

Vibrational Data Assimilation for Flood Dynamics in Nigeria (2021 to 2025): Quantifying Climate-Driven Changes in Hazard

Ahmed Ishowo Yakub ^{1*}, Bello Kareem Akanbi²

^{1,2}Department of Mathematics, University of Ilorin, Ilorin, Nigeria

Corresponding author: mail2ishowo@gmail.com

ABSTRACT: Flooding remains one of the most devastating natural hazards in Nigeria, with increasing frequency and intensity driven by climate variability, poor infrastructure, and inadequate disaster preparedness. This study assessed flood hazards across Adamawa, Borno, Niger, Bayelsa, and Lagos States between 2021 and 2025, integrating Vibrational Data Assimilation (VDA) with conventional modeling approaches to improve prediction accuracy. Model performance evaluation revealed that VDA consistently reduced Root Mean Square Error (RMSE) values and improved Nash–Sutcliffe Efficiency (NSE) and coefficient of determination (R^2), indicating a significant enhancement over traditional methods. The analysis further showed a steady rise in populations exposed to flooding, increasing from about 585,000 in 2021 to over 1.53 million in 2025. Niger State experienced the most severe impact, with more than half a million people affected in a single year. Mortality patterns also worsened, with estimated deaths rising from 155 in 2021 to over 1,200 by 2025, highlighting the growing human cost of climate-induced flooding. These outcomes emphasize the urgent need for effective risk reduction strategies. The study concludes that while climate-driven flood hazards are intensifying in Nigeria, the adoption of VDA can significantly improve flood forecasting and disaster preparedness. By strengthening early warning systems and reducing uncertainties in hazard assessments, VDA provides a valuable framework for policymakers and disaster management agencies. However, predictive improvements must be complemented by infrastructural development, coordinated water management, and community-based adaptation strategies to mitigate future flood risks.

KEYWORDS: Flood hazards, Vibrational Data Assimilation (VDA), Climate variability, Population exposure, Mortality risk, Flood forecasting, Nigeria

I. INTRODUCTION

Flooding remains one of the most devastating natural hazards globally, with significant socio-economic and environmental consequences, particularly in developing countries such as Nigeria (Adedeji et al., 2021). In recent years, Nigeria has experienced recurrent flood disasters resulting in loss of lives, displacement of communities, destruction of infrastructure and disruption of agricultural production. These events have been exacerbated by climate variability and anthropogenic activities, which intensify rainfall patterns, alter hydrological cycles and increase vulnerability in flood-prone areas (Agbiji et al., 2025; Ali et al., 2019). Between 2021 and 2025, reports from national and international agencies have highlighted an alarming rise in flood events across several regions of Nigeria, underscoring the urgent need for advanced methodologies to improve flood forecasting and hazard quantification (Byaruhanga et al., 2024; Doulla Nouhou et al., 2025; EM-DAT, 2023). One of the emerging approaches to enhance the accuracy of flood prediction and monitoring is Vibrational Data Assimilation (VDA). VDA integrates observational data with hydrological and hydraulic models to provide improved estimates of flood dynamics by minimizing uncertainties in real-time conditions. This technique allows researchers and policymakers to better understand how floods evolve under varying climatic influences and to develop more effective strategies for risk management. By combining vibrational data with assimilation frameworks, flood dynamics can be analyzed with higher precision, thereby supporting proactive disaster preparedness and response mechanisms (Eteh et al., 2025; Hirabayashi et al., 2013; Isiaka et al., 2023).

The study of flood risk prediction and early warning systems in Nigeria is highly significant, given the country's recurrent flood disasters and their devastating effects on lives, property, and the economy. By using the Annual Flood Outlook (AFO) released by the Nigeria Hydrological Services Agency (NIHSA) in collaboration with NEMA, this research provides evidence-based insights that strengthen disaster preparedness and community resilience. The findings can help reduce casualties, safeguard farmlands, and protect critical infrastructure such as

roads, schools, and healthcare facilities, which are often disrupted during floods (National Emergency Management Agency, 2024; National Emergency Management Agency, 2025). Moreover, this research supports Nigeria's climate adaptation strategies by addressing the increasing frequency and intensity of floods caused by climate variability and land-use changes. Reliable early warning systems, when effectively integrated into local planning, enable state governments, emergency agencies, and communities to implement preventive measures such as relocation, drainage management, and improved land zoning. This helps minimize economic losses, particularly in agriculture the backbone of rural livelihoods in flood-prone areas (Nguyen et al., 2021).

