Disaster Risk Forecasting, Data Analytics, Strategic Foresight and The Future of Disaster Risk Management

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https://doi.org/10.56201/jhsp.vol.12.no11.2026.pg12.24

Abstract
Forecasting and data analytics have advanced rapidly, but better information about hazards does not automatically reduce disaster losses. This narrative review brings together research and policy evidence on hazard and impact forecasting, vulnerability analytics, strategic foresight, and anticipatory action. It uses Nigerian flood episodes from 2022 and 2024, alongside the 2025 Annual Flood Outlook, as illustrative cases. Sources were purposively selected from peer-reviewed studies, multilateral reports, and Nigerian official records. Bibliographic details and selected quantitative claims were checked against accessible publisher and institutional records. A structured comparison of the cases distinguishes the availability of forecasts, information about infrastructure, actionable protocols, and reported consequences. Because the analysis relies on secondary accounts, it does not claim causal attribution. The paper proposes a four-function decision architecture that brings together probabilistic warnings, evidence on exposure and vulnerability, scenario-based foresight, and pre-authorised action protocols, with feedback and accountability built in. Its contribution lies not in a new forecasting algorithm, but in operationalising these functions through testable governance indicators. Priorities for Nigeria and other African institutions include interoperable risk information, asset-level monitoring, locally meaningful warnings, funded triggers, and evaluation of anticipatory decisions. The proposed framework has not been validated and requires prospective field testing.

Keywords: *disaster risk management; impact-based forecasting; data analytics; strategic foresight; anticipatory action*; risk governance; Nigeria

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1. Introduction

This paper makes three related arguments. First, forecasting, data analytics, and strategic foresight are often treated as separate technical fields, each with its own specialist community and funding. Yet they answer different questions and fail in different ways. Second, much of the value lost in disaster risk management lies at the points where these fields meet: when a forecast does not lead to a decision, when available data fail to show who is exposed, or when long-term assumptions go unexamined. Third, institutions in countries such as Nigeria can strengthen many of these connections without waiting for the most advanced technology. The key is to treat information as part of a decision system, rather than as a finished product in itself.

1.1 Aim and Review Questions

This review examines how forecasting, analytics, and foresight can be brought together institutionally to strengthen anticipatory disaster risk management in African settings where data are constrained. It addresses three questions: (1) What complementary decisions does each of these knowledge functions support? (2) Which institutional interfaces appear weak in selected Nigerian flood-risk episodes? (3) What decision protocols and indicators could make an integrated model testable?

1.2 Review Design, Evidence Identification and Limitations

This is a critical, purposive narrative review. Its purpose is conceptual synthesis, not exhaustive aggregation of all available evidence. The evidence base includes peer-reviewed research on forecasting, hydrology, risk analysis, foresight, and anticipatory action; policy documents from the United Nations Office for Disaster Risk Reduction (UNDRR), the World Meteorological Organization (WMO), the Intergovernmental Panel on Climate Change (IPCC), and the African Union; and official Nigerian material supplemented by dated news reports. The original manuscript's reference list provided the starting set of sources. For this revision, selected high-stakes factual claims and bibliographic details were checked against accessible primary publisher, federal-government, and NEMA webpages on 31 October 2026. The review does not claim to have conducted a comprehensive database search or an independent audit of every reference.

Sources were retained when they informed at least one of four analytical categories: (a) forecast skill and uncertainty; (b) evidence on exposure and vulnerability; (c) strategic foresight and institutional adaptation; and (d) triggers, authority, financing, and evaluation. Peer-reviewed syntheses and official records were preferred for quantitative and event-specific claims. Where sources disagreed, their accounts were retained as competing evidence rather than silently reconciled. The synthesis compares the functions of the different approaches and applies an explicit evidence matrix to three Nigerian episodes. No primary interviews, administrative datasets, or causal impact estimates were used. The case findings should therefore be read as plausible interpretations of governance arrangements, not as demonstrated causal mechanisms.

