

A Neural Lotka–Volterra Approach to Modeling Sustainability Risks in Finance

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Abstract: - This article explores the challenges of sustainable finance and innovative risk management approaches in Georgia, employing a neural differential equation based on the Lotka–Volterra perspective (NLV) to model the complex interactions among financial institutions, environmental factors, and regulatory bodies. By applying this model, we examine how various risk management strategies—such as green bonds, carbon pricing, and environmental stress testing—can affect the stability and sustainability of Georgia's financial ecosystem. The study concludes with policy recommendations for the National Bank of Georgia and other stakeholders to foster a resilient and sustainable financial sector. To emphasize the interdisciplinary nature of the research, the article explicitly integrates insights from finance, environmental science, and mathematical modeling.

Key-Words: - environmental science, sustainable finance, ecosystem, neural differential equations, Lotka–Volterra.

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1 Introduction

Modern financial systems increasingly resemble complex adaptive ecosystems, where agents interact in nonlinear, competitive–cooperative ways. Traditional linear risk models often fall short of capturing these interdependencies, particularly when addressing sustainability-linked risks such as ESG instability and climate-induced financial stress. Recent research uses Lotka–Volterra (LV) dynamics—originally predator-prey equations—to model economic and sustainability interactions because they offer tractable nonlinear feedback structures across ecological, economic, and social dimensions. At the same time, neural networks and hybrid physics-informed models can correct, enhance, or adapt LV systems under uncertainty and noise, making them suitable for real-world financial modeling.

LV frameworks capture exactly these interdependent growth–suppression feedback loops, as demonstrated in new sustainability modeling work that embeds LV dynamics into the economic–environmental–social nexus.

As Georgia continues its journey toward economic modernization and environmental resilience, sustainable finance has emerged as a critical pillar for long-term development. The integration of environmental, social, and governance (ESG)

principles into financial systems is no longer a luxury—it's a necessity. Georgia's financial sector is dominated by commercial banks, with growing interest in green bonds, climate finance, and ESG integration. The National Bank of Georgia has taken steps to promote financial stability and transparency, but a comprehensive sustainable finance framework is still evolving. Key sectors such as agriculture, energy, and infrastructure are particularly vulnerable to climate risks, making sustainability-linked investments increasingly relevant. Yet, the path is riddled with challenges: regulatory gaps, limited ESG awareness, and fragile data ecosystems. Georgia lacks a unified taxonomy for sustainable finance, making it difficult for banks and investors to classify green assets or measure ESG performance. Many financial institutions and SMEs are unfamiliar with ESG metrics, leading to inconsistent reporting and missed investment opportunities. Reliable ESG data is scarce, hindering risk assessment and the development of sustainability-linked financial products. Investors remain cautious about the long-term profitability of green projects, especially in emerging markets like Georgia. To navigate this complexity, innovative modelling tools are needed. This article is devoted to develop the Neural Differential Equations of Lotka–Volterra model [1] as a conceptual framework that explores the topic of sustainable finance and risk management in Georgia. Using Neural Differential

Equations for LV systems allows for hybrid modelling approaches that combine the interpretability of classical differential equations with the expressive power of neural networks [2]. This can lead to improved modelling of ventricular interactions inspired by LV dynamics to understand the interactions between financial actors, sustainability forces, and regulatory influence.

The study identifies key obstacles to sustainable finance, including a lack of robust regulatory frameworks, insufficient investor awareness, and limited access to green technologies[4]. We propose a Lotka–Volterra model that conceptualizes the relationship between economic growth (prey) and environmental degradation (predator) as a dynamic system. The findings suggest that while traditional risk management focuses on financial metrics, a more holistic approach is needed to address the systemic risks posed by climate change. Our analysis highlights the importance of fostering a symbiotic relationship between financial institutions and sustainable development goals to ensure long-term economic stability[5].

2 Applying the NLV Model to Finance Sustainability Risk

Recent research explores hybrid LV models augmented with neural networks, offering:

- robustness under noisy or biased data,
- adaptive correction of structural model errors,
- improved predictive performance under uncertainty.

