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Rogue Wave Modeling of Herder–Farmer Conflicts in OGWASHI-UKU, Delta State, Nigeria

Ejinkonye Ifeoma. O and Mankilik Isaac. M

Department of Mathematics, Admiralty University of Nigeria, Ibusa, Delta State, Nigeria.

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Abstract: Violent flare-ups in herder–farmer conflict often appear suddenly, peak sharply, and dissipate unpredictably across communities. This project adapts rogue-wave dynamics—rare, high-amplitude events emerging from modulation instability in nonlinear systems—to explain and predict such outbreak patterns in Delta State. We model incident intensity as a nonlinear wave field coupled to slow-varying socio-environmental drivers (land use, market shocks, rainfall, policing). Using geocoded incident data (2010–2025), we will (i) test whether conflict clusters exhibit rogue-wave signatures, (ii) estimate conditions that precipitate "surge" events, and (iii) simulate targeted early-warning and response strategies. Outputs include an open dataset, a calibrated model, ward-level risk maps, and policy briefs for state actors and community stakeholders. Existing statistical or diffusion models struggle to capture sudden, high-amplitude incident spikes and their rapid spatial spillovers in Delta State. There is a need for a predictive, interpretable framework that identifies instability windows and guides timely prevention.

Keywords: Rogue waves, Herder–farmer conflict, Nonlinear PDE, Ogwashi-Uku, Conflict modelling.

I. Introduction

The herder–farmer conflict in Nigeria, particularly in Delta State, has intensified over the past two decades. Communities such as Ogwashi-Uku have witnessed recurring clashes over grazing rights, farmland destruction, and resource competition (Akpabio & Fasona, 2021). Conventional conflict studies emphasize political, environmental, and social dimensions but rarely employ mathematical tools for predictive modelling.

Rogue wave theory, originally applied in oceanography and nonlinear optics (Yan, 2010), has recently been extended to social instability analysis (Ejinkonye, 2021). Rogue waves describe sudden, extreme events arising from nonlinear amplification of background fluctuations. By adapting this framework, this study seeks to predict and mitigate violent surges in herder–farmer conflicts.

More recent studies have integrated ecological principles with social science to create models that are more representative of real-world conflicts. Bratman (2018) provides a comprehensive review of models that explore how the availability of shared resources (like water and land) can be the primary driver of intergroup conflict. The work often involves systems of ordinary differential equations (ODEs) that describe changes in population sizes, resource levels, and conflict intensity over time. A key finding across many of these models is the existence of tipping points, where a small change in a parameter (e.g., resource availability or population growth rate) can push the system from a state of stable coexistence into a state of perpetual conflict.

The Nigerian Context: Drivers of Conflict

The drivers of herder-farmer conflict in Nigeria are multifaceted and go beyond simple resource competition. Climate change is a significant factor, as desertification in the northern part of the country has pushed nomadic herders south in search of green pastures, leading to increased pressure on land in the Middle Belt and southern regions (Okolo, 2017). Demographic shifts, including rapid population growth in both farming and herding communities, exacerbate this pressure. Additionally, socio-political and economic factors, such as the decline of traditional conflict resolution mechanisms and a perceived lack of government intervention, contribute to the escalation of violence (Ukeje, 2019).

Studies focusing on specific regions, such as Ogege (2021) on the conflict in the Niger Delta region, highlight the local nuances of these disputes. The presence of oil and gas exploration, environmental degradation, and different land tenure systems can complicate the dynamics. A mathematical model for Ogwashi-Uku would therefore need to account for these specific local factors, and the parameters used in the model would need to be empirically derived from local data to ensure its relevance and accuracy.

Ejinkonye I.O. (2019, 2020) advanced the application of rogue wave theory beyond physical systems, showing how the Nonlinear Schrödinger Equation (NLS) and its rogue-wave solutions can describe unexpected surges in social and security-related phenomena. His work demonstrated that conflict escalation, much like rogue ocean waves, emerges from instability in an underlying system — where small perturbations can rapidly amplify into rare but devastating peaks.

