End-to-End Climate Services for Public Health: A Novel Earth-System Forecasting Framework and Operational Toolkit for Vector Borne Disease Prevention in Latin America and the Caribbean

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Abstract

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The Earth's climate system plays a central role in shaping the spatial and temporal dynamics of dengue transmission through its influence on temperature-dependent vector competence, precipitation-driven habitat availability, and large-scale modes of variability. In the Caribbean and Latin America, processes such as the El Niño–Southern Oscillation (ENSO), the Intertropical Convergence Zone (ITCZ), and regional circulation patterns modulate rainfall and temperature on seasonal to interannual timescales, generating a predictable environmental signal that precedes dengue outbreaks by several weeks to months. Despite this predictability, climate information remains underutilized in public health decision-making. This dissertation advances the development of climate-informed early warning systems for dengue by examining how environmental signals can be translated into operational decision-support tools. It presents four interconnected studies across the Caribbean and Latin America. First, a climate services for health, demand-driven implementation framework is developed through transdisciplinary engagement, identifying how we can move from modelling tool to operational service. Second, a novel climate-driven dengue budget forecasting system (PROA) is developed with Panama, integrating rainfall variability, lagged environmental effects, immunological dynamics, and transmission momentum into a hybrid statistical–mechanistic framework that produces probabilistic projections of disease burden and associated resource needs. Third, the dissertation examines how uncertainty (inherent in seasonal climate prediction) can be structured and

communicated to support interpretation and use of climate tools in health decision making. Fourth, a monitoring and evaluation framework is co-developed to assess climate-informed early warning system performance, usability, and sustainability. The findings demonstrate that the utility of climate information depends not only on predictive skill, but on how environmental signals are structured, interpreted, and embedded within decision-making systems. In the context of climate change, where shifts in temperature and precipitation are altering dengue risk, climate-informed early warning systems represent a critical mechanism for anticipatory public health action and climate adaptation.

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Preface

I) The Climate–Disease Interface and the Failure of Operational Translation

The Earth's climate system shapes dengue risk, the world's most rapidly spreading vector-borne disease. The spatial extent and seas6766onal timing of the tiger mosquito (*Aedes aegypti),* which transmits dengue virus, is bounded by temperature envelopes that determine vector competence and the extrinsic incubation period of dengue virus [1]. Precipitation regimes regulate the availability and persistence of larval breeding habitat. Large-scale modes of climate variability (i.e., the El Niño–Southern Oscillation (ENSO), the Madden–Julian Oscillation (MJO), and Atlantic sea surface temperature anomalies) modulate rainfall and temperature across the Caribbean and Latin America on interannual to intraseasonal timescales, generating predictable periods of elevated epidemic risk months before case counts begin to rise [2]. Furthermore, the Caribbean basin, sits at the intersection of several large-scale atmospheric circulation systems that generate the region's characteristic climate variability [3]. The Intertropical Convergence Zone (ITCZ) drives the unimodal to bimodal rainfall cycle across much of the Lesser Antilles and Central America. The Caribbean Low-Level Jet (CLLJ) modulates moisture transport and mid-summer drought in the northern Caribbean. ENSO exerts a strong influence on regional precipitation anomalies: El Niño years tend to suppress rainfall across much of the Caribbean through a combination of anomalous subsidence and reduced easterly wave activity, while La Niña years enhance moisture convergence and can produce anomalous wet seasons. Atlantic Multidecadal Variability (AMV) and sea surface temperature anomalies in the tropical North Atlantic further modulate these patterns on decadal timescales.

These signals are directly epidemiologically relevant. Temperature controls the thermal dependence of *Aedes aegypti* biting rate, gonotrophic cycle duration, and dengue virus replication rate; small increases above the optimum (approximately 26–29°C) reduce vector competence measurably. Precipitation, particularly rainy-day frequency and total rainfall, determines container water availability and larval survival in peridomestic environments where *Ae. aegypti* breed or can determine population water storage practice and habitat availability [4]. The lag between a rainfall signal and epidemic onset (reflecting the time for larval development, adult emergence, host-seeking, virus incubation, and case detection) is typically 6–12 weeks, which is precisely the lead time that makes climate-informed early warning actionable. ENSO-based seasonal forecasts issued 3–6 months in advance can therefore, in principle, provide genuine decision-relevant signal well before health systems would otherwise register elevated risk [5].

This predictability has been demonstrated empirically across multiple study regions and model architectures, and it represents a legitimate basis for building operational public health tools [6], [7], [8], [9], [10]. And yet, the gap between that scientific potential and operational reality remains wide. Across the Caribbean and Latin America, vector control programs are still largely reactive, budgets are set using multi-year rolling case averages rather than prospective risk estimates, and the climate information available through global monitoring and seasonal forecasting systems goes substantially underutilized in health decision-making[11], [12], [13]. The reasons for this failure are not primarily technical. They reflect a structural mismatch between how climate science produces and communicates forecast information and what health systems need to act on it.

This dissertation addresses that mismatch directly. It presents four interconnected studies, conducted across Barbados, Panama, and the Eastern Caribbean (St. Lucia, Grenada), that collectively advance the science and practice of climate services for health. Each study targets a distinct bottleneck in the pipeline from climate signal to public health action: 1) the design of a demand-driven climate services for health implementation framework intended not as a post-hoc deployment checklist but as a living process guide that orients transdisciplinary teams from the earliest stages of partnership building through to sustained funding; 2) the technical architecture of amongst the first climate-to-budget forecasting and resource allocation systems in the LAC region; 3) the communication of climate-driven forecast uncertainty to health decision-makers moving from output to action; and 4) the co-development of monitoring and evaluation infrastructure to sustain these early warning systems beyond the research phase. Together, these studies constitute not a collection of parallel case studies but a sequential interrogation of the conditions under which climate science can generate a durable operational impact in health systems.