The paper proceeds as follows. Section 2 establishes the concepts. Sections 3, 4, and 5 review forecasting, analytics, and foresight. Section 6 considers Nigerian and wider African experience. Section 7 presents the integrated framework, and Section 8 concludes.

2. Conceptual Foundations

2.1 Risk Is Made of More Than Hazard

A flood or drought is a hazard. It becomes a disaster when it affects people and assets that are exposed and unable to cope. This is a central insight of the vulnerability tradition developed by Wisner et al. (2004): extreme natural events do not become disasters until vulnerable groups are exposed, and vulnerability can be traced from unsafe locations and limited access to resources to wider social and political conditions. This distinction matters for forecasting. A forecast describes the hazard, while exposure and vulnerability account for much of the variation in harm.

Hallegatte et al. (2017) add an important point about measurement. Aggregate asset losses reveal little about human suffering: the same monetary loss can mean very different things to a low-income household and a wealthy one. Poorer people may account for only a fraction of total economic losses while bearing the most severe consequences. A risk system focused on monetary losses alone will therefore understate the needs of the people it most needs to reach.

Two further ideas inform current thinking. Kelman et al. (2015) argue that climate change is one of several contributors to disaster risk, that adaptation belongs within disaster risk reduction, and that disaster risk reduction itself belongs within development. Pescaroli and Alexander (2018) distinguish compound, interconnected, interacting, and cascading risks. Their framework addresses situations in which hazards, systems, and vulnerabilities influence one another, and is intended to help put the Sendai Framework into practice. Both perspectives challenge the single-hazard view that forecasting most readily encourages.

2.2 Three Activities, Three Questions

This paper uses three terms in specific ways.

Forecasting produces statements about what is likely to happen in a particular place and period, usually with an associated probability. Its time horizon may range from hours to a season. Data analytics uses statistical, computational, and spatial methods to turn data into evidence about hazards, exposure, vulnerability, and response. It can describe the past or present, or contribute to a forecast. Strategic foresight systematically explores alternative futures to improve decisions made today. Voros (2003) describes a process that begins with gathering information and ends with outputs that inform strategy and planning. Inayatullah (2008) sets out six pillars of futures work—mapping, anticipating, timing, deepening, creating alternatives, and transforming—and argues that futures thinking can help people regain a sense of agency over what lies ahead.

The key difference is the claim each activity makes. A forecast estimate what will probably happen. Analytics helps establish what is happening and who is affected. Foresight does not claim to predict the future; it asks what could happen and how decision-makers might respond. Confusing these claims can lead to poor decisions. Treating a scenario as a forecast can create false confidence, while treating a forecast as foresight can leave plans tied to the rainfall patterns of a single season.

3. Disaster Risk Forecasting

3.1 What Has Improved

Modern forecasting is the result of sustained progress over many years. Bauer et al. (2015) describe numerical weather prediction as a quiet revolution, built on steady improvements in observation, physical understanding, and computing rather than on any single breakthrough. Forecasts are now commonly produced as ensembles, which provide an explicit probabilistic assessment. The authors also emphasise the connection between weather and climate prediction: reliable climate prediction depends on representing weather processes well. Machine learning has opened another path for progress. Lam et al. (2023) trained GraphCast, a graph neural network, directly on reanalysis data. They reported that it outperformed the leading operational deterministic system on 90% of 1,380 verification targets, generated a ten-day global forecast at 0.25° resolution in under a minute, and performed better on tropical cyclone tracks, atmospheric rivers, and extreme temperatures. Price et al. (2025) extended this approach to probabilistic forecasting. Their model, GenCast, generates ensemble forecasts for more than 80 variables over 15 days in about eight minutes and was reported to outperform the best operational ensemble system. For flood risk, the findings of Nearing et al. (2024) may be especially relevant. Floods are among the most common natural disasters, and their impacts are often greatest in places with few river gauges. The authors showed that an AI-based model could predict extreme river events in ungauged basins up to five days ahead, with reliability comparable to or better than same-day output from a leading global system. For events with a five-year return period, it performed about as well as the older system did for one-year events. The

model has been incorporated into an operational service that provides free forecasts in more than 80 countries. The study also makes clear that further improvement depends on better hydrological data.