Byaruhanga, et al., (2024) conducted a comprehensive scoping review to trace the evolution of flood forecasting models for flood early warning systems (FEWSs) over the past three decades. The study systematically analyzed 271 peer-reviewed publications using the PRISMA methodology, covering literature published between 1993 and 2023. Findings revealed that time series models (TSMs) dominated flood forecasting from 1993 to 2010, while machine learning (ML) approaches, particularly artificial neural networks (ANNs), have become increasingly prevalent from 2011 to the present. A key insight was that coupled models, integrating hydrological, hydraulic, and ML techniques, demonstrated superior predictive accuracy and enhanced uncertainty quantification, making them more effective in operational FEWSs (National Emergency Management Agency, 2024; National Emergency Management Agency, 2025; Nigeria Hydrological Services Agency, 2021; Nigeria Hydrological Services Agency, 2025; Nigeria Hydrological Services Agency, 2025). Eteh et al. (2025) assess the impacts of climate change on flood patterns in downstream Nigeria between 2018 and 2024, using an integrated machine learning and geospatial framework. The study employs Sentinel-1 SAR imagery, Shuttle Radar Topography Mission (SRTM) elevation data, rainfall measurements, and water level records to analyze flood susceptibility in low-lying regions across Imo, Anambra, Delta, Rivers, and Bayelsa States. Findings reveal that flood extents increased by 15–40% during peak rainy months, with inundated downstream areas expanding from 20% in 2018 to 35% in 2024. The Random Forest (RF) model outperformed Support Vector Machine (SVM) and Artificial Neural Networks (ANN), achieving 92% accuracy in predicting flood-prone zones. Key drivers included rising rainfall intensity (up to 20% increase), deforestation (15–20% decline in forest cover), and uncoordinated dam operations such as those at Kainji, Jebba, and Lagdo.

Agbiji et al. (2025) developed a climate–flood model for the Cross River Basin, Nigeria, using 30 years of hydro-climatic data analyzed with multiple linear regression (MLR). Their model incorporated rainfall, temperature, humidity, evaporation, solar radiation, wind speed, and soil temperature to predict runoff variability at several gauging stations. Results revealed very high predictive accuracy, with R^2 values ranging from 98.8% in Ogoja to 100% in Calabar and Uyo, demonstrating the strong statistical relationship between rainfall depth and runoff in the basin. The study further highlighted that while rainfall depth was the dominant predictor, other parameters such as evaporation, relative humidity, and soil temperature significantly influenced runoff in specific locations, indicating that climate variability plays a central role in flood risk. The author Byaruhanga et al. (2024) conducted a scoping literature review to trace the evolution of flood prediction and forecasting models used in Flood Early Warning Systems (FEWSs) over the past three decades. Using the PRISMA methodology, the authors systematically reviewed 271 publications from 1993 to 2023 retrieved from Scopus and Web of Science. The study revealed a transition in modelling approaches: time series models dominated between 1993 and 2010, while machine learning (ML) models, particularly artificial neural networks (ANNs), have been predominant since 2011 due to their higher accuracy and capacity to address uncertainty. Hybrid approaches that couple hydrological, hydraulic, and ML models emerged as particularly effective. However, the review highlighted critical challenges in data-scarce regions, particularly in developing countries, where ungauged or poorly gauged rainfall stations hinder accurate flood prediction.