A neural term can “correct” LV dynamics when real financial data deviates from pure theoretical assumptions—vital for ESG, climate, and macro-financial instability modeling.

Let us consider **Lotka–Volterra equations** to simulate interactions within the financial ecosystem [3]:

$$\begin{aligned}\frac{dx}{dt} &= \alpha x - \beta xy - \mu xz \\ \frac{dy}{dt} &= \delta xy - \gamma y(1) \\ \frac{dz}{dt} &= \eta x + \theta y - \lambda z\end{aligned}$$

Where

- **Prey (x):** ESG-compliant banks and sustainable finance initiatives
- **Predator (y):** Traditional banks and legacy financial institutions

- **Regulator (z):** Government and central bank policies influencing both

- α : growth rate of ESG-compliant banks
- β : competitive pressure from traditional banks
- μ : regulatory burden on ESG banks
- δ : benefit traditional banks gain from ESG partnerships
- γ : decline of traditional banks without ESG adaptation
- η, θ : influence of ESG/traditional banks on regulatory activity
- λ : regulatory inertia

These equations model how ESG finance grows, competes with traditional finance, and is shaped by regulatory forces. If ESG banks grow rapidly (α high), they attract more regulatory attention (μ increases), but also influence policy positively (η). Traditional banks may resist ESG adoption, but if they fail to adapt (γ high), they lose market share. Regulators adjust their stance based on the balance of ESG and traditional banking activity [6].

Let us consider a simulation of a business ecosystem using the **LV** model with three entities includes environmental dynamics by varying each firm's growth rate over time:

The cooperative partner benefits from mutualism but also faces its own environmental constraints.

The predator-prey Algorithm simulate resource consumption and regeneration in **ESG**:

Resource Regeneration Rate: How quickly the environment can replenish.

Consumption Rate: How fast businesses deplete resources.

Carrying Capacity: The maximum sustainable level of resource use.

Feedback Loops: Overconsumption leads to scarcity, which in turn affects business sustainability.

Here is the relevant Python code that simulates and compares two environmental policy scenarios using a predator-prey model. This code helps visualize how sustainable and unsustainable policies affect the balance between natural resources and business activity

```
import numpy as np
import matplotlib.pyplot as plt
# Time steps
time = np.linspace(0, 50, 1000)
# Predator-prey model function
def predator_prey_model(alpha, beta, delta, gamma, mu, eta, theta, lambda, R0, B0):
    dt = time[1] - time[0]
    R = np.zeros_like(time)
    B = np.zeros_like(time)
    R[0] = R0
```

```

B[0] = B0
for t in range(1, len(time)):
    dR = alpha * R[t-1] - beta * R[t-1] * B[t-1]
    dB = delta * R[t-1] * B[t-1] - gamma * B[t-1]
    R[t] = R[t-1] + dR * dt
    B[t] = B[t-1] + dB * dt
return R, B
# Scenario 1: Unsustainable policy
R1, B1 = predator_prey_model(alpha=0.5,
    beta=0.03, delta=0.01, gamma=0.4, R0=40, B0=9
)
# Scenario 2: Sustainable policy
R2, B2 = predator_prey_model(alpha=0.8,
    beta=0.015, delta=0.01, gamma=0.4, R0=40, B0=
9)
# Plotting
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(time, R1, 'g-', label='Resources')
    plt.plot(time, B1, 'r-', label='Business Activity')
plt.title('Unsustainable Policy')
plt.xlabel('Time')
plt.ylabel('Population')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(time, R2, 'g-', label='Resources')
    plt.plot(time, B2, 'r-', label='Business Activity')
plt.title('Sustainable Policy')
plt.xlabel('Time')
plt.ylabel('Population')
plt.legend()
plt.tight_layout()
plt.show()

```

where
alpha: Resource regeneration rate
beta: Resource consumption rate
delta: Business growth rate
gamma: Business decline rate