3.2 From Hazard Forecasts to Impact Forecasts

A forecast of rainfall or river levels is not, by itself, a forecast of harm. Merz et al. (2020) examine this gap. Early warning systems commonly predict an event's magnitude, location, and timing, but rarely estimate its consequences—for example, physical damage, effects on people, service disruption, or financial costs. Impact estimates can give decision-makers a stronger basis for choosing emergency measures and provide different disciplines with a shared focus. Merz et al. also identify the challenges and pitfalls of impact forecasting, which depends on exposure and vulnerability information that is often limited. This dependence connects forecasting directly to the analytics discussed in Section 4.

3.3 Limits That Practitioners Should Keep in View

Forecast skill is uneven. Observation networks remain sparse in many low-income countries. WMO's 2025 report on hazard monitoring and forecasting describes continuing efforts to expand basic observing networks and address data gaps in least developed countries and small island developing states (WMO, 2025). Data-driven models inherit these limitations. Reichstein et al. (2019) caution that machine learning does not guarantee physical consistency, relies heavily on data quality, and may struggle to extrapolate beyond the conditions represented in its training data. They argue for combining learning methods with an understanding of physical processes. This caution is particularly important for rare extreme events—the very events that matter most to disaster managers. There is also a conceptual limit. The Global Assessment Report 2022 acknowledges that no model can accurately predict a fundamentally unpredictable future. It also points to cases where human experience and modelling are combined to support better decisions (UNDRR, 2022). Forecasting helps managers understand what is probable in the near term. It cannot tell them whether the systems they manage will remain resilient a decade from now. That is a question for foresight.

4. Data Analytics in Disaster Risk Management

4.1 Evidence About Exposure and Vulnerability

If forecasting describes the hazard, analytics must help establish the rest of the risk picture. That means knowing where people live, which buildings and roads they rely on, how they earn a living and receive information, and who may have no practical way to leave. Merz et al. (2020) show that impact forecasts depend on this kind of information. Wisner et al. (2004) and Hallegatte et al. (2017) explain why it matters: vulnerability shapes how harm is distributed, while aggregate loss totals can conceal that distribution. Combining hazard footprints with population, housing, livelihood, and service data can help identify which households face the greatest losses and which measures could protect them. Pelling and Wisner (2009) show how much can be overlooked when data capture only large, officially declared disasters. Their African urban case studies examine everyday disasters affecting households and roads, as well as smaller events in informal settlements whose cumulative impacts may exceed those of officially declared disasters. An analytical system that relies only on disaster declarations will miss these risks.

4.2 Using Data Without Losing Judgment

Kitchin (2014) examines how big data and new analytical methods are reshaping research. In particular, he questions the claim that large datasets make theory unnecessary—that algorithms can find patterns and replace explanation. He argues that this form of empiricism is disruptive, but requires critical reflection and a situated, context-aware approach to knowledge. The practical lesson for disaster management is straightforward: a model that identifies a statistical relationship between rainfall and flood losses in one decade may fail when land use, drainage, or settlement patterns change. Reichstein et al. (2019) make a related argument in Earth system science: data-driven methods are most useful when grounded in an understanding of the processes they represent. Analysts in emergency agencies therefore need enough knowledge of both the hazard and the local context to distinguish a plausible pattern from a spurious one.

4.3 Systemic and Cascading Risk

Analytics must also account for risks that do not occur as isolated hazards. Pescaroli and Alexander (2018) distinguish compound, interconnected, interacting, and cascading risks, and argue that these concepts can inform new analyses and decision tools. The Global Assessment Report 2022 notes that impacts increasingly cascade across places and sectors, as food systems, supply chains, and economies become more connected—and, in turn, more vulnerable (UNDRR, 2022).

In practice, this means mapping dependencies. A flood that closes a bridge, cuts a food supply route, and overwhelms a clinic is one event with several connected consequences. No single sector is likely to see the whole picture. Yet many national agencies still organise data hazard by hazard and sector by sector, making it difficult to analyse these dependencies.

