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A Remark on Stochastic Climate-Finance SEIR Model for Climate-Induced Infectious Diseases in Southern Nigeria

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Abstract: Climate change has worsened the spread of infectious diseases across the tropics, especially in Southern Nigeria, where fluctuations in temperature, rainfall, and flood aid the spread of vector-borne and waterborne diseases. These environmental disruptions raise levels of morbidity and cost the health and community sectors heavily. The counteractions against these disruptions, hence, demand an inclusive strategy of public health interventions, linked with adaptive climate finance mechanisms. In this study, a stochastic climate–finance SEIR model is developed to investigate the dynamic interaction between infectious disease transmission, climate variability, and financial intervention policies. This work sets the stage for studying the stochastic investment SEIR model intact, which is a representative model to study the complex intrinsic relationship involving climate variability, financial interventions, and the transmission of infectious diseases. A thorough analysis, seasoned with the global existence and uniqueness, ruled positivity and boundedness of the system, and stochastic stability of the disease-free equilibrium were performed using Lyapunov techniques and Itô calculus. Following a careful investigation process made in this study, a stochastic reproduction number was derived, showing how noise affects epidemic thresholds. Numerical simulations were also performed to further show the impact of climate variability and financial responsiveness on epidemic trajectories. The numerical results showed that adaptive management of climate change and climate finance diminished the highest magnitudes of infections while compressing the time needed for epidemics to spiral all out of control in the presence of effectively and tactically employed environmental forcing. The outcome serves as the creation of a structural definition within mathematics, with the sole aim of enabling robust climate-health financing towards the mitigation of infectious disease risks in Southern Nigeria.

Keywords: Stochastic Epidemiological Model, Climate Finance, Seir Model, Stochastic Differential Equations, Climate-Induced Diseases, Southern Nigeria

1. Introduction

Global climate change has become one of the most important determinants for the spread of infectious diseases in the world [1, 2]. The changes in the environment caused by temperature increase, rainfall change, and increased frequency of extreme weather events will affect the survival of the pathogen in the environment, the breeding habitat of the vectors, and human exposure to these infectious agents. Factors have perpetuated the rapid spread of infectious diseases in different areas of the world, especially tropical countries. Southern Nigeria is particularly prone to climate-induced disease events [3, 4]. The increase in variable rainfall, flooding, and temperature changes sets ideal conditions for vectors such as mosquitoes, as well as the malaria parasites and other disease entities [5-7]. Therefore, diseases such as malaria, cholera, dengue fever, and meningitis are now increasingly becoming endemic in this zone [8, 9]. Apart from health consequences, epidemics also have a major impact on the economy, as such growth in health expenditures,

depletion of workforces, and disruption in the economic sphere have imposed immense financial burdens on households, as well as on national governments [10-12]. A set of fortified financial mechanisms is supposed to address these dilemmas through the support training for disease prevention and response. Climate finance basically leads to the foraging of resources to resist and mitigate climate impacts. This will empower the pubic health aspects: strengthening the capability of public health ethical considerations to cite resources in healthcare infrastructure, disease surveillance systems, vector control programs, and so forth. Given how they are supposed to aid in the development of the climate change-related health impacts, the necessary contributions often lag, however, leaving high societal costs [13, 15]. Modeling is very important for understanding the interaction among climate variations, disease transmission, and financial interventions [16-18]. Classical deterministic epidemiological models are very popular for describing disease dynamics. Yet, inherently, environmental processes are most probably unstable. Climate animals move around, and financial reactions to outbreaks may be brought about by unpredictable political and economic conditions [19, 20]. Currently, some stochastic modeling schemes in this kind of uncertain world are required to model transmission events, random staggering of actual guesses, in incorporating random fluctuations [21, 22]. This is built on the note that dynamics and financial responses, stochastic models allow researchers to investigate how environmental variability influences epidemic outcomes and policy effectiveness. This study develops a stochastic climate-finance SEIR model to investigate the dynamics of climate-induced infectious diseases in Southern Nigeria. The model integrates epidemiological processes with adaptive financial interventions while incorporating stochastic climate variability. Analytical and numerical results provide insights into the role of climate finance in strengthening resilience against infectious disease outbreaks.