II) The Operational Gap in Climate Services for Health

Despite this mechanistic and empirical foundation, climate services for health decision making have consistently underperformed relative to their potential. Several well-documented barriers drive this gap.

First, most climate forecast products are designed by and for climate scientists: probabilistic ensemble outputs, standardized against climatological baselines, with uncertainty quantification that is technically rigorous but operationally opaque [14]. A national health ministry setting an annual vector control budget or a district health officer authorizing preventive spraying does not

need a probability density function, they need a risk category, a recommended action, and a confidence level they can defend to their supervisor. The translation from probabilistic forecast to categorical decision remains a persistent failure point.

Second, the technical architecture of most climate-health forecasting systems reflects data availability and methodological convenience rather than operational requirements [15]. Systems built on pre-selected climate predictors (typically minimum temperature and total monthly rainfall) fail to capture the spatially heterogeneous and temporally non-stationary character of climate-disease relationships. Panama, for example, has large scale teleconnections that influence a Pacific coast with a pronounced dry season, a Caribbean coast that is wet year-round, and an interior that straddles both regimes; a single national rainfall predictor considering no lags is a poor representation of the epidemiologically relevant climate signal [16].

Third, even technically sophisticated systems routinely fail at the point of institutional embedding [17]. Sustainable implementation requires that climate non-specialist health staff receive full training to run, interpret, and act on the system within their existing workflows, and that there is a mechanism for monitoring whether the system is achieving its intended public health purpose.

This dissertation addresses all three of these failure modes, treating them not as separate technical problems but as interconnected challenges that must be solved together, through a methodology that keeps decision-maker needs at the center of the design process from the outset. This is where transdisciplinary science comes into play. This body of work supports the argument that research teams that involve climate scientists, health experts, social scientists etc.

in a true co-production process, and one which *listens to the needs and priorities* of the end-user, leads to better product development and is more likely to be used in the health sector.

III) The Research Program that Shaped this Work

This dissertation grew from a decade of co-learning alongside climate scientists, epidemiologists, meteorologists, health ministries and regional actors across Latin America and the Caribbean (LAC), a process that progressively clarified both what the field needed and what I was positioned to contribute.

My earliest contributions to this work appear in the co-learning process documented in Stewart-Ibarra et al. (2022) [18], which examined the knowledge exchange between climate scientists and health sector actors during initial stages of the co-creation of a dengue early warning system in Barbados. Participating in that process and navigating the gap between what a forecast model could produce and what a ministry could act on helped shape my understanding of co-production not as a methodological choice but as a scientific necessity. Around the same time, contributing to the Wellcome funded landscape analysis led by Ryan et al. (2023) [19] made the scale of the climate tool limitations visible in a way that no single case study could: over 9,500 papers in the climate-sensitive infectious disease modelling tool literature, of which only 37 operational tools were made available to decision-makers and only 19 had actually been used. That finding did not suggest to me that the science was insufficient. It confirmed that the problem was one of design, translation, and sustainability, and that those were serious problems worth devoting my dissertation to.

My contribution to the Fletcher et al. (2025) [8] forecasting system for the Eastern Caribbean is the technical component directly attached to chapter 1 and 4 of this dissertation (implementation and monitoring and evaluation frameworks). That system, which uses a Bayesian hierarchical framework with compound and cascading climatic extremes and long-lag and short-lag interactions, represents the regional climate science in which I worked to move from forecasting models to a true operational climate service. It also pushed me to think about what other climate tools we could produce that would have a benefit to public health. Building off my work in the Caribbean and the International Research Institute for Climate and Society's (IRI) Next-Gen AeDES Map Room collaboration [7] with the Pan American Health Organization (PAHO), led to the creation of Chapter 2 (PROA-Prediction and Risk - Optimization of Alerts) where we built the framework for the first climate-driven dengue budget forecasting system in Panama. It was from my interactions with Ministries of Health across many countries where I heard repeatedly that understanding what resources (i.e., cost) they would need to move from alert to action would be critical to improve climate adaptation and health system resilience. So, I wanted to build a climate driven forecasting system that went beyond translating a forecast into a disease risk signal but into an actionable budget planning tool. These two forecasting systems are methodologically complementary, and together they represent the technical heart of a larger body of work on novel operational climate services for health that I have both contributed to and led in the LAC region.

IV) Theoretical Framework: Transdisciplinary Co-Production

The unifying methodological framework across all four studies is transdisciplinary co-production. Co-production in the climate services context denotes a process in which climate

scientists and end-users, in this case, health authorities, epidemiologists, budget planners, and vector control managers, jointly define the research questions, design the forecast products, validate outputs against operationally meaningful benchmarks, and establish the institutional protocols that govern system use [20]. This is distinct from stakeholder consultation (in which scientists present outputs and solicit feedback) and from participatory research (in which communities co-define problems). Co-production in the climate services sense requires genuine joint design authority: the end-user shapes not just the question but the architecture of the answer.

The transdisciplinary framing serves a specific scientific purpose in this work. Each of the four studies investigates a different dimension of the climate services pipeline, but the transdisciplinary method is what allows findings from one study to inform the design of the next. The implementation framework developed in Chapter 1 directly shaped the co-production process in Chapter 2. The forecast system built in Chapter 2 surfaced the uncertainty communication challenges examined in Chapter 3. The operational insights from Chapter 3 in part informed the design of the M&E framework in Chapter 4. This sequential dependence is the architecture of the dissertation's contribution.