4.4 The Data Problem in Africa

For many African agencies, a first obstacle is simply the availability of data. The IPCC's Africa chapter identifies significant data and research gaps across the continent. It finds that greater funding for African partners, together with African control over research design and resources, would produce more actionable insight (Trisos et al., 2022). The chapter also describes exposure and vulnerability in Africa as multidimensional, shaped by overlapping social, political, and environmental factors. Nearing et al. (2024) conclude that improved hydrological data are necessary to strengthen flood warnings. WMO (2025) reports progress in expanding observing networks and automating national systems, suggesting that the gap is being addressed, but not yet closed. Several practical steps follow. Agencies need data-sharing arrangements with universities, utilities, mobile operators, and survey organisations, because no single institution holds everything required. They also need staff who can build, test, and question models—not simply procure them. Open global products can provide a useful starting point, but they should be checked against local records and should never replace local observation.

5. Strategic Foresight and the Long View

5.1 What Foresight Adds

Forecasts look days or months ahead. The Sendai Framework extends to 2030 (UNDRR, 2015), while the assets that shape risk—dams, drainage networks, settlements, and institutions—often last for decades. Decisions about these assets must be made under deep uncertainty. Strategic foresight is designed to help organisations work within that uncertainty. Voros (2003) proposed a general process with distinct phases, from gathering information to producing outputs that inform strategy and planning. He also presented the framework as a diagnostic tool for examining how

foresight and strategy are practised, and as a guide for designing foresight projects suited to particular needs. Inayatullah (2008) offers a complementary set of tools through his six pillars: mapping, anticipating, timing, deepening, creating alternatives, and transforming. His foundational concepts include the "used future" and the "disowned future," which prompt organisations to ask why they hold particular images of what lies ahead. For an emergency agency, this is a useful question. Many agencies implicitly assume that next year will resemble this year, without testing that assumption.

5.2 Why Disaster Risk Management Needs It

The first reason is that risk is continually changing. Kelman et al. (2015) describe climate change as one driver among many, entangled with development choices. The Global Assessment Report 2022 finds that risk creation is outpacing risk reduction (UNDRR, 2022). Planning based on the assumption that past hazard patterns will remain stable is therefore likely to leave agencies underprepared. The second reason is that systems are connected. Pescaroli and Alexander (2018) explain how dependencies can produce interacting and cascading risks that single-hazard planning fails to capture. Foresight methods can map these dependencies and explore combinations of events before they occur. The third reason is institutional habit. Organisations often plan around the last disaster. A scenario asking what might happen if a spillway failed during a regional rainfall peak can put an uncomfortable possibility on the table. An agency that has rehearsed that possibility may respond differently from one that has not—even if the eventual event unfolds differently from the scenario.

5.3 Foresight and Forecasting Together

Forecasting and foresight can strengthen one another. Forecasts provide the near-term signal; foresight provides the context in which to interpret it. The forecast-based financing model described by Coughlan de Perez et al. (2015) illustrates this connection. It sets thresholds, actions, and funding arrangements in advance of a particular season. That preparation is itself a form of anticipatory planning. Foresight can strengthen such arrangements by testing whether planned actions will remain useful as rainfall patterns, settlement patterns, or institutional capacity change. It can also test the triggers themselves. A threshold calibrated to the past ten years may not be appropriate for the next ten. For an agency, the planning calendar offers a practical starting point. A foresight cycle could be linked to the annual flood outlook, so that each year's outlook is considered alongside a small set of scenarios and a review of the assumptions behind current plans. Scenario exercises can bring in organisations that hold essential but often separate information, including dam operators, water and health authorities, and state agencies. The intended output should be a short record of decisions that changed—not another lengthy report.

5.4 Cautions

Foresight has its own failure modes. It can become a workshop with no consequences, producing a document that nobody uses. Or it can narrow to one official scenario that is then mistakenly treated as a forecast. Voros (2003) emphasises the connection between foresight outputs and strategy and planning, while Inayatullah (2008) directs attention to alternative futures and transformation. Together, these arguments point to a practical safeguard: every foresight exercise should identify the decision it is meant to inform and record what the organisation did differently as a result.