2. Model Formulation

This section presents the formulation of the climate–finance SEIR model describing the interaction between infectious disease transmission, climate variability, and financial intervention mechanisms. The model integrates epidemiological dynamics with climate-sensitive transmission processes and adaptive financial responses aimed at mitigating disease outbreaks.

2.1. Population Structure

We consider a human population divided into four epidemiological compartments representing different disease states. Let $S(t)$ denote the number of susceptible individuals at time t, $E(t)$ represent the exposed individuals who have been infected but are not yet infectious, $I(t)$ denote the infectious population capable of transmitting the disease, and $R(t)$ represent recovered individuals who have gained temporary immunity.

The total population size at time t is therefore given by

$$N(t) = S(t) + E(t) + I(t) + R(t) \tag{1}$$

In addition to the epidemiological compartments, we introduce a dynamic variable $F(t)$ representing the level of climate finance allocated to disease mitigation and control. This financial resource may include government health expenditures, climate adaptation funds, international aid, or emergency response funding directed toward disease prevention and treatment.

Disease transmission is assumed to depend on environmental conditions such as temperature and humidity. These climatic variables influence vector reproduction, pathogen survival, and exposure risk. Consequently, the transmission rate is represented by a climate-dependent function $\beta(T, H)$ where T denotes temperature and H denotes humidity.

2.2. Deterministic Climate–Finance SEIR Model

The deterministic model describing the interaction between disease transmission and climate finance is given by the system of differential equations

$$\begin{cases} \dfrac{dS}{dt} = \Lambda - \beta(T,H)SI - \mu S + \rho R - f(F)S, \\ \dfrac{dE}{dt} = \beta(T,H)SI - (\sigma + \mu)E, \\ \dfrac{dI}{dt} = \sigma E - (\gamma + \mu + \delta)I - \eta FI, \\ \dfrac{dR}{dt} = \gamma I - (\mu + \rho)R, \\ \dfrac{dF}{dt} = \xi I - \omega F. \end{cases} \tag{2}$$

The climate finance variable $F(t)$ plays an important role in disease control. Financial resources reduce disease transmission through preventive actions represented by the term $f(F)S$ and improve treatment or intervention capacity through the term ηFI.

2.3. Stochastic Climate–Finance SEIR Model

Environmental conditions and financial interventions are subject to uncertainty. Climate variability may cause fluctuations in disease transmission rates, while financial responses may vary due to economic or political factors. To capture these uncertainties, stochastic perturbations are introduced into the model.

The resulting stochastic climate–finance SEIR system is described by

$$\begin{cases} dS = [\Lambda - \beta(T,H)SI - \mu S + \rho R - f(F)S]dt \\ \qquad +\sigma_1 S\, dW_1(t), \\ dE = [\beta(T,H)SI - (\sigma+\mu)E]dt + \sigma_2 E\, dW_2(t), \\ dI = [\sigma E - (\gamma+\mu+\delta)I - \eta FI]dt + \sigma_3 I\, dW_3(t), \\ dR = [\gamma I - (\mu+\rho)R]dt, \\ dF = [\xi I - \omega F]dt + \sigma_4 F\, dW_4(t). \end{cases} \tag{3}$$

Here, $W_i(t)$ for $i = 1, 2, 3, 4$ denote independent Wiener processes and σ_i represent the intensities of stochastic fluctuations affecting epidemiological and financial variables.

2.4. Model Assumptions

The formulation of the climate–finance SEIR model is based on several biological, environmental, and economic assumptions. The population is assumed to be homogeneous with respect to disease exposure, meaning every individual has an equal probability of contacting infectious individuals. Recruitment into the susceptible population occurs at a constant rate Λ, while natural mortality occurs at a rate μ. Recovered individuals may lose immunity and return to the susceptible class at a rate ρ.