V) Research Aim and Questions

The overarching aim of this dissertation is to advance both the innovation and operational sustainability of climate services for vector-borne disease early warning in the Caribbean and Latin America through transdisciplinary co-production across four dimensions of the service pipeline.

This aim is pursued through four research questions:

RQ1 (Chapter 1): Can we produce a demand-driven climate services for health implementation framework, derived from transdisciplinary engagement with climate and health system actors to help research teams to move from models to truly actionable public health tools?

RQ2 (Chapter 2): 1) Can we build a novel climate-driven forecasting system that not only predicts when the next outbreak will happen, but how much it will cost to prevent it? 2) Can we then use that information to more equitably allocate resources across Panama which possess varying levels of structural vulnerability?

RQ3 (Chapter 3): How can climate scientists better support health decision-makers by communicating and interpreting forecast uncertainty in ways that enable confident, actionable decision-making rather than stalling it?

RQ4 (Chapter 4): Can we co-produce an M&E framework capable of assessing whether climate-informed dengue early warning systems are achieving their intended public health outcomes and not simply producing good model skill?

VI) Overarching Hypothesis

This dissertation tests the proposition that the operational limitations in climate services for health is not primarily a technical problem, it is a design and translation problem. A transdisciplinary approach that centers decision-maker needs at every stage of service development, from system architecture through uncertainty communication to sustainability infrastructure, will produce climate services that are more accurate, more usable, and more

durable than those developed through conventional science-to-practice knowledge transfer. This claim is tested across four geographically and institutionally distinct contexts, with the expectation that convergent findings across those contexts will constitute evidence for the generalizability of the approach.

VII) Dissertation Structure Details

Chapter 1 establishes the demand side of the problem, deriving a climate-informed dengue early warning system implementation framework from deep transdisciplinary engagement with health and climate sector actors (i.e., Caribbean Institute for Meteorology and Hydrology, National Meteorological Services, Caribbean Public Health Agency, and Ministries of Health) in Barbados, a Small Island Developing State (SIDS), located on the hurricane belt, where the intersection of ENSO-driven rainfall variability, *Aedes aegypti* ecology, and resource-constrained health systems makes the translational challenge both acute and representative of the broader Caribbean context. Chapter 2 addresses the supply side, presenting PROA (Prediccion de Riesgo y Optimizacion de Alertas), to our knowledge the first climate-to-budget dengue forecasting system for Latin America, co-produced with the Ministry of Health and Pan American Health Organization which integrates rainy-day frequency lag 1-3 derived from NOAA CPC gridded observations and extended through Copernicus SEAS5.1 51 member seasonal ensemble forecasts, a serotype novelty multiplier encoding inter-annual immunological susceptibility, and a transmission momentum amplification layer, into a validated hybrid statistical-mechanistic framework capable of translating a climate signal into a probabilistic budget planning tool. Chapter 3 examines the critical interface between probabilistic climate science and health decision-making, investigating how the ensemble forecast uncertainty that is

intrinsic to seasonal climate prediction is perceived and acted upon by non-climate-specialist users, and developing evidence-based strategies for communicating uncertainty in ways that support rather than stall action. Chapter 4 closes the loop, presenting the co-development of a regional M&E framework across St. Lucia, Barbados, and Grenada, three Caribbean SIDS sharing the same climate drivers but distinct epidemiological and institutional contexts that provide the evaluation infrastructure without which no climate service can demonstrate, or systematically improve, its operational impact on public health outcomes. A concluding general discussion synthesizes findings across all four studies and articulates the implications for climate service innovation, design, regional health policy, and future research.

Chapter 1: A demand-driven climate services for health implementation framework: A case study for climate-sensitive diseases in Caribbean Small Island Developing States

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1.1 Introduction

According to the World Health Organization, “climate change is the single biggest health threat facing humanity” [1]. Changing temperature and precipitation patterns, and more frequent extreme weather events threaten human health worldwide [2,3]. These impacts are further compounded by the distribution of socioeconomic and demographic factors, placing vulnerable populations at greater risk, including low-income communities, children, the elderly, individuals with pre-existing health conditions, and those residing in low-lying coastal cities prone to flooding and sea level rise [4]. The Caribbean Small Island Developing States (SIDS) are uniquely vulnerable to climate-related health hazards due to their location within the North Atlantic hurricane belt, composition of small, low-lying islands, and dependence on natural resources and tourism. Critical climate and health concerns in the Caribbean include the increased frequency and intensity of tropical storms, heat waves, droughts, worsening air pollution, disruption of food production and supply, interruption of water supply and sanitation services, and increased transmission of infectious diseases [5]. Thus, it is critical that current and future climate-related human impacts are embedded into public health decision-making, primarily through the development of climate services for the health sector.

Climate services for health leverage climate information to support health sector decisions by improving the efficiency and effectiveness of long-term planning and short-term response. This in turn can improve the efficiency of resource mobilization in anticipation of climate-related health risks, enabling more effective prevention and response strategies. The Caribbean region is placing significant emphasis on developing climate services to improve preparedness and

response to vector-borne diseases (VBDs), that is, dengue, Zika, and chikungunya [6]. To enhance regional integrated surveillance efforts for the prevention of VBD outbreaks, the Caribbean Public Health Agency (CARPHA), the Pan American Health Organization (PAHO) and the World Meteorological Organization (WMO)-designated Regional Climate Centre for the Caribbean (Caribbean RCC) hosted by the Caribbean Institute for Meteorology and Hydrology (CIMH) are focusing on the co-production of climate-driven impact based disease early warning systems (EWS) with member states in the region [Fig 1] [7–11]. At its operational core, an EWS can be defined as a system that collects, analyzes, and disseminates information about potential hazards or risks. We will hereinafter refer to this operational core as the EWS. However, it should be noted that an EWS further comprises (1) an information portal where the early warning information is stored and accessed and from where the information is disseminated; and (2) awareness, education and outreach to enhance capacity for both the providers and the users of the information."

