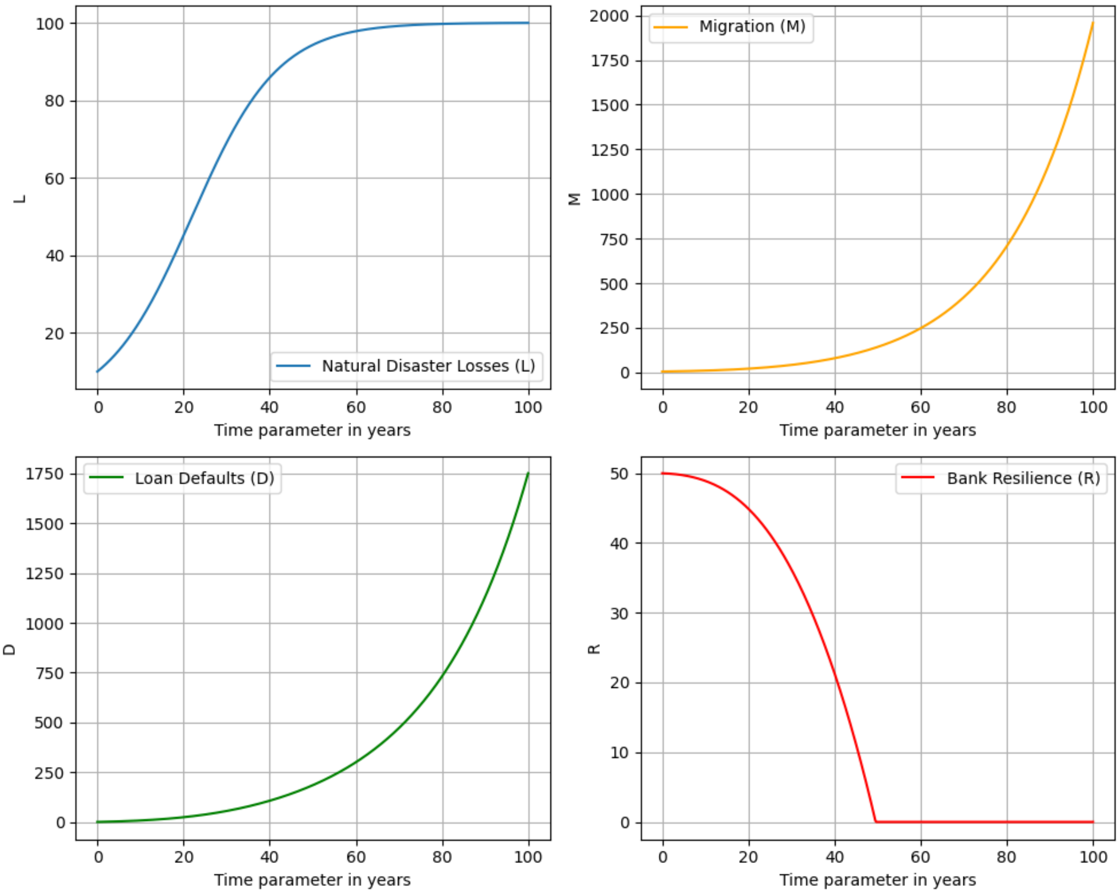

Figure 2: Time evolution of system variables *L(t), M(t), D(t),* and *R(t)* based on truncated ADM approximations

The graph in Figure 2 represents the system model solution regarding the time evolution of all variables. First natural disaster loss grows almost exponentially, then stabilizes at a point where increase is not a threat to financial stability. Migration becomes more stable, more likely to resist disaster, and provides economic activity. Loan defaults would stop moving around and go higher spontaneously-exploited a natural disaster and migrations, thus focusing on warning that the banking sector becomes shocked when a significant crisis hits them. After the collapse, banks eventually recover based on the reduction in hard-earned capital. This means the institutions are less poised toward liquidating and are finding ways to block the pathway, questioning their integrity and vulnerability. The coupling events occurring between disaster losses, migration, defaults on loans, and bank resilience are noticeably tight as depicted in Figures 2 and 3. A shock in any of these variables would result in a full system effect, thus emphasizing the necessity for an integrated approach to risk management and proactive policies as a means of strengthening financial resilience.