6. Nigerian and African Experience

6.1 The Policy Frame

At the African Union's 28th Extraordinary Summit, held in Addis Ababa in January 2017, Heads of State and Government adopted a Programme of Action for implementing the Sendai Framework in Africa. The African Union Commission is required to report on progress every two years (African Union Commission, 2020). The Programme adds five African targets to the seven Sendai targets, bringing the total to twelve. These include targets on access to and availability of multi-hazard early warning systems and disaster risk information, domestic financing, and the integration of disaster risk reduction into education (African Union, 2017). The policy framework is therefore in place. The practical question is what happens when a flood arrives.

6.2 Comparative Case Analysis: Evidence and Inference

The comparison below separates documented warning information from reported outcomes and identifies questions that require further investigation. The 2025 case concerns a forecasting-policy development, not a completed disaster outcome; it cannot be used to infer that losses were prevented.

Table 1

Comparative Evidence From Three Nigerian Flood Episodes

Episode	Documented signal or record	Reported outcome or policy response	Analytical implication and uncertainty
2022 national floods	Forecasts were available; a minister reported uneven preparedness across states (Archie, 2022).	More than 600 deaths and approximately 1.3 million displaced people were reported in October 2022.	Points to a possible warning-to-action gap, but does not establish which state decisions caused particular losses.
2024 Maiduguri / Alau Dam	Borno was included in a high-risk outlook; official accounts differ on whether the dam overflowed or partly collapsed (Federal Ministry of Information and National Orientation, 2024; National Emergency Management Agency [NEMA], n.d.).	NEMA's dashboard reports 414,176 people affected, 389,267 displaced, and 37 deaths (snapshot).	Underscores the need for asset-level information, operating protocols, and downstream triggers; the precise failure mechanism remains contested.
2025 Annual Flood Outlook	1,249 high-risk communities across 176 LGAs and 2,187 moderate-risk communities across 293 LGAs (Kolade, 2025).	More localised, community-focused risk communication; this review contains no outcome evaluation.	Evaluation should measure whether messages were received, whether protective action followed, and whether access was equitable. Greater local detail alone does not prove effectiveness.

On 10 September 2024, severe flooding affected Maiduguri and Jere following exceptional inflows into Alau Dam. The Federal Ministry of Water Resources and Sanitation described the disaster as largely caused by overflow and said a technical assessment was under way (Federal Ministry of Information and National Orientation, 2024). NEMA's 2024 flood dashboard, by contrast, reported that a section of the dam collapsed after inflows exceeded its capacity (NEMA, n.d.). Public accounts therefore support the conclusion that a major flood was associated with the dam, but they do not establish one uncontested failure mechanism. NEMA's dashboard lists 414,176 people affected, 389,267 displaced, and 37 deaths in its Borno summary. These are snapshot figures and should not be combined with earlier press estimates (NEMA, n.d.). The 2024 Annual Flood Outlook had identified Borno as a state at high risk of flooding (Federal Ministry of Information and National Orientation, 2024). The 2025 Annual Flood Outlook further disaggregated risk at community level. Public reporting identified 1,249 high-risk communities in 176 local government areas and 2,187 moderate-risk communities in 293 local government areas (Kolade, 2025). This indicates more localised forecast communication; it does not, on its own, show that warnings reached households or led to effective protective action. These figures describe forecast risk categories, not observed flood impacts in 2025. A third institutional gap lies between national products and local decisions. The move towards community-level outlooks recognises that warnings issued only at local-government-area level can be difficult to act on. Greater local detail also increases the need for reliable data. Community-level impact estimates depend on information about exposure and vulnerability—data that, as Pelling and Wisner (2009) and Trisos et al. (2022) note, are often missing in African settings.

6.3 The Wider African Position

A second gap concerns the connection between hydrological warnings and infrastructure intelligence. The 2024 outlook identified Borno as being at risk, but conflicting descriptions of Alau Dam's physical behaviour mean that the case cannot establish the precise mode of structural failure. It does, however, underline why dam telemetry, maintenance records, reservoir operating rules, and downstream evacuation triggers should be considered alongside regional rainfall forecasts.