Every transmission mechanism depends critically on climatic determinants through the function $\beta(T, H)$, which reflects the joint influence of environmental variables such as temperature and humidity on risk of infection. Exposed individuals move into the infectious stage at a rate σ while infectious individuals recover at an exponential rate determined by the human-to-human parasite transmission probability, disorder-inherent restrictions, and possible bed filters that prevent the complete malaria transmission. Disease-induced mortality is expected to decrease at a rate δ. Response to the level of infection is called ξ for this reason and unfolds as a gradual reinforcement cycle corresponding to increased funding for global health activities once an outbreak hits. Financial resources are depleted over time due to operational costs and inefficiencies at a rate ω. The financial intervention reduces susceptibility through the function $f(F)$ and decreases infection intensity through the coefficient η.

The stochastic perturbations introduced in the model represent random environmental fluctuations affecting transmission dynamics and financial processes [24, 25].

2.5. Biological Feasibility Region

The biological feasibility of the model requires that all state variables remain non-negative and bounded over time.

Theorem 2.1. Let the initial conditions satisfy

$$S(0), E(0), I(0), R(0), F(0) \geq 0$$

Then the solutions of the deterministic system remain in the region

$$\Omega = \{(S, E, I, R, F) \in \mathbb{R}^5_+ : N(t) \leq \frac{\Lambda}{\mu}\}$$

Proof: Let $N(t) = S(t) + E(t) + I(t) + R(t)$. Summing the first four equations of the deterministic system gives

$$\frac{dN}{dt} = \Lambda - \mu N - \delta I - f(F)S - \eta FI \tag{4}$$

Since all parameters are nonnegative, we obtain

$$\frac{dN}{dt} \leq \Lambda - \mu N$$

Solving the differential inequality yields

$$N(t) \leq \frac{\Lambda}{\mu}$$

Thus, all solutions remain bounded in the region Ω, which establishes biological feasibility.

2.6. Dimensionless Scaling of the Model

To simplify the analysis and reduce the number of parameters, the system can be rescaled using the total population size. Let

$$s = \frac{S}{N}, \quad e = \frac{E}{N}, \quad i = \frac{I}{N}, \quad r = \frac{R}{N} \tag{5}$$

Substituting these normalized variables into the deterministic system yields the dimensionless model

$$\begin{cases} \dfrac{ds}{dt} = \lambda - \beta(T,H)si - \mu s + \rho r - f(F)s, \\ \dfrac{de}{dt} = \beta(T,H)si - (\sigma+\mu)e, \\ \dfrac{di}{dt} = \sigma e - (\gamma+\mu+\delta)i - \eta Fi, \\ \dfrac{dr}{dt} = \gamma i - (\mu+\rho)r. \end{cases} \tag{6}$$

The dimensionless system simplifies mathematical analysis and allows easier comparison of model behavior across different parameter regimes.

3. Mathematical Analysis

This section investigates the qualitative dynamics of the proposed climate–finance SEIR model. The analysis begins with the deterministic systemt to derive the epidemic threshold and equilibrium points. Subsequently, stochastic properties of the model are examined, including the existence and positivity of solutions and stochastic stability conditions [23, 26-28].

For analytical convenience, we consider the deterministic climate–finance SEIR system

$$\begin{cases} \dfrac{dS}{dt} = \Lambda - \beta SI - \mu S + \rho R - f(F)S, \\ \dfrac{dE}{dt} = \beta SI - (\sigma + \mu)E, \\ \dfrac{dI}{dt} = \sigma E - (\gamma + \mu + \delta)I - \eta FI, \\ \dfrac{dR}{dt} = \gamma I - (\mu + \rho)R, \\ \dfrac{dF}{dt} = \xi I - \omega F. \end{cases} \tag{7}$$

3.1. Basic Reproduction Number

The basic reproduction number R_0 represents the average number of secondary infections generated by a single infectious individual introduced into a fully susceptible population.

To compute R_0, the next-generation matrix method is used. The infected compartments are E and I, and we define the vector

$$x = (E, I)$$

The system can be written as

$$\frac{dx}{dt} = F(x) - V(x)$$

where $F(x)$ denotes the rate of new infections and $V(x)$ represents transitions between infected compartments.