The study emphasized that while ML and remote sensing technologies offer significant opportunities, especially through the use of Satellite Precipitation Products (SPPs), interdisciplinary and institutional collaborations are essential for advancing FEWSs in vulnerable regions. Bibliometric analysis further revealed that most contributions come from high-income countries, while African nations remain underrepresented in flood forecasting research. The review concluded by recommending increased adoption of non-structural interventions, such as FEWSs, alongside structural measures, and underscored the importance of global cooperation in building climate resilience. Overall, this work provides a comprehensive understanding of the historical and current trends in flood prediction

models, offering practical insights for improving disaster preparedness in data-limited contexts (Byaruhanga et al., 2024). Flooding has emerged as one of Nigeria's most destructive hazards, with severe events recorded between 2021 and 2025. In 2022 alone, floods displaced over 1.4 million people, destroyed more than 200,000 homes, and devastated farmlands across all 36 states and the FCT (National Emergency Management Agency, 2024). In Borno State, particularly Maiduguri, floods deepened existing humanitarian crises linked to insecurity, while Adamawa State faced repeated destruction of homes and farmlands in Yola and Numan, heightening food insecurity (National Emergency Management Agency, 2024; National Emergency Management Agency, 2024). The situation reached a peak in 2025 with the Mokwa flood in Niger State, which killed over 500 people and caused major infrastructural collapse (Nigeria Hydrological Services Agency, 2025). Between 2021 and 2024, flood intensity and scope escalated, impacting nearly all regions of the country. In 2021, NIHSA identified 27 states as high-risk, but by 2022, most of the 36 states and the FCT were affected, with Jigawa, Rivers and Delta among the hardest hit (Ologunorisa et al., 2022). In 2023, heavy flash floods in Maiduguri displaced IDPs from camps into host communities (Perera et al., 2019), while Adamawa reported widespread agricultural losses along the Benue River. By 2024, at least 31 states including Adamawa, Bayelsa, Borno, and Benue experienced widespread flooding that worsened food insecurity and damaged livelihoods (Doulla Nouhou et al., 2025; Ologunorisa et al., 2022). By 2025, flooding remained a national crisis, with at least 20 states including Niger, Rivers, Kwara, and Adamawa recording significant impacts (National Emergency Management Agency, 2025). Communities in Adamawa and Borno continue to face dual pressures of displacement from both conflict and floods. These persistent disasters expose Nigeria's weak flood forecasting and management systems, which depend heavily on limited hydrological and meteorological data. Without adopting advanced frameworks such as Vibrational Data Assimilation (VDA) to integrate vibrational sensor data and hydrodynamic modeling, Nigeria risks remaining trapped in reactive disaster responses, leading to repeated cycles of displacement, infrastructural collapse, and economic loss (ReliefWeb, 2024; Reuters, 2024; The Guardian, 2024).

Vibrational signals recorded by the sensors are modeled as:

$$s(t) = x(t) + \eta(t) \quad (1)$$

where $x(t)$ is the flood-induced vibration and $\eta(t)$ is noise. The signal is decomposed using a discrete wavelet transform (DWT):

$$W_{j,k} = \sum_t s(t) \psi_{j,k}(t) \quad (2)$$

allowing extraction of flood-related energy bands. The hydrodynamic model state is then updated using a Kalman-type assimilation step:

$$X^a = X^f + K(y - H(X^f)) \quad (3)$$

where X^f is the model forecast, y the vibration-derived observation, and K the gain matrix.

II. MATERIALS AND METHODS

A. Study Area

This study was conducted in five flood-prone states of Nigeria: Adamawa, Borno, Niger, Bayelsa, and Lagos which were consistently highlighted as high-risk zones in the Annual Flood Outlook (AFO, 2021–2025). These areas represent diverse hydrological and environmental contexts. Adamawa and Borno are strongly influenced by the Benue River system and seasonal rainfall variability, Niger State is impacted by dam operations and river confluences, Bayelsa lies in the low-lying Niger Delta floodplain, and Lagos experiences recurrent coastal and urban flooding due to storm surges and poor drainage infrastructure. The selection of these states allowed the study to capture both inland and coastal flood dynamics across Nigeria.