7. An Integrated Framework for the Future of Disaster Risk Management

7.1 Four Functions in One System

The proposed framework places forecasting, analytics, and foresight within a single decision system. A fourth function—the protocols that turn information into action—connects them. Each function addresses a different question, operates over a different time horizon, and has characteristic failure modes. Each also depends on the others. Table 1 summarises the argument developed in Sections 3–6.

7.2 Conceptual Decision Architecture

Figure 1 presents a decision-centred architecture rather than a strictly linear process. Forecasting and analytics exchange information about hazards and exposure. Foresight stress-tests their assumptions and the plans built around them. Protocols establish thresholds, authority, and funding. Monitoring of outcomes then feeds lessons back into all four functions.

Figure 1

Integrated Decision Architecture

Knowledge and risk intelligence	Governance and action
Forecasting: probability, lead time, uncertainty ↕ Analytics: exposure, vulnerability, cascading dependencies	Decision protocols: risk thresholds → accountable authority → pre-arranged funds → protective action
Strategic foresight: alternative futures, stress tests, adaptive options	Monitoring: reach, timeliness, equity, avoided harm, and post-event learning

Note. Author's synthesis. Bidirectional feedback links forecasts, analytics, foresight, protocols, and outcome monitoring.

The architecture builds on impact-based forecasting (Merz et al., 2020), forecast-based financing (Coughlan de Perez et al., 2015), and general foresight processes (Voros, 2003). Its proposed contribution is to make the governance interface explicit: the evidence functions are linked to named decisions, financing, accountability, and feedback that can be evaluated. This is a conceptual synthesis, not a new theory proven empirically.

7.3 Operational Indicators and Validation Strategy

Table 2

Proposed Indicators for Testing the Integrated Framework

Domain	Proposed indicator	Evidence and disaggregation
Warning performance	Forecast lead time; calibration; false-alarm and missed-event rates	By hazard, locality, and model version
Last-mile reach	Percentage of at-risk households receiving and understanding a warning	By sex, disability, language, and settlement type
Decision conversion	Median time between a threshold being exceeded and authorised action	By agency, hazard, and action type
Financing readiness	Percentage of agreed triggers with funds available before the season	By budget line and release date
Protective outcome	Percentage completing evacuation or asset protection; harm avoided where it can be estimated	By community and vulnerability group
Learning and foresight	Percentage of scenario recommendations implemented and retested	By annual planning cycle and decision record

A prospective pilot should pre-register its thresholds and indicators. It should collect warning logs, decision authorisations, financial releases, and household follow-up data. Comparisons could be made between matched high-risk communities or across successive seasons, while accounting for differences in hazard severity. Independent evaluation and ethical safeguards are essential. Avoided losses should not be claimed without an appropriate counterfactual.

7.4 Implementation and Data Governance

In Nigeria, the Nigeria Hydrological Services Agency (NIHSA) and the Nigerian Meteorological Agency (NiMet) could jointly support hydrometeorological intelligence. Dam owners and water authorities should maintain reservoir and asset-condition records. NEMA and the State Emergency Management Agencies (SEMAs) could coordinate pre-agreed preparedness actions with local governments, health services, and community organisations. These responsibilities should be confirmed in written inter-agency procedures rather than assumed from broad mandates. Data-sharing agreements should specify custodianship, interoperability standards, update frequency, audit trails, access controls, privacy protections, and model accountability. Community representatives—including people with disabilities and residents of informal settlements—should help design warning messages and assess whether they are usable. Begin with decisions. For each major hazard, agencies should identify which decisions must be made at each lead time, who is responsible for making them, and what forecast products those decisions require. This follows the logic of forecast-based financing, in which thresholds are linked to actions and the funding needed to carry them out (Coughlan de Perez et al., 2015). It also reflects Merz et al.'s (2020) argument that impact information is more useful to emergency managers than hazard information alone.