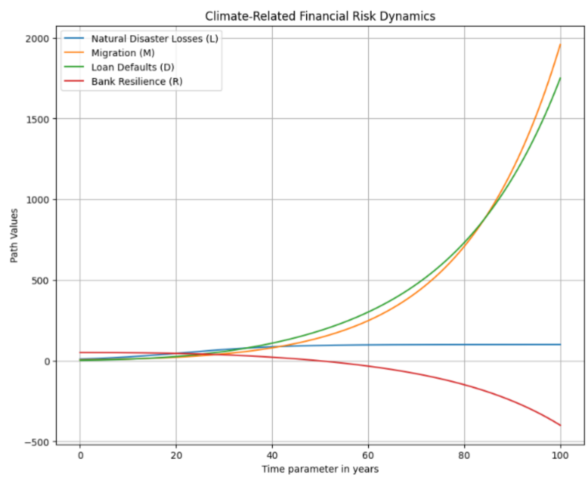

Figure 3: Combined dynamics of *L, M, D*, and *R* demonstrating long-run equilibrium behavior

3.1.7. Remarks on the Combined Graph and Findings

Figure 3 shows the combined graph of natural disaster losses (L), migration (M), loan defaults (D), and bank resilience (R), providing a general idea of the evolution of climate-related financial risks over time. What follows is a detailed discussion and interpretation of the results based on the simulated results. Natural disaster losses (L) grow quickly at the beginning because of the growth rate parameter r_L. The growth rate decelerates when the losses get close to the carrying capacity, K_L, following a logistic growth. The upward trend in natural disaster losses indicates financial institutions' exposure to environmental shocks. Initial rapid growth followed by stabilized growth indicates that losses can be sustained at an environmentally determined level after a while.

Migration (M) rises with time and depends on the migration rate, r_M, and the effect of natural disaster losses (α_L). The figure shows how environmental stressors can cause population movement. The rising trend in migration is utilized to show the socio-economic repercussions of climatic events. Rising levels of migration can overburden infrastructure and facilities, possibly causing economic instability and influencing the ability to repay loans.

Loan defaults (D) are sensitive to fluctuations depending on the default rate r_D, and the effect of natural disaster losses (β_L) and migration (β_M). One of the indicators that can show the economic uncertainty caused by environmental pressures and people moving is the fluctuations. Unpredictability in loan defaults is an indicator of the financial system's vulnerability to shocks from outside. When the environment causes more stress, and defaults are high, it means that there are difficulties in holding the creditworthiness and the financial stability.

Bank resilience (R) illustrates the capacity of financial institutions to absorb shocks over a period. Exposed to recovery mechanisms (δ), negative impacts of natural disaster losses (γ_L), and defaults in loans (γ_D), resilience may change or decrease under stress. Falling trends or negative indications in bank resilience indicate vulnerabilities in financial stability. Sustaining or strengthening resilience is essential to reduce risks related to climate-related events and achieve sustainable economic growth.

3.2. Comparative Analysis with Existing Climate Finance Studies

The results of the coupled nonlinear system offered a structured analytical perspective that further complemented and considerably extended existing studies on climate finance and financial stability. The development of dynamic climate-related financial risk models requires the integration of physical climate projections, financial institution responses, and adaptation mechanisms within a unified analytical framework. Advanced temperature forecasting methods, such as AutoDeepDenT, enhance hazard prediction capabilities while improving the climate shock modeling, which leads to displacement and credit stress (Kara et al., 2026). Banks need to recognize their climate risk exposure because existing measurement methods, together with their non-linear hazard effects and real estate market weaknesses, create a situation where actual exposure levels stay hidden (De Bandt et al., 2025). Evidence shows that shadow banks increase their mortgage lending activities by 5.3 percent after significant flood incidents, which demonstrates how credit supply changes create increased systemic vulnerabilities in affected areas (Bikakis, 2025). The adoption of technological solutions, which include antifouling methods that strengthen marine ecosystem protection, leads to improved environmental stability, which connects to economic productivity (Khairul et al., 2025). The study results provide evidence that supports the need for dynamic frameworks that enable researchers to evaluate climate-related stress events, which cause cascading default risks. The effect of climate risks and natural disasters on financial systems has attracted an increasing amount of research in recent years, particularly with respect to network phenomena, the pricing of assets, and stress testing frameworks. Our results add to this emerging literature by imparting a deterministic dynamical structure that explicitly treats the feedback influence among natural disaster losses, migration dynamics, loan defaults, and bank resilience.

The systemic risk perspective introduced in the Journal of Financial Stability, especially by the work of Battiston et al. (2021), views the transmission of climate risks through interconnected financial networks and relevant balance sheet exposures. While this type of research is obviously focused on the contagion and amplification during the financial networks, our research takes up this Clean Network address from a continuous-time dynamical systems perspective. Instead of the network topology, our model emerges from the equilibrium conditions and their own criteria of local stabilities given by a set of nonlinear ODEs. Therefore, this approach makes it explicitly possible to identify parameter thresholds beyond which the financial resilience remains stable or stretches to scenarios that would potentially render them vulnerable to climate-induced shocks. For instance, in the case of various empirical studies published in the Review of Financial Studies, documents like those of Giglio et al. (2021) investigating the capitalization of climate risk illustrate that climate exposure affects asset prices and long-run discount rates. These contributions prove that the market will value climate risk. However, they never actually incorporate a dynamic feedback loop between environmental shocks, migration pressures, credit deterioration, and the resilience of the banking sector. Our results, relating again to the consolatory literature, model the mindscape of structured climate shocks in which it is finacial stability essentially pursues a path rather than valuation mechanisms toward demographic and credit transmission mechanisms.