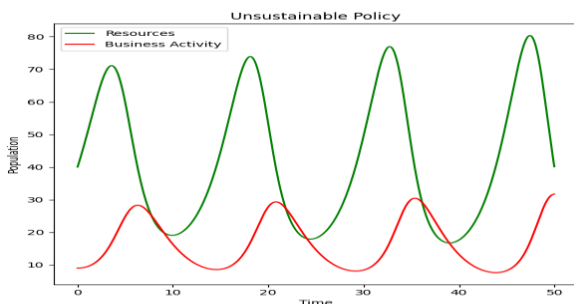


Fig. 1: unsustainable policy

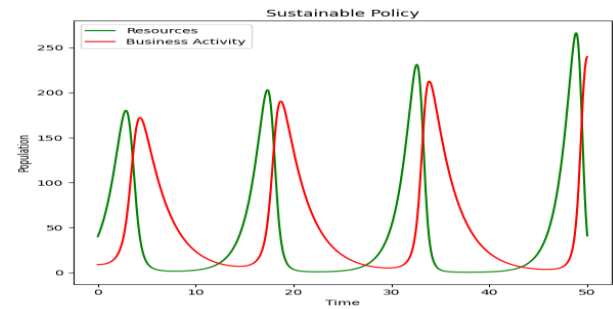


Fig. 2: Sustainable policy

Let us consider a simulation of a business ecosystem using the LV model with three entities: Where

Incumbent: A dominant firm with stable but slightly fluctuating growth; Start-up: A fast-growing new; entrant with more volatile dynamics; Cooperative Partner: A firm that supports both others, with moderate growth.

Where

The start-up shows rapid growth early on but is influenced by both competition and cooperation.

The incumbent maintains a relatively stable market share but is affected by the start-up's rise.

Here's a simulation of sustainable environmental dynamics in a business ecosystem using the LV model:

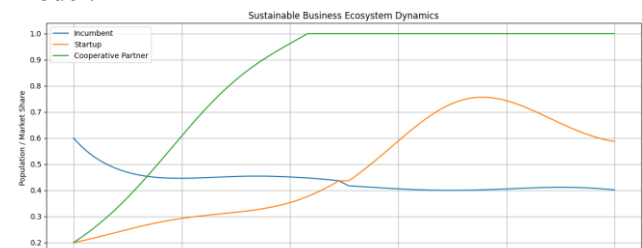


Fig. 3: Sustainable business

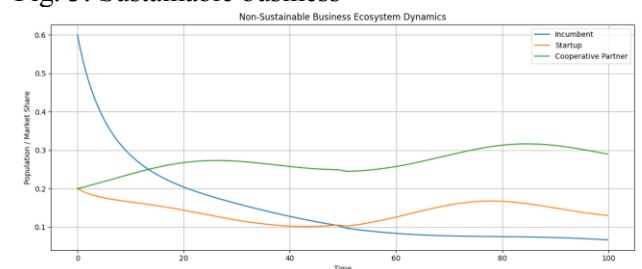


Fig. 4: Unsustainable business

Key Features of the Model:

Time-varying growth rates simulate changing environmental conditions (e.g., regulations, resource availability).

Sustainable interactions:

Cooperation between firms (especially with the cooperative partner).

Reduced competition to reflect resource sharing and mutual resilience.

Normalization ensures total market share remains bounded, simulating a finite-resource environment.

2.1 Applying the Model to Georgia

There are scenarios to Apply NLV Model in Georgia:

Scenario 1: ESG Growth under Incentives

If the government introduces tax breaks for green investments, the growth rate α increases, leading to a rise in ESG-compliant banks. Traditional banks (y) may respond by adopting ESG practices, reducing β (competitive suppression).

Scenario 2: Regulatory Pressure

A new ESG disclosure mandate increases μ , placing pressure on ESG banks to comply. If λ (regulatory inertia) is low, regulators adapt quickly, stabilizing the system.

Scenario 3: Climate Stress

A climate shock (e.g., drought affecting agriculture) could disrupt x , triggering a cascade effect on y and z , revealing vulnerabilities in the financial system.