Fig 1.1 When developing climate services for climate-sensitive infectious diseases (CSIDs), stakeholders across multiple sectors are involved. *Therefore, developing comprehensive public health action requires collaboration, cooperation, communication, and an understanding of common goals and outcomes, as well as recognition of the contributions from different parts of the stakeholder community to the decision-making and response processes [12].*

Climate variability and change have both short- and long-term effects on VBDs, interacting with many biological, social and environmental factors [13]. For example, climate impacts human interactions with pathogens, vectors, and non-human hosts, affecting the transmission dynamics, geographic spread and re-emergence of VBDs. Vector abundance, survival, and feeding activity increase with rising temperatures (up to thermal optima) due to the dependence of arthropod body temperature on the external environment. Rising temperatures may also increase viral

production in the host, thus making it more infectious [14]. The relationship between precipitation and VBD is complex and context specific. Increased precipitation can fill containers and provide more suitable breeding sites for disease vectors (it is important to note that too much precipitation can also flush oviposition sites). However, drought can also increase the number of breeding sites around households due to the increased need to store water-if improperly stored [9].

Together with the CARPHA, PAHO, CIMH and other regional partners, we are working to co-develop tailored statistical climate-and-health models and simultaneously co-design sustainable tools that can be implemented and operationalized to support long-term decision-making and help build resilience to climate-sensitive infectious disease threats [Fig 2]. Here, 'operationalization' is defined as the act to turn disease surveillance, demographic data and climate indicators into valuable tools and information that health practitioners and disease control and prevention teams can use to protect the public from climate-related health risks. We define climate tools as a resource, application, or technology designed to help decision-makers; these tools can encompass a range of functionalities, such as climate data visualization, vulnerability mapping, and decision-support. Finally, we distinguish between partner and stakeholder as the following: a partner is actively involved in the co-creation and decision-making processes of a project, while a stakeholder is affected by or has an interest in the outcomes of the project but may not be directly involved in its execution.

Fig1. 2. Partners involved in the co-production of the Early Warning System (EWS). *Top left: National-level partners; top right: Regional partners; bottom right: Academic institutions and inter-governmental organizations; bottom left: Funders who have supported this process. All partners excluding funders were present at the 2022 regional meeting where we discussed early warning system opportunities and challenges for implementation. Partners present at the meeting are co-authors on the paper.*

Developing climate services for the health sector is a prominent subject in climate adaptation [15,16]. However, transitioning from theoretical models to practical implementation can be challenging [17]. Disease early warning systems provide tools for decision-makers in the health sector to proactively manage and mitigate epidemic risks, enabling more targeted and timely responses to protect public health. EWSs which employ seasonal climate forecasts can predict changes in impending disease risk up to 3–4 months in advance [18]. This is critical in resource-

limited areas where sufficient lead time permits the timely optimization of resource allocation and preventive measures, reducing the overall burden on healthcare systems. The extended disease response time provided by early warnings can improve the likelihood that community members, hospitals and healthcare facilities are prepared and do not collapse [19], particularly in resource-constrained contexts such as Caribbean Small Island Developing States (SIDS). Further, the health sector can develop tailored interventions to support communities in taking action to prevent an outbreak from occurring [Fig 3] [20].

Fig 1.3. The co-production of climate services, information, and resources for the health sector is an important step in addressing the health impacts of climate change and variability. *It is critical that the health sector is equipped with proper climate services that can help to reduce negative health outcomes and crises [21,22].*

Although EWSs are invaluable climate-and-health services, few of these systems have been implemented and operationalized. A 2021 landscaping analysis on available climate tools for infectious diseases [23] showed that globally over the last ten years, of the 9,500 papers identified in the literature review, only 37 tools were available for use by decision-makers. One example is the AeDES interactive map room climate-and-health service which incorporates four different environmental suitability models, considering climate factors and mosquito life cycles, that allow decision-makers to monitor and forecast diseases in several parts of the Americas [24]. However, the low number of available tools suggests a lack of investment or incentives for researchers in academia or companies to develop operational climate tools for the health sector. Finally, most of the identified tools (81.1%) were focused on vector-borne diseases, demonstrating a shortage of tools for respiratory, foodborne, and waterborne diseases [23].

The 2021 landscaping study also featured interviews with worldwide experts to determine the top barriers that prevent decision-makers from using climate tools in the health sector [25]. Key barriers included a lack of funding to move from tool to service, lack of political mandate for the health sector to address climate issues, lack of communication between decision-makers and scientists, language barriers, lack of formal education (e.g., university curriculum or professional training), and lack of formal collaboration agreements between climate and health sectors to facilitate joint work plans [10]. A 2021 literature review of climate change and health in the Caribbean found very few examples of integrated early warning information systems to increase the availability and dissemination of climate information to inform health sector planning. The study recognised the need for more comprehensive and responsive national systems based on multi-sectoral design and implementation approaches [26].

Implementing climate services can be challenging. Here, a demand-driven implementation guideline is proposed. This guideline was developed through years of capacity building dialogues and stakeholder meetings across the Caribbean region and further refined during a 2022 multi-sectoral national workshop held in Barbados, which focused on implementing a climate-driven dengue early warning system with key stakeholders across the climate and health sectors. This study aims to create a general implementation framework for climate services for the health sector that is useful for scientists and decision-makers in the Latin America and Caribbean (LAC) region. Here, a case study from Barbados is being used to validate guidelines for the implementation process. Finally, the objective of this work is to provide a framework for the effective design, development, and integration of climate services into health systems, with the aim of enhancing public health resilience, reducing climate-related health risks, and promoting informed decision-making in response to and in anticipation of changing climate conditions.