The infection terms are

$$F = \begin{pmatrix} \beta SI \\ 0 \end{pmatrix}$$

while the transition terms are

$$V = \begin{pmatrix} (\sigma + \mu)E \\ (\gamma + \mu + \delta)I - \sigma E \end{pmatrix}$$

Linearizing the system at the disease-free equilibrium yields

$$F = \begin{pmatrix} 0 & \beta S^* \\ 0 & 0 \end{pmatrix} \quad V = \begin{pmatrix} \sigma + \mu & 0 \\ -\sigma & \gamma + \mu + \delta \end{pmatrix}$$

The next-generation matrix is given by

$$K = FV^{-1}$$

The spectral radius of K determines the basic reproduction number

$$R_0 = \frac{\beta \sigma S^*}{(\sigma + \mu)(\gamma + \mu + \delta)} \tag{8}$$

Since at the disease-free equilibrium

$$S^* = \frac{\Lambda}{\mu}$$

the reproduction number becomes

$$R_0 = \frac{\beta \sigma \Lambda}{\mu(\sigma + \mu)(\gamma + \mu + \delta)} \tag{9}$$

This threshold parameter determines whether the disease will invade or die out in the population.

3.2. Disease-Free Equilibrium

The disease-free equilibrium corresponds to the absence of infection in the population. Setting

$$E = I = R = 0$$

yields the equilibrium point

$$E_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0, 0 \right) \tag{10}$$

This equilibrium represents a state in which the entire population remains susceptible and no infection persists.

3.3. Endemic Equilibrium

The endemic equilibrium represents a steady state in which the disease persists in the population. Let the endemic equilibrium be denoted by

$$E^* = (S^*, E^*, I^*, R^*, F^*)$$

At equilibrium,

$$\frac{dS}{dt} = \frac{dE}{dt} = \frac{dI}{dt} = \frac{dR}{dt} = \frac{dF}{dt} = 0$$

From the financial equation

$$F^* = \frac{\xi}{\omega} I^* \tag{11}$$

From the recovered equation

$$R^* = \frac{\gamma}{\mu + \rho} I^* \tag{12}$$

From the exposed equation

$$E^* = \frac{\beta S^* I^*}{\sigma + \mu} \tag{13}$$

Substituting these expressions into the infectious equation leads to a nonlinear equation determining I^*. A biologically feasible positive solution exists whenever

$$R_0 > 1$$

3.4. Local Stability of the Disease-Free Equilibrium

The Jacobian matrix evaluated at the disease-free equilibrium E_0 is

$$J(E_0) = \begin{pmatrix} -\mu & 0 & -\beta S^* & \rho & -f'(0)S^* \\ 0 & -(\sigma+\mu) & \beta S^* & 0 & 0 \\ 0 & \sigma & -(\gamma+\mu+\delta) & 0 & 0 \\ 0 & 0 & \gamma & -(\mu+\rho) & 0 \\ 0 & 0 & \xi & 0 & -\omega \end{pmatrix}$$

Three eigenvalues are immediately negative:

$$-\mu, \quad -(\mu+\rho), \quad -\omega.$$

The remaining eigenvalues arise from the infected subsystem

$$\begin{pmatrix} -(\sigma+\mu) & \beta S^* \\ \sigma & -(\gamma+\mu+\delta) \end{pmatrix}$$

Theorem 3.1. If $R_0 < 1$, the disease-free equilibrium E_0 is locally asymptotically stable. If $R_0 > 1$, the disease-free equilibrium is unstable.

3.5. Global Stability of the Disease-Free Equilibrium

Consider the Lyapunov function

$$V = E + \frac{\sigma+\mu}{\sigma} I \tag{14}$$

Differentiating along the solutions gives

$$\frac{dV}{dt} = (\sigma+\mu)(R_0 - 1)I \tag{15}$$

Theorem 3.2. If $R_0 < 1$, the disease-free equilibrium E_0 is globally asymptotically stable in the feasible region.