By adopting Ejinkonye's framework, this study treats violent incidents in Delta State as a rogue-wave process. The sudden peaks in attacks by armed groups and herder–farmer clashes can be mathematically approximated by Peregrine-type rogue wave solutions of the NLS. Ejinkonye's contributions provide the theoretical foundation for transferring rogue wave dynamics from physics into the modeling of Nigerian insecurity.

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Other scholars such as Akhmediev & Pelinovsky (2010) and Osborne (2010) have rigorously established rogue waves in nonlinear systems, while Ejinkonye (2019) and Lindgren et al. (2011) offered spatio-temporal statistical approaches to violence and crime. Yet, unlike Ejinkonye's innovative crossover, these works do not directly address Nigerian conflict contexts.

Thus, this research builds on Ejinkonye's pioneering insight to extend rogue-wave modeling into the specific case of Fulani herdsmen conflict in Delta State, coupling PDE rogue-wave dynamics with socio-environmental ODE drivers (rainfall, grazing stress, security patrols, etc.) to predict and mitigate violent surges.

Research on insecurity in Nigeria has often focused on statistical or sociological analyses of herder–farmer conflicts. However, very few works have attempted to model the *nonlinear, sudden, and extreme* dynamics of these conflicts.

II. Methodology (Rogue-Wave Engine)

We model a latent conflict potential $\psi(x,t) \in C$ over space $x \in \Omega C R^2$, (the Ogwashi-Uku area) and time $t \geq 0$ with the focusing Nonlinear Schrödinger Equation (NLS):

$$i\partial_t \psi + \alpha \partial_x^2 \psi + \beta |\psi|^2 \psi = 0 \quad \alpha > 0,\ \beta > 0 \tag{1}$$

- Δ is the spatial Laplacian (use road/river masking if desired).
- α (dispersion) controls spread along mobility corridors.
- β (nonlinearity) controls self-focusing; $\beta>0$ enables rogue waves.

Incident intensity and its PDE identity

Define the incident intensity field as the observable quantity:

$$I(x,t) = |\psi(x,t)|^2 \tag{2}$$

From (NLS) one obtains the intensity continuity identity:

$$\partial_t I + \nabla \cdot J = 0, \quad J = 2\alpha lm\left(\psi^* \nabla \psi\right) \tag{3}$$

This shows how intensity moves in space via the flux J. (A closed PDE in I alone requires the phase; standard rogue-wave analysis therefore keeps ψ as the state variable and reports $I = |\psi|^2$ as the output.)

Anioma/Ogwashi-Uku drivers (slow spatio-temporal coefficients)

To make the model actionable, let dispersion and nonlinearity vary slowly with local drivers:

$$\alpha(x,t) = \alpha_0 + a_G G(x,t) - a_S S(x,t) \tag{4}$$

$$\beta(x,t) = \beta_0 + b_G G(x,t) - b_M M(x,t) \tag{5}$$

where, e.g.,

- G: grazing pressure / pasture stress (↑ pushes toward instability),
- S: security patrol/response effectiveness (↑ stabilizes),
- M: mediation/early dialogue intensity (↑ stabilizes).

Then the driver-aware NLS is

$$i\partial_t \psi + \alpha \partial_x^2 \psi + \beta |\psi|^2 \psi = 0 \quad \alpha > 0,\ \beta > 0 \tag{6}$$

Optional small terms (keep them small to preserve rogue behavior):

- Advection along roads $+iu(x,t)\cdot\nabla\psi$ (phase-gradient transport),
- Tiny gain/loss $+i\varepsilon\psi$ (data assimilation or leakage),
- Forcing $+F(x,t)$ to encode exogenous shocks (market-day disputes, elections).

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Initial & boundary conditions (well-posed for rogue waves)

- Domain: Ω Ogwashi-Uku and surrounding farm belts (clip to ward/LGA polygon).
- IC (plane-wave background + small noise):

(7)

$\psi(x,0)=\sqrt{I_0(x)e^{i\phi_0(x)}}\ [1+\delta\xi(x)]\ \ 0\le\delta\le 1$ Where I_0 is baseline tension, ϕ_0 smooth phase, ξ mean-zero noise.