1.2 Methods

General approach

Our approach to developing this implementation framework is rooted in dynamic collaboration rather than traditional methodologies (i.e., survey or interviews). This process was finely honed and brought to fruition during a key regional meeting held at the Caribbean Institute for Meteorology and Hydrology (CIMH) in Bridgetown, Barbados, in 2022 with core project

partners who are all co-authors on this paper [Fig 2]. The meeting was scheduled as part of the CARPHA project to create, implement and operationalize a climate-driven dengue early warning system. The goal of the meeting was to discuss how we would use our tool and implement the EWS at both national and regional levels.

Since 2016, key participating experts and stakeholders have continuously and collaboratively contributed their knowledge and insights regarding early warning and climate-sensitive disease in the Caribbean. This ongoing engagement has ensured a rich base of expertise that underpins our entire framework. At the regional meeting (2022), which marked a pivotal moment in our process, we (the co-authors of the paper), who represent diverse partners involved in this work, engaged in in-depth discussions. This was not merely a meeting; it was a culmination of years of collaborative efforts, where every voice was not just heard but integrated into the planning process [Fig 4]. Through our discussions, we identified key themes and ideas as well as plans to move implementation of the EWS forward. These discussions were then organized into distinct themes and categories. To ensure these categories were actionable and relevant, we reverse-engineered the questions that we felt were essential for implementing a successful Early Warning System (EWS). The partners felt that this framework was applicable to many others in the field and decided to publish the framework to help guide new projects and teams in this type of transdisciplinary collaborative process.

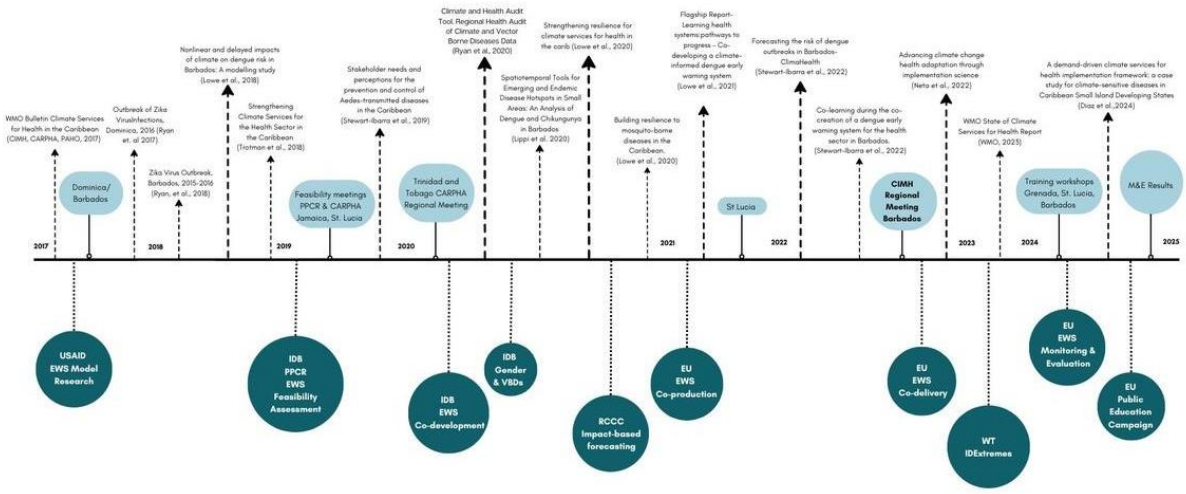

Fig 1.4. Timeline of past co-authored work, in-person key meetings, and funding mechanisms.

Top Row *lists co-authored papers resulting from years of dynamic collaboration ordered by the year published.* ***Middle row*** *in light blue are key in person meetings with partners and stakeholders to advance the co-production and implementation of the EWS.* ***Bottom row*** *in dark teal are funding mechanisms and associate project names. From left to right, funder followed by project name:* ***USAID****, Building Regional Climate Capacity in the Caribbean, Development of health-climate spatio-temporal modeling framework for the Caribbean,* ***Inter-American Development Bank (IDB)*** *via the Pilot Programme for Climate Resilience, Regional Health Audit of Climate and Vector Borne Diseases Data,* ***Inter-American Development Bank (IDB)*** *via the University of West Indies (UWI), Vector Borne Diseases and Gender Dynamics Study in the Caribbean.* ***Inter-American Development Bank (IDB)*** *via the University of West Indies (UWI), Integrating Climate Variability into Surveillance, Prevention and Control of Vector-Borne Diseases. Red Cross Climate Centre (RCCC), Impact-based forecasting for epidemics.* ***European Development Fund****, Developing, Designing, Piloting and Implementing an Early Warning System Integrating Climate Variability for Climate Sensitive Diseases in Order to Support Public Health Planning in the Caribbean. This project funding was extended twice, the first time to include new funding for implementation /co-delivery and then again to include funding for monitoring and evaluation.* ***Wellcome Trust****, IDExtremes: Co-production of a modelling tool to predict the probability of infectious disease outbreaks given compound extreme climatic events.* ***European Development Fund****, the Implementation of a vector borne disease focused public education campaign in one CARPHA member state.*

The framework's guiding questions and models were inspired by both past published work and recent discussions. These include influential modeling and co-learning papers and the wealth of knowledge generated from years of meetings and workshops, which involved many of our partners [Fig 4]. This method emphasizes co-creation, recognizing all contributors as partners rather than mere participants. By engaging in a process that values each partner's input equally,

we have built a foundation of trust that is crucial for the ongoing success and expansion of our initiative. This trust has also been instrumental in securing new funding to support continued collaboration and implementation. The regional meeting was the final step before formalizing our findings and recommendations in a comprehensive paper. This document not only reflects a consensus on how to move forward but also serves as a testament to the robust, cooperative approach we advocate for in environmental and climate-related projects.