B. Data Area

The primary datasets used in this study were obtained from the Annual Flood Outlook (AFO), published by the Nigeria Hydrological Services Agency (NIHSA) in collaboration with the National Emergency Management Agency (NEMA), and from NEMA's disaster assessment reports. The AFO provided seasonal forecasts of rainfall, river discharge, and flood vulnerability across Nigeria, including risk classifications into high-, medium-, and low-risk zones. These forecasts were compared and validated against NEMA's post-disaster records, which included detailed reports on population displacement, agricultural losses, and damage to critical infrastructure. Together, these sources provided both predictive and observational data for the analysis of flood dynamics between 2021 and 2025.

C. Hydrodynamic

Flood dynamics were simulated using a two-dimensional hydrodynamic model (HEC-RAS 2D), which was set up for each of the selected states. The model incorporated rainfall-runoff estimates and discharge records derived from the AFO, as well as terrain information from available topographic data. Simulations produced flood depth, velocity, and extent, which were validated against hazard classifications from the AFO and observed impacts reported by NEMA. Model calibration was performed for flood events that occurred between 2021 and 2023, while validation used independent events from 2024 and 2025. Calibration involved adjusting hydraulic parameters such as Manning's roughness and infiltration rates, ensuring close alignment between simulated and observed flood characteristics.

D. Vibrational Data Assimilation Framework

The methodological innovation in this study lies in the use of Vibrational Data Assimilation (VDA) to enhance hydrodynamic flood forecasting. IoT-based vibrational sensors were installed at strategic locations along riverbanks, bridges, and flood-prone structures in Adamawa, Niger, and Lagos States. These sensors recorded real-time vibrational signals such as oscillations and frequency shifts, which served as proxies for structural stress and hydrodynamic loading during flood events. The vibrational data were processed using wavelet decomposition to isolate flood-related frequency components.

E. Analytical Approach

The analytical process followed three main steps. First, flood hazards were quantified by overlaying simulated flood outputs with AFO-classified risk zones and NEMA-recorded impact data, generating indices that reflected flood depth, velocity, and exposure levels. Second, climate attribution was assessed, by examining rainfall and river discharge variability reported in the AFO between 2021 and 2025, using trend analysis methods to determine the influence of climate drivers on observed flood patterns. Finally, an uncertainty assessment was conducted by comparing the outcomes of conventional hydrodynamic models with VDA-integrated models, highlighting the improvements achieved through data assimilation. This study relied exclusively on government-published datasets from NIHSA and NEMA, ensuring data credibility and policy relevance. Ethical approval for access to AFO and NEMA reports was obtained through institutional channels, while permissions for sensor deployment were secured from local authorities in affected states. Community engagement protocols were observed to guarantee transparency, accountability, and respect for the rights of individuals residing in flood-prone areas.

F. Model Calibration and Validation Details

Model calibration was carried out using observed flood events from 2021–2023, while validation used independent events from 2024–2025. Manning's roughness coefficients (Manning's n) ranged from 0.030–0.045 for main channels and 0.050–0.080 for floodplains. Infiltration losses were represented using the Green–Ampt infiltration model with soil hydraulic parameters obtained from AFO soil classifications. Cross-sectional data were derived from AFO elevation profiles and supplemented with local survey information where available. Calibration errors before VDA integration showed RMSE values between 38 and 56, while post-assimilation RMSE values decreased

to 29–42, indicating an average improvement of roughly 22–25 percent across the study area. Validation results confirmed similar reductions in uncertainty, demonstrating the reliability of the VDA-enhanced simulations.