3.6. Existence and Uniqueness of the Stochastic System

For the stochastic model, the system can be written as

$$dX = b(X)dt + \Sigma(X)dW$$

where

$$X(t) = (S, E, I, R, F)$$

Theorem 3.3. For any non-negative initial conditions, the stochastic system admits a unique global solution.

Proof: The drift function $b(X)$ and diffusion matrix $\Sigma(X)$ satisfy the local Lipschitz condition and linear growth condition:

$$|b(X)|^2 + |\Sigma(X)|^2 \leq C(1 + |X|^2)$$

Applying Itô's formula to the Lyapunov function

$$V = S + E + I + R + F$$

shows that $E[V(t)]$ remains bounded. Hence the explosion time is infinite and the solution exists globally.

3.7. Positivity of the Stochastic Solutions

Theorem 3.4. If the initial conditions are positive, then the stochastic solution remains positive for all time with probability one.

Applying Itô's formula to $\ln S$ gives

$$d(\ln S) = \left(\frac{\Lambda}{S} - \beta I - \mu + \frac{\rho R}{S} - f(F) - \frac{\sigma_1^2}{2} \right) dt + \sigma_1 dW_1$$

Similar arguments apply for $E(t)$, $I(t)$, and $F(t)$.

3.8. Stochastic Reproduction Number and Global Stochastic Stability

In the presence of environmental noise, the effective reproduction number becomes

$$R_s = R_0 \exp\left(-\frac{\sigma_3^2}{2(\gamma+\mu+\delta)} \right) \tag{16}$$

Theorem 3.5. If $R_s < 1$, then the disease-free equilibrium

$$E_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0, 0 \right)$$

is globally stochastically asymptotically stable.

The result follows by constructing the stochastic Lyapunov function

$$V(E, I) = aE + bI$$

This result shows that environmental noise reduces the effective reproduction number and can enhance disease extinction when $R_s < 1$.

$$LV \leq (\gamma+\mu+\delta)(R_s - 1)I$$

3.9. Model Parameters and Numerical Simulation Framework

Numerical simulations of the stochastic model can be performed using the Euler–Maruyama method. Example parameter values are presented in Table 1.

Table 1. *Model parameters and descriptions.*

Parameter	Description	Value
Λ	Recruitment rate	0.02
β	Transmission rate	0.45
μ	Natural death rate	0.01
σ	Progression rate ($E \to I$)	0.20
γ	Recovery rate	0.15
δ	Disease mortality rate	0.02
ρ	Immunity loss rate	0.05
η	Finance impact on treatment	0.10
ξ	Finance response rate	0.08
ω	Finance depletion rate	0.05

Parameter	Description	Value
σ_1	Noise intensity for S	0.03
σ_2	Noise intensity for E	0.03
σ_3	Noise intensity for I	0.04
σ_4	Noise intensity for F	0.02

Simulations indicate that increasing the responsiveness of climate finance significantly reduces epidemic peaks and accelerates stabilization even under strong stochastic climate fluctuations.

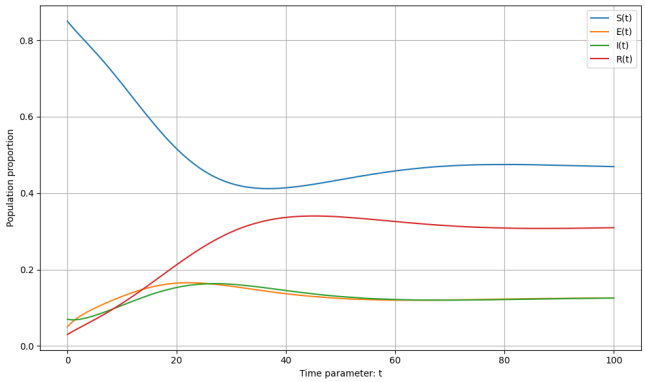

Figure 1. *Time evolution of SEIR compartments.*

Figure 1 shows how the susceptible, exposed, infectious, and recovered populations of the study develop over time. The susceptible population decreases initially as infection spreads, while the exposed and infectious classes rise before reaching their respective peaks. The infectious population decreases because of three factors: recovery, disease-related removal, and climate-finance-sponsored intervention, while the recovered population grows simultaneously. The proposed SEIR model shows the expected epidemic pattern according to this result. The initial conditions used here match those stated in the numerical simulation section.