Our approach demonstrates that effective implementation frameworks can emerge from processes that prioritize transdisciplinary partnership, dialogue, and mutual respect over hierarchical methodologies. By focusing on collaboration and co-creation, we ensure that our framework is not only inclusive but also equipped to address the complex challenges of environmental and climate justice.

Details on the development of the framework

The development of the implementation framework was refined through a process of identifying recurring themes from the discussions and debates over strategies for pathways forward held at the 2022 regional meeting held at CIMH in Bridgetown, Barbados. We then reverse engineered these discussions to outline clear implementation questions and guidance. The framework consists of key components such as partnership building and stakeholder engagement, data collection, audit tool outputs, public communication, health interventions, server and storage

management, human resources and technical capacity development, funding and resource mobilization, training, and monitoring and evaluation.

Throughout the collaborative meeting, partners shared insights, challenges and successes, and certain themes emerged. These recurring themes were grouped and analyzed to identify common patterns, areas needing improvement, and critical challenges across different aspects of the project. Questions addressed critical aspects of climate services implementation, such as data collection, analysis, communication, and decision-making. We then identified different strategies for addressing issues and opportunities highlighted by these themes. This aspect was critical for planning practical pathways and solutions that leverage the collective expertise and resources of the partners. Once we had concrete strategies in place to address all key themes we reverse engineered from theme to question. We looked at the proposed solution of a theme and asked, "What did we need to ask or know to arrive at these solutions?" This questioning helped to outline the specific steps and groups of questions per theme needed for implementing the EWS. It ensured that each step was directly linked to an element of the discussion and tied back to initial themes (themes are the headings in the framework i.e., funding, data, etc.). From the reverse engineered steps, we formulated specific implementation questions. These questions were designed to be general enough to guide any team in addressing climate service implementation challenges.

The questions and corresponding implementation guidance were then reviewed by all partners. The feedback phase was essential to ensure the questions were practical, relevant and could be adapted to various contexts. Based on partner feedback, questions were refined, and guidance

(see results section) was updated. The final questions and implementation guidelines were compiled into the final framework [Fig 7]. We used the software *Canva* to create a visual representation of the framework for teams to view the whole picture in an easy to understand and visually appealing way. Guiding questions and themes can be found in S1 Annex. Finally, the entire framework and corresponding visuals were meticulously reviewed to ensure consensus among all partners, affirming the collaborative and participatory nature of the process.

This approach and output ensure that the resulting framework is actionable, directly tied to identified needs of various sectors, and equipped with practical steps for successful implementation. This framework is meant to be flexible and guide transdisciplinary teams working across sectors to think about the big picture and major components of implementing a climate service in the health sector. We encourage teams to build on these questions and adapt them to meet the needs of their specific endeavor.

Approach to collaboration

The framework development process placed a strong emphasis on fostering collaboration among stakeholders and promoting effective communication and coordination throughout its creation. As a result, the framework is better equipped to address diverse needs and facilitate the successful integration of climate services into public health decision-making and resource allocation. Our approach to enhancing collaboration and communication is multi-faceted and tailored to the unique challenges of climate-sensitive health issues in the Caribbean. We have identified and engaged a diverse group of stakeholders, including health professionals, climate

experts, and regional and local authorities. This engagement is facilitated through a variety of platforms, including both digital (Zoom and Microsoft Teams–for data sharing and regular updates, RShiny–for training, and Miro Boards–for collaborative mapping) and in-country visits (for feasibility assessments, knowledge exchange, and training). Additionally, we place significant emphasis on regular meetings (bi-weekly for project entirety) among the partners (the co-authors of this paper), which serve as platforms for brainstorming, problem-solving, and tracking project progress. These interactions are crucial for ensuring all voices are heard and integrated into the decision-making process. Furthermore, we actively solicit and incorporate feedback from stakeholders through online meetings and during the visits. This feedback is vital in refining our strategies and ensuring they remain aligned with stakeholder needs and expectations. We are also implementing training sessions aiming at enhancing stakeholders' understanding of the intersection between climate data and health outcomes. This is crucial for building a knowledgeable base of stakeholders. Lastly, we have designed our collaboration and communication strategies to be scalable and adaptable, for example hybrid participation i.e. in person or virtual, accommodating moving schedules, and meeting with different stakeholders at varying times, and using WhatsApp instead of email for best communication. This ensures that they can be effectively applied in different contexts or regions, particularly in the Caribbean Small Island Developing States.

This dynamic and collaborative approach has helped to shape a detailed and adaptable implementation framework for climate services in the health sector and serves as a guide for effectively implementing health interventions at regional and national levels, ensuring robust climate services meet the needs of diverse stakeholders. It has the potential to guide future efforts

in climate and health adaptation, though it is still undergoing testing and validation in Barbados and soon in two other CARPHA member states (St. Lucia and Grenada.

In set box: Case study Barbados

In 2017, a co-creation process to build a dengue EWS began in Barbados [8,9]. This was led by the national health sector, the Regional Climate Center (RCC), Caribbean Institute for Meteorology and Hydrology (CIMH), the Caribbean Public Health Agency (CARPHA), the national meteorological services (Barbados Meteorological Services), and other governmental, intergovernmental, and academic institutions [7]. Stakeholder engagement plans were used to conduct both formal and informal meetings to gain insights into the demand, which informed the co-design process of a set of climate-and-health services for the country, including a prediction model [11,27]. The concluding demands of the health sector were to create a system that uses a minimum three-month lead time to alert the healthcare system of increased disease risk in the country. This risk would trigger a health system intervention that includes, but is not limited to, community engagement campaigns, increased medical personnel training of disease symptomatology, more frequent vector control visits, and re-allocating funds to prevent outbreaks.