Some climate research suggests that integrating policy settings and stress-tested risk factors into central-bank valuation frameworks is perceived as crucial for establishing a temperature target for the banking system. In particular, such exercises would enable the optimal valuation to be reached based on STs that might include macrofinancial derivatives instead of just assigning more value to classical macrofinancial derivatives. Meanwhile, Nature Climate Change, for example, presents somewhat selected ways as indicators of the systemic risk of banking under climatic data in the long run. On the other hand, they will depend absolutely on scenario analysis and stress tests. In contrast, this paper offers mathematically derived equilibrium expressions and explicit local asymptotic stability conditions. The analytical structure implies that long-term system stability is determined by the interplay of disaster intensities, migration sensitivities, default responses, and recovery mechanisms. Hence, the relative importance of this study lies in three distinct aspects. Firstly, it moves away from empirical correlations and pricing exercises and approaches non-linear dynamic analyses. Secondly, it directly links parameter magnitudes to financial resilience effects owing to the formal stability conditions. Thirdly, it shows explicitly and in a unified framework the influence of climate shocks through various environmental, demographic, and credit pathways. Accordingly, viewed from a comparative or differential perspective, the model provisioned does not duplicate any existing work in the realm of the financing of climate change, but rather it strengthens the theoretical foundations of this field by putting forward a coupled dynamical system that simultaneously incorporates the relation between environmental stress, socioeconomic adjustment, and financial stability.

4. CONCLUSION

This study developed and thoroughly analyzed a coupled nonlinear dynamical system that integrates natural disaster losses, migration dynamics, loan defaults, and bank resilience. The model establishes well-posedness through positivity, boundedness, and uniqueness results, which demonstrate its existence while providing local stability conditions that show how parameter values affect financial resilience. The integration of environmental shocks in the context of a socio-economic framework permits the simultaneous analysis of economic variables and the ecological stressors. In an effort to provide for the rigorous and effective interpretative process, for the sake of system dynamics, the interplay of mathematical properties and guarantees, primarily those concerning signs of stability and boundedness, was secured to establish a viable and robust theoretical platform by which to analyze and shed light upon the management of climate-related financial risks. Theoretical considerations showed the well-posedness of the model. Theorem 2.1 justified the non-negativity of the state space properties. Theorem 2.2 confirmed the solutions being uniformly bounded, which is a crucial factor in assuring that when there is an increase in losses, defaults, or the resilience indicators, there will not be unbounded growth. In addition to Theorem 2.3, which guarantees global existence and uniqueness of solutions, these results confirm that the model is mathematically robust and fit for long-term dynamic analysis. Local stability features were obtained by equilibrium and Jacobian analyses. Theorem 2.4 offered explicit parameter settings under which the interior equilibrium is locally asymptotically stable. This extends a significant association between model parameters and system actions. It indicates the stability of an environmentally-financial system in relation to a growth-decay-recovery balance. As a means to support the theory-based analysis, the Adomian decomposition method was applied to the governing equations. Boundedness and uniqueness in Theorems 2.1-2.3 went towards ensuring convergence of the Adomian decomposition method series, whereas ADM solutions truncated to a certain degree could accurately capture local dynamics about the equilibrium. Numerical simulations, based on these truncated solutions, validated the results of Theorem 2.4, with all the trajectories tending toward the equilibrium with admissible parameter regions. Consequently, these combined analytical results and numerical proof have consistently confirmed our proposed framework as reliable for considering the dynamical implications of any climate-related shock on the socio-economic and financial systems. Explicit stability criteria, converting ADM approximations, further provide some insight into how to maintain resilience under an appropriate set of parameter values. For further research, this work could address the extension of empirical testing practices through the incorporation of calibrated parameters, stochastic forcing, and spatial disaggregation. An additional run-through of the model may enhance its centrality in capturing climate-related financial risks more accurately and significantly affect its applicability in a way that could contribute to making or supporting a conducive, policy-contingent suggestion.

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CONFLICT OF INTEREST
The authors declare no known competing financial or conflicts of interest regarding this work.

AUTHOR CONTRIBUTION
Sunday Onos Edeki: Conceptualization, Writing original draft, Methodology. Ozioma Ogoegbulem: Data collection, Visualization, and Investigation. Ini Adinya: Writing, Methodology, Validation. Imekela Donaldson Ezekiel: Methodology, Validation, Software. Chaudry Masood Khalique: Reviewing and Supervision.

DATA AVAILABILITY
All data generated or analyzed during this study are included in this published article.

DECLARATION OF GENERATIVE AI
During the preparation of this work, the author used Grammarly software to check the content. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

ETHICS
Not applicable.

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