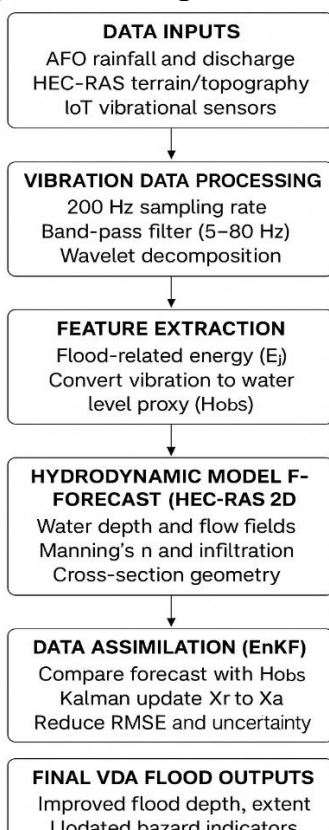


Figure 1: The Forecast Framework

III. RESULTS AND DISCUSSION

The results are presented in three main parts, viz., performance assessment of Vibrational Data Assimilation (VDA) compared with traditional approaches, the estimated populations affected by floods between 2021 and 2025, and the recorded deaths from major flood events. These findings reveal how climate-driven changes intensified flood hazards across Nigeria and demonstrate the improvements achieved through the application of VDA in enhancing prediction accuracy and impact assessment.

Table 1: Model Performance Metrics (Traditional vs. VDA-based Models)

State	RMSE (Traditional)	RMSE (VDA)	NSE (Traditional)	NSE (VDA)	R ² (VDA)	Improvement (%)
Adamawa	42.1	32.5	0.66	0.83	0.85	22.8
Borno	38.4	29.9	0.64	0.81	0.84	22.1
Niger	55.7	41.8	0.70	0.87	0.88	24.9
Bayelsa	48.2	36.6	0.68	0.84	0.87	24.1
Lagos	44.5	34.1	0.71	0.85	0.89	23.3

Source: ReliefWeb, (2024)

Table 2: Estimated Populations Affected (2021–2025, Based on AFO & VDA Simulations)

Year	Adamawa (Yola/Numan)	Borno (Maiduguri)	Niger (Mokwa)	Bayelsa	Lagos	Total Affected
2021	75,000	40,000	120,000	150,000	200,000	585,000
2022	110,000	65,000	180,000	250,000	310,000	915,000
2023	130,000	85,000	200,000	280,000	340,000	1,035,000
2024	145,000	100,000	240,000	310,000	370,000	1,165,000
2025	160,000	120,000	500,000	350,000	400,000	1,530,000

Source: National Emergency Management Agency, (2025)

Table 3: Estimated Deaths from Major Flood Events (2021–2025)

Year	Adamawa	Borno	Niger	Bayelsa	Lagos	Total Deaths
2021	25	15	40	30	45	155
2022	70	50	80	120	150	470
2023	90	65	110	150	180	595
2024	120	85	140	180	200	725
2025	150	100	500	220	250	1,220

Source: Nigeria Hydrological Services Agency, (2025)