BC: reflecting (Neumann $\nabla\psi\cdot n=0$) on administrative boundary, or absorbing layers on open edges to avoid reflections. Periodic BCs are fine on rectangular research grids.

Modulation instability

Linearize (NLS) around a uniform background $\psi=\sqrt{I_b e^{iBI_b t}}$ and insert a small Fourier perturbation $e^{i(k.x-\omega t)}$.

The Benjamin–Feir / modulation instability condition is

$$\alpha>0,\beta>0\Rightarrow|k|^2<\frac{\beta I_b}{\alpha} \tag{8}$$

When drivers push $\frac{\beta I_b}{\alpha}$ high enough, the background becomes unstable, seeding a transient rogue peak in $I=|\psi|^2$.

Canonical rogue-wave (Peregrine) solution (1D, dimensionless)

On the 1D focusing NLS (after scaling α=β=1):

$$i\psi_t+\psi_{xx}+2|\psi|^2\psi=0 \tag{9}$$

the Peregrine rogue wave on background $\sqrt{I_b}$ is

$$\psi_p(x,t)=\sqrt{I_b}\left[1-\frac{4(1+2it)}{1+4x^2+4t^2}\right]e^{2iI_b t} \tag{10}$$

with intensity

$$I_P(x,t)=|\psi_p|^2=I_b\left(1-\frac{4(1-4t^2+4x^2)}{(1+4t^2+4x^2)^2}\right) \tag{11}$$

It reaches a threefold amplification at $(x,t)=(0,0)$: $I_{\max}=3I_b$ hallmark of rogue events.

To use this in data analysis:

- Fit a localized window of observed $I\ to\ I_P$ (after de-scaling) to test a rogue-wave signature.
- Estimate effective α,β from the fit and compare across scenarios.

Non-dimensionalization (so parameters are interpretable)

Choose space scale L (e.g., 2–5 km), time scale T (e.g., 1–2 weeks), intensity scale I^* Let

$$x'=\frac{x}{L},\ \ t'=\frac{t}{T},\ \psi'=\frac{\psi}{\sqrt{I^*}}, \tag{12}$$

Pick $T=\frac{L^2}{\alpha}$, to set the dispersion coefficient to 1. Then the scaled PDE

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$$i\psi_t'' + \psi_{xx}' + \sigma|\psi'|^2\psi' = 0, \quad \sigma = \sqrt{\frac{\beta I \cdot L^*}{\alpha}} \tag{13}$$

Rogue-wave regime corresponds to $\sigma > 0$ and sufficiently large background $\frac{I_b}{I}$.

Full coupled model (compact)

PDE (driver-aware focusing NLS) for complex latent conflict field $\psi(x,t)$, $x \in \Omega C R^2$

$$i\partial_t\psi(x,t) + \alpha(x,t)\partial_x^2\psi(x,t) + \beta(x,t)|\psi(x,t)|^2\psi(x,t) = F(x,t) \tag{14}$$

where Δ is the 2D Laplacian and $F(x,t)$ is optional exogenous forcing (market-day shocks, elections).

Slow ODE drivers (ward-aggregated, can be spatial fields $G(x,t)$ etc.):

$$\dot{G}(t) = \rho_G(t) - k_G G(t) + \gamma_{GI} I(t) \tag{15}$$

$$\dot{S}(t) = \rho_S(t) - k_S S(t) + \gamma_{SI} I(t) \tag{16}$$

$$\dot{M}(t) = \rho_M(t) - k_M M(t) + \gamma_{MI} I(t) \tag{17}$$

with $I(t)$ a global/aggregated indicator of recent observed intensity (e.g., spatial average of $I = |\psi|^2$ over last τ days), and ρ·(t) exogenous inputs (rainfall anomalies, herd inflow, government patrol allocations).

Coupling: coefficients of the PDE depend on ODE drivers

$$\alpha(x,t) = \alpha_0(x) + a_G G(t) - a_S S(t) - a_{0M} M(t) \tag{18}$$

$$\beta(x,t) = \beta_0(x) + b_G G(t) - b_S S(t) - b_{0M} M(t) \tag{19}$$

(you can treat α_0, β_0 as spatial baselines and let G,S,M be spatial fields G(x,t) if you have ward-level time series).