Throughout the COVID-19 pandemic, stakeholder engagement was maintained using virtual methods despite strict travel restrictions. New methods of bringing stakeholders together were used, including virtual breakout rooms, and other virtual interaction techniques. In 2022, strict travel restrictions were lifted, and a one-week long set of meetings with key institutional partners was held in Barbados to continue discussing EWS construction along with implementation and operationalization plans for the climate-driven dengue EWS. Meetings were held with the health and climate sectors to revisit past goals and ensure that model outputs were still consistent with decision-makers' needs. It was also pertinent that model inputs be revisited to determine whether the model configuration needed to be updated. Key discussions regarding stakeholder involvement and roles, human resources and technical capacity, design and usability of user interfaces, return on investments, and monitoring and evaluation of the EWS took place [Figs 5 & 6].

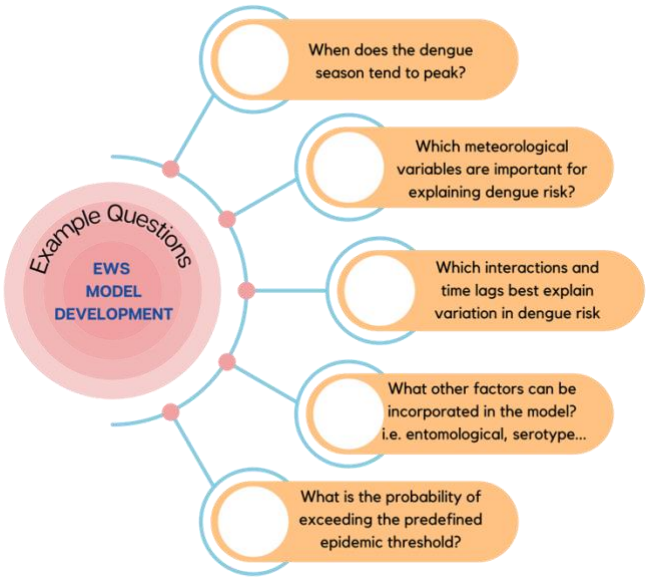

Fig 1.5. Example of guiding questions used to create predictive models for the climate-driven Dengue EWS in Barbados by Lowe et al. 2018 [9].

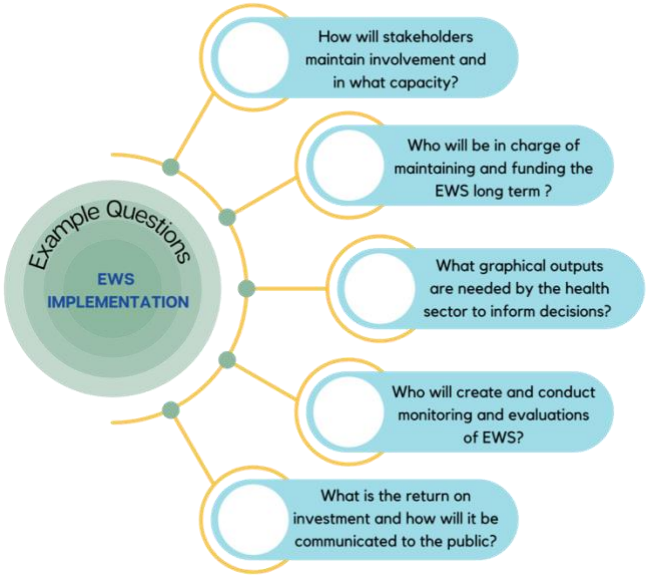

Fig 1.6. Example of guiding questions used in the development of the implementation framework for climate-driven Dengue EWS.

Ethics statement

IRB approval from the regional governing body and project implementation partner the Caribbean Public Health Agency was received (FWA #: FW A00023242 and HHS IRB Registration Number: IRB00010238). In addition, formal consent to publish meeting discoveries which led to the development of the framework was granted by the Barbados Ministry of Health and Wellness. A meeting was arranged to discuss the guidelines presented here, meeting invitations were sent to partners on October 11th and the meeting was held on November 3rd, 2022. Verbal informed consent was obtained to publish the implementation framework questions defined during the meeting. All partners present at the meeting contributed to this work and are co-authors of this paper. See S1 Checklist for all information regarding inclusivity protocols and S1 Data for summary of data.

1.3 Results

Partnership building and stakeholder engagement

The workshop in Barbados sought to understand partners' perspectives and responses to key implementation themes. The meeting also established clear roles and responsibilities for each of the sectors involved, for example, who will be accountable, consulted, and/or informed. The Barbados Ministry of Health and Wellness would be responsible and accountable for providing health data to formulate and inform early warning models, interpreting model outputs, enacting

health interventions, and communicating model results to the public. The Barbados Meteorological Services would be responsible for generating seasonal forecasts and running health-impact models, which are informed by a combination of observed and forecast climate data. As the technical arm of the Caribbean Meteorological Organisation–of which Barbados is one of 16 member states–, the Caribbean Institute for Meteorology and Hydrology (CIMH), would be consulted when running the model and work to automate inputs of climate forecasts. As the regional lead health organization, CARPHA would monitor the outputs of the EWS, ensure communication between different member states and facilitate regional and local collaborations. Finally, academic institutions would be consulted for maintenance and hiccups that may evolve during the implementation and operation of the EWS.