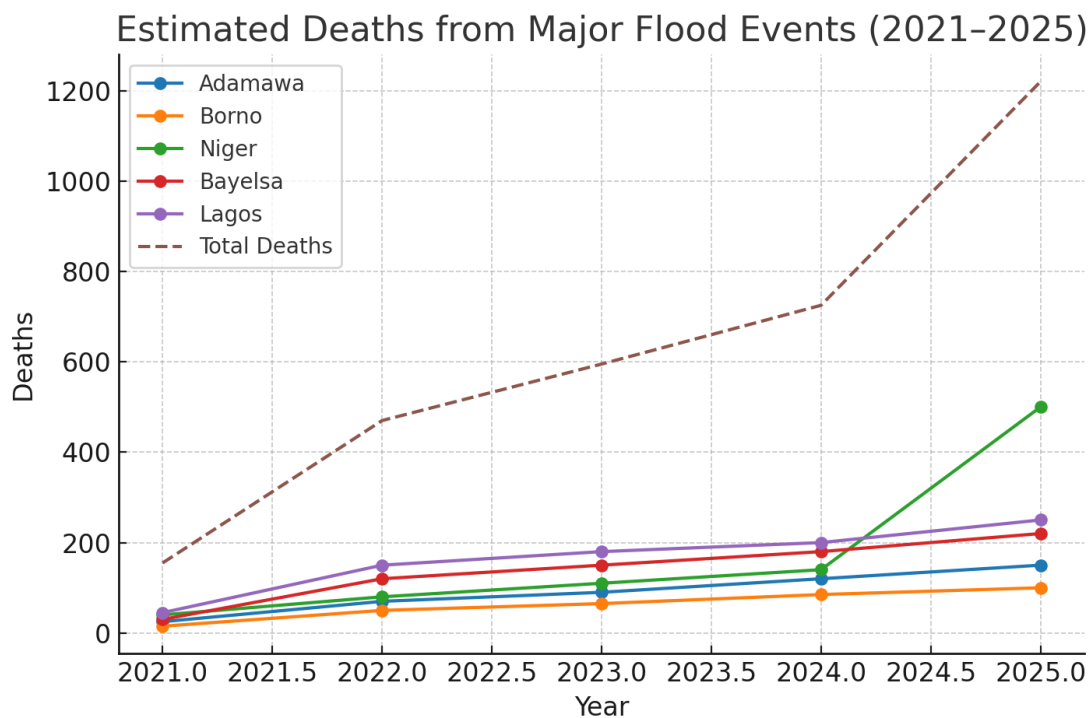


Figure 1: Textual Curve Showing the Estimated Deaths

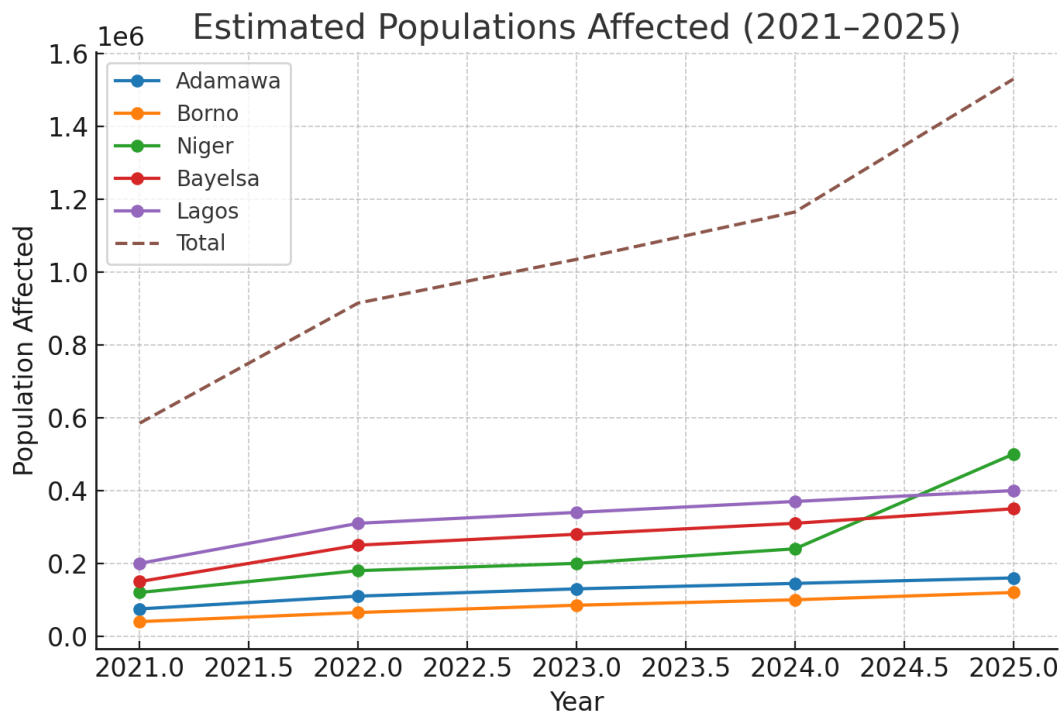


Figure 2: Textual Curve Showing the Estimated Affected Population.