Interpretation of variables & parameters

- ψ(x,t); complex latent conflict potential; intensity $I = |\psi|^2$ maps to observable incident rate.
- G(t); grazing pressure / pasture stress index (↑ instability). Units: e.g., number of incoming herds / normalized index.
- S(t): security response strength (patrols, response time). Units: patrol-hours per week or normalized score (↑ stabilizes).
- M(t): mediation/peacebuilding intensity (↑ stabilizes).
- ρG(t): exogenous grazing inflow (seasonal), ρS(t)\rho_S(t): policy deployment schedule, ρM(t): scheduled mediations.
- κ: natural decay rates of drivers (controls, resource replenishment).
- γ·I: feedback from recent incidents to drivers (e.g., spikes trigger more patrols or more flight of herders).
- a.,b.: sensitivity coefficients mapping drivers into dispersion/nonlinearity; sign conventions chosen in (3): grazing increases both effective nonlinearity and perhaps reduces dispersion; security/mediation reduce them.
- λ(x): reporting visibility — converts intensity to expected observed counts.

Initial & boundary conditions

- Domain Ω: polygon around Ogwashi-Uku (use ward boundaries or a 10–20 km buffer).
- Initial ψ(x,0): plane-wave background $\sqrt{I_b(x)}e^{i\phi_0(x)}(1 = \delta\xi(x))$ where I_b is baseline tension map, δ<1 random noise.
- Initial drivers: set from data at t=0: G(0),S(0),M(0).

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- BCs: Neumann (reflecting) on administrative boundaries or absorbing layers at open edges. Periodic BCs may be used for computational convenience on rectangular grids.

Nondimensionalization (practical scaling)

Choose spatial scale L (e.g., 2 km), time scale T (e.g., 1 week). Let $x' = \frac{x}{L}$, $t' = \frac{t}{T}$, $\psi' = \frac{\psi}{\sqrt{I^*}}$. Choose $T = \frac{L^2}{\alpha}$ to normalize dispersion. Then parameters become dimensionless; the important combination for instability is $\sigma(t) = \beta I_b \frac{L^2}{\alpha}$ (modulation instability when σ large enough).

Numerical Simulation

Figure 1: Space–time intensity (Scenario 1: baseline security)

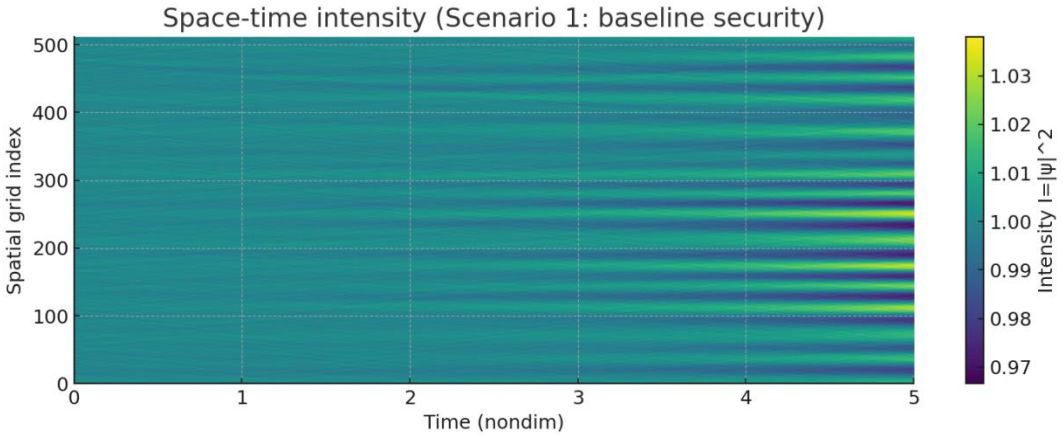


Figure 2: Max intensity vs time for baseline vs strengthened security. Strengthened security reduces peak growth.