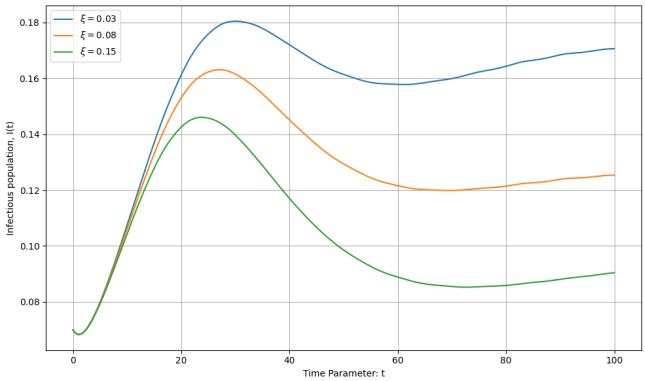

Figure 2. *Effect of climate finance responsiveness on infection dynamics.*

Figure 2 shows that enhanced climate finance systems create greater benefits for public health because they decrease infection peaks and accelerate the reduction of infected people. The financial response to infection increases when ξ achieves higher values which results in faster resource mobilization to support control efforts that effectively reduce disease spread. The numerical result demonstrates that adaptive climate finance systems under climate-induced unpredictability boost epidemic control efforts.

4. Conclusion

This study developed and analyzed a stochastic climate–finance SEIR model to investigate the interaction between climate variability, infectious disease transmission, and financial intervention mechanisms in Southern Nigeria. The model integrates epidemiological dynamics with climate-sensitive transmission processes and adaptive financial responses aimed at mitigating disease outbreaks.

A deterministic analysis of the model was first conducted to establish fundamental epidemiological properties. Using the next-generation matrix method, the basic reproduction number R_0 was derived and shown to serve as the critical threshold determining whether the infection dies out or persists in the population. The disease-free equilibrium and endemic equilibrium were identified, and stability analysis demonstrated that the disease-free equilibrium is locally and globally asymptotically stable whenever $R_0 < 1$, while an endemic equilibrium emerges when $R_0 > 1$.

To account for environmental and economic uncertainties, stochastic perturbations were incorporated into the model. Rigorous stochastic analysis established the existence and uniqueness of global solutions and proved the positivity of the epidemiological variables. A stochastic reproduction number R_s was also derived in the study, showing how environmental noise modifies epidemic thresholds. It was seen that when $R_s < 1$, the disease-free equilibrium is globally stochastically asymptotically stable, leading to disease persistence when $R_s > 1$. Numerical simulations with the Euler-Maruyama scheme illustrate the effect of stochastic climate variability and cost-effective response to epidemic dynamics. The quantitative results indicate that flexible climate change and cost-effective intervention can significantly decrease infection peaks and speed the epidemic's attenuatione on attenuates at a non-trivial scale under large environmental perturbations.

Overall, the findings showcased the essential role of climate-responsive financial mechanisms in building public health resilience against climatic conditions-induced infectious disease threats. Incorporation of climate finance into policies and efforts aimed at building an epidemic preparedness and response system greatly enhances disease control outcomes in vulnerable climatic regions, such as in Southern Nigeria. Future research based on the present framework may still incorporate some spatial heterogeneity for a more robust statement on optimal control strategies for resource investments and real climatic data for model calibration and simulation.

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Abbreviations

SEIR	Susceptible–Exposed–Infectious—Recovered
ODE	Ordinary Differential Equation
SDE	Stochastic Differential Equation
DFE	Disease-Free Equilibrium
EE	Endemic Equilibrium

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Author Contributions

Imekela Donaldson Ezekiel: Conceptualization, Writing – Original Draft, Resources, Investigation

Sunday Onos Edeki: Data curation, Methodology, Formal analysis, Writing – Review & Editing, Supervision

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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