Maintain exposure and vulnerability data as a standing resource. Hazard maps change from season to season, but information about who lives where and what resources they have can be built and updated over time. The evidence reviewed in Section 4 suggests that impact forecasting cannot work without this layer, and that the poorest households will otherwise remain less visible (Hallegatte et al., 2017; Pelling & Wisner, 2009).Put foresight on the planning calendar. Before each flood season, a short scenario exercise based on the outlook could bring together relevant asset owners, including dam operators. It would test plans against combinations of events and examine whether existing triggers remain appropriate. Its value should be judged by the decisions it changes, and those changes should be recorded. Keep professional judgment and local knowledge involved. Models, including machine-learning systems, are tools whose limitations need to be understood. Kitchin (2014) and Reichstein et al. (2019) argue for pairing data-driven methods with theory and knowledge of the processes involved; the Global Assessment Report 2022 makes a related point (UNDRR, 2022). Agencies should be able to explain in plain language why a model generated a warning, and communities should have a way to challenge or supplement it with local knowledge. Fund the connections and measure their results. The number of countries with early warning systems is useful to know, but it reveals little about whether people were warned in time and acted on the warning (UNDRR & WMO, 2025). Agencies should track actions taken before impacts occur, the time between warning and action, and harm avoided. Funding should also support the protocols and data work needed to produce those results.

7.5 Implications for Nigeria

In Nigeria, the framework can build on existing institutions rather than requiring new ones. NIHSA produces outlooks; NEMA and state agencies lead response; and dam operators and water authorities hold essential asset information. The 2025 outlook's move towards community-level forecasts and the introduction of a flood insurance programme (Kolade, 2025) create opportunities to strengthen the protocols layer, since both insurance and pre-arranged financing depend on clearly defined triggers. Practical first steps include a joint annual scenario exercise before the rainy season, a shared register of high-consequence structures and the communities downstream, and written trigger tables specifying the forecast level, required action, responsible office, and funding source.

7.6 Questions for Further Research

The framework remains a proposal and has not yet been tested. Three questions could guide its evaluation. How do forecast-triggered actions compare with post-event response in cost and harm avoided in data-constrained African settings? What is the minimum set of exposure and vulnerability data needed to produce useful community-level impact forecasts? Do routine foresight exercises in emergency agencies change decisions, and, if so, which decisions? Answering these questions will require case studies that follow a flood season from outlook to outcome, supported by agency records that press reports cannot provide.

8. Conclusion

Forecasting science has advanced substantially in a short time. Machine-learning models can produce global forecasts in minutes, flood prediction has extended to ungauged basins, and more countries report operating early warning systems than a decade ago. Yet recorded harm has not declined at the same pace. The Nigerian floods of 2022 and 2024 illustrate how warnings, outlooks, or known structural weaknesses may be present before a disaster without preventing it.

This paper argues that much of the explanation lies in the connections between functions. Forecasting estimates what is likely; data analytics helps establish who is exposed and how severely they may be affected; and strategic foresight asks what could change and how an organisation would respond. None is sufficient on its own, and each can fail in a different way. The proposed framework adds a fourth element: agreed protocols that convert information into action. It treats all four functions as parts of one decision system. For national agencies in Nigeria and elsewhere in Africa, the implications are practical. Observation networks and local data need sustained investment because forecasts and impact estimates depend on them. Agencies need analysts who understand both models and the places to which they are applied. Foresight should be part of the planning calendar and assessed by the decisions it changes. Triggers, funding rules, and responsibilities should be agreed in writing before the season, not negotiated during it. None of these steps depends on adopting the newest technology. Many depend instead on steady institutional work that attracts little attention.This review has limitations. As a narrative review, it does not claim to cover every relevant study. Its account of Nigerian events relies on official statements and press reports, which do not provide a complete explanation of causes; it also uses no primary agency data. The proposed framework remains to be tested in practice. Even so, the central argument is clear: with the Sendai Framework running to 2030, the greatest gains are likely to come from connecting information to decisions, rather than from improving forecasts alone.

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