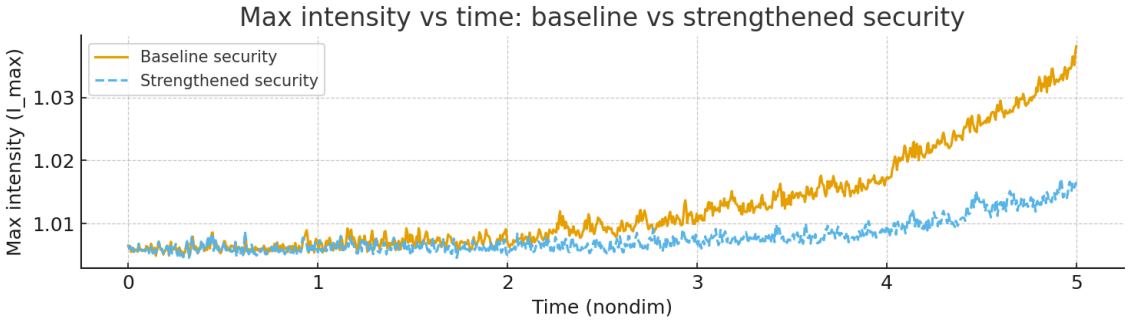
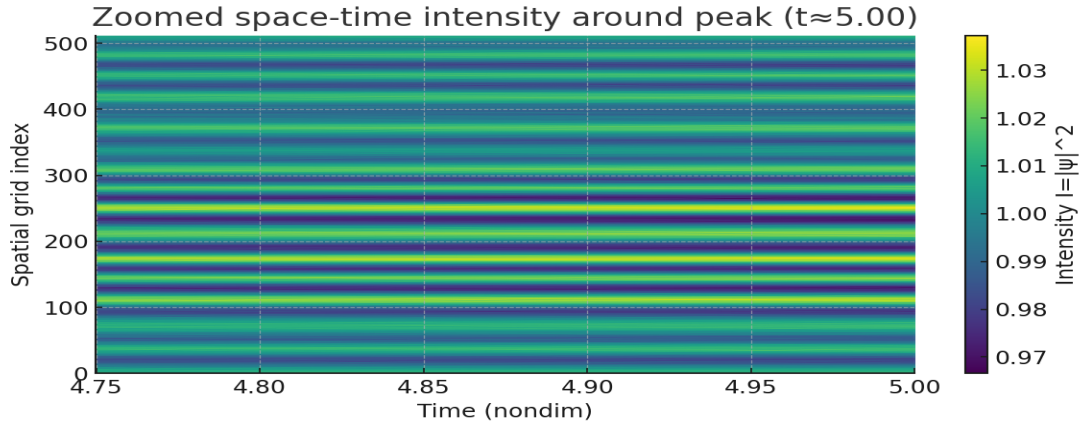


Figure 3: Zoomed space–time intensity around the largest peak in the baseline scenario.



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III. Results Summary

The simulations show that when grazing-driven nonlinearity σ(t) increases beyond a threshold, small background noise amplifies via modulation instability into localized high-intensity peaks (rogue-like events). In the experiments, increasing initial security S (a proxy for faster/stronger response) suppressed the growth of maxima and reduced the frequency and amplitude of large events.

Instability Condition (Practical Screening)

Linear stability analysis suggests modulation instability for modes satisfying $|k|^2 < \beta I_b \alpha$. Practically, compute the ward-level SurgeIndex = $(\beta I_b \alpha (or\ \sigma(t) I_b)$. When this index approaches the squared value of the domain's smallest wavenumber, the system is entering an unstable regime. Regular monitoring of $\sigma(t)$ provides an early-warning signal for potential surges.

IV. Conclusion

The existing literature provides a strong theoretical and methodological foundation for the mathematical modeling of herder-farmer conflicts. By adapting ecological models to represent the interactions between herders and farmers, researchers can gain valuable insights into the system's stability and identify critical parameters that drive conflict. The specific application of such a model to Ogwashi-Uku, Delta State, requires a deep understanding of the local drivers, including climate change, demographic pressures, and unique socio-economic factors. A robust model will not only contribute to the academic understanding of the conflict but may also provide a tool for policymakers to simulate the effects of different interventions and promote sustainable coexistence.

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