AI Integration offers:

- To learn parameters from Georgian banking data
- To simulate policy changes (e.g., mandatory ESG reporting)
- To forecast systemic risks (e.g., credit instability from climate shocks)

Let us say:

- ESG banks start small but grow due to green bond incentives
- Traditional banks dominate but face reputational risk
- Regulators introduce ESG stress testing

The simulation how these forces evolve over time, and identify tipping points where ESG finance becomes mainstream or where regulatory pressure destabilizes the system is possible

3 Simulating Neural Dynamics

Here's a basic Python setup using SciPy for simulation:

```
import numpy as np
from scipy.integrate import odeint
import matplotlib.pyplot as plt

def model(vars, t, alpha, beta, mu, delta, gamma, eta, theta, lambda):
    x, y, z = vars
    dxdt = alpha*x - beta*x*y - mu*x*z
    dydt = delta*x*y - gamma*y
```

```
dzdt = eta*x + theta*y - lambda*z
return [dxdt, dydt, dzdt]
```

Initial values

$x_0, y_0, z_0 = 10, 5, 2$

$\text{vars}_0 = [x_0, y_0, z_0]$

Time points

$t = \text{np.linspace}(0, 50, 500)$

Parameters (tweak these!)

$\text{params} = (0.5, 0.02, 0.01, 0.01, 0.3, 0.05, 0.05, 0.1)$

Solve ODE

$\text{results} = \text{odeint}(\text{model}, \text{vars}_0, t, \text{args}=\text{params})$

$x, y, z = \text{results.T}$

Plot

$\text{plt.plot}(t, x, \text{label}=\text{'Green Finance'})$

$\text{plt.plot}(t, y, \text{label}=\text{'Traditional Finance'})$

$\text{plt.plot}(t, z, \text{label}=\text{'Regulators'})$

$\text{plt.legend}()$

$\text{plt.xlabel}(\text{'Time'})$

$\text{plt.ylabel}(\text{'Population'})$

$\text{plt.title}(\text{'Lotka-Volterra Simulation for Sustainable Finance in Georgia'})$

$\text{plt.grid}()$

$\text{plt.show}()$

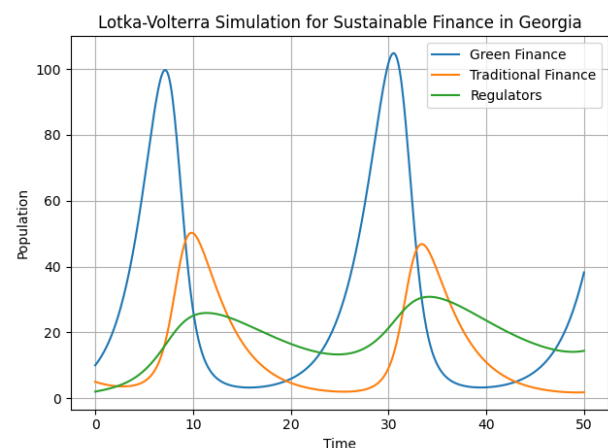


Fig. 5:NLV Model in Georgia

4 Conclusion

Georgia stands at a crossroads. The challenges of sustainable finance are real, but so are the opportunities. With strategic regulation, technological innovation, and a commitment to ESG principles, Georgia can build a resilient financial ecosystem that thrives in harmony with its environment. By embracing innovative modeling approaches like the Lotka–Volterra framework with AI integration, policymakers and financial institutions can better

understand the dynamic interplay of forces shaping the future:

- Banks simulate climate scenarios to assess portfolio resilience, using AI-enhanced Lotka–Volterra models to forecast systemic risk.
- Financial institutions embed ESG metrics into lending decisions, shifting the dynamics between x and y .
- Digital platforms improve ESG data transparency, reducing γ (decay of traditional finance) and boosting η (positive influence on regulators).
- Collaborations between government and banks foster innovation, stabilizing z and promoting sustainable growth.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Giorgi Chachua has investigated the challenges of sustainable finance in Georgia and applied the NLV model.

Manana Chumburidze has created the algorithm and implemented it in Python.

Teimuraz Sakhelashvili has organized and conducted the experiments and simulated neural dynamics.

Alternatively, the following text will be published:

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

Please declare anything related to this study.

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