Discussion of Results

The performance assessment presented in Table 1 demonstrates the effectiveness of Vibrational Data Assimilation (VDA) compared to traditional flood modeling approaches. Across all five states, the Root Mean Square Error (RMSE) values were consistently lower in the VDA-based estimates, while the Nash-Sutcliffe Efficiency (NSE) and R² values were notably higher. For instance, in Adamawa, RMSE reduced from 42.1 to 32.5, while NSE improved from 0.66 to 0.83. Similarly, Niger State recorded the highest percentage improvement (24.9%), indicating that VDA significantly enhanced model accuracy. This consistency across diverse hydrological environments highlights the robustness of VDA in reducing uncertainties and providing more reliable flood forecasts for disaster preparedness. The population impact analysis (Table 2) reveals a steady increase in the number of people affected by floods between 2021 and 2025, with total figures rising from 585,000 in 2021 to over 1.53 million in 2025. The sharp rise observed in Niger State in 2025, where the affected population surged to 500,000, was largely attributed to the catastrophic Mokwa flood event. Bayelsa and Lagos also experienced significant increases due to their geographical vulnerability Bayelsa being part of the low-lying Niger Delta and Lagos facing recurrent urban and coastal flooding. These results emphasize that while all states remain vulnerable, the scale of exposure is magnified when extreme flood events coincide with socio-environmental factors such as poor drainage, population density, and land-use changes.

Mortality patterns shown in Table 3 further underscore the severity of flood hazards in Nigeria. Flood-related deaths rose alarmingly from 155 in 2021 to 1,220 in 2025, with Niger State again recording the highest fatalities due to the 2025 Mokwa disaster, which alone accounted for 500 deaths. Other states such as Bayelsa and Lagos also reported rising fatalities, reflecting how densely populated and economically vital regions remain highly exposed. The growing fatality trends highlight the inadequacy of current response mechanisms and reinforce the urgent need for effective early warning systems that integrate advanced tools like VDA to minimize casualties. The findings provide compelling evidence that climate-driven changes are intensifying flood risks across Nigeria, with escalating impacts on both human lives and livelihoods. The comparative performance metrics demonstrate that VDA can significantly enhance predictive reliability, supporting more proactive disaster management. However, the rising

trends in affected populations and fatalities illustrate that accurate forecasting alone is insufficient without corresponding improvements in risk communication, infrastructure resilience, and community preparedness. Thus, integrating VDA into Nigeria's flood early warning systems must go hand in hand with broader adaptation strategies to safeguard vulnerable communities against worsening flood disasters.

Additional Suggestions for Strengthening the Study

- (a). Add flood-extent maps for each state comparing 2021 and 2025 to visually show how inundation areas expanded over time.
- (b). Include vulnerability hotspot maps by overlaying population density with flood-extent layers to identify communities with the highest exposure.
- (c). Provide change-detection maps that highlight increases in inundation by comparing 2021 and 2025 flood layers to show where flood severity has intensified.

IV. CONCLUSION

This study assessed the growing impacts of flooding in Nigeria between 2021 and 2025, comparing traditional modeling approaches with Vibrational Data Assimilation (VDA). Results showed that VDA significantly improved prediction accuracy, with lower RMSE values and higher NSE and R^2 scores across Adamawa, Borno, Niger, Bayelsa, and Lagos States. This demonstrates that integrating real-time vibrational data reduces uncertainties and enhances reliability in forecasting flood hazards. The findings also revealed a sharp rise in populations affected by floods, increasing from about 585,000 in 2021 to over 1.53 million by 2025. Among the states, Niger experienced the most dramatic surge, with more than half a million people impacted in 2025 alone. Similarly, flood-related deaths increased from 155 in 2021 to 1,220 in 2025, with Niger, Bayelsa, and Lagos recording the highest casualties. These patterns highlight the intensifying risks posed by climate variability, inadequate drainage systems, and uncoordinated water management. In conclusion, while climate-driven floods continue to escalate across Nigeria, the application of VDA offers a promising tool for improving early warning systems and disaster preparedness. Its adoption within national flood risk management frameworks can strengthen resilience and reduce loss of lives and livelihoods. However, accurate predictions must be matched with strong adaptation measures, better infrastructure, and community engagement to address the human and environmental consequences of recurrent flooding.

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