The workshop held in Barbados allowed for discussion and negotiation of roles and responsibilities between stakeholders. For example, dialogue around location of host servers to run models and expansion and application to other Caribbean Small Island Developing States in the future. Opportunities for stakeholders to come together should be provided to discuss both major and minor details of implementation, ensuring that all who should be involved are up to date and in agreement about pathways forward.

Building a strong partnership amongst stakeholders and partners is critical. It is important to outline the role and capacity of each stakeholder's involvement and make sure all are aware of each other's duties. A table can help break down roles and actions using the following categories: involved, oversight, managing, and/or operating. Continued engagement from the beginning to the end of the project will help maintain ownership, create confidence, and build

trust which will support the move from model to EWS implementation more efficiently. Moreover, involving local community members in the climate and health adaptation plans is crucial for building resilient health systems. Their unique knowledge, experiences, and perspectives can enhance the effectiveness and relevance of adaptation measures, leading to more sustainable solutions. Targeted educational programs and campaigns can empower communities to understand the connections between climate change and variability, health impacts, and the importance of climate driven early warning systems. Equipped with this knowledge, community members can actively participate in and support the development of health-resilient strategies, fostering a collective effort to address climate-related health challenges [Fig 7, section 1].

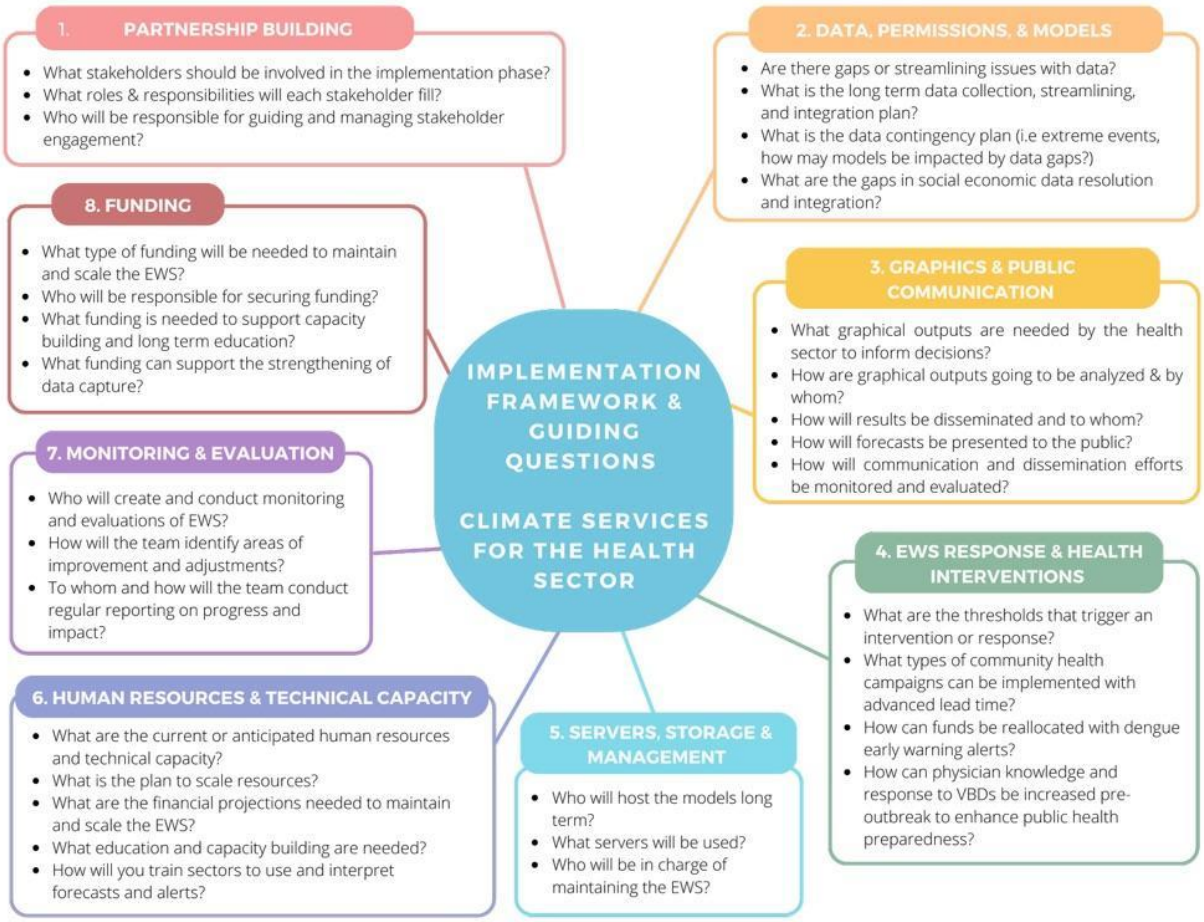

Fig 1.7. Visual representation of implementation framework and guiding questions for climate services for the health sector. *See S1 Annex for extended list format.*

Data, permissions, and models: In many places, long-term weather and climate data is more consistent and accessible than health data. Climate data are often collected and analyzed over long periods of time and can be used to identify patterns and trends in variables relevant to disease transmission, including temperature, precipitation and humidity. The Barbados Meteorological Services has long-term records (more than 5 decades) from weather stations on the island (one at the airport and the other at CIMH). Elements recorded through BMS include wind vectors, temperature, precipitation, humidity, pressure, cloud cover and type, visibility, and

present weather. The historical datasets have been digitized and cleaned. On the other hand, health data refers to information related to an individual's or population's health. Health data can be more complex to obtain as it involves sensitive information and is subject to privacy laws that vary by country and state. Examples of health data include disease case data, mortality, hospitalization, and vaccination coverage. Health data collection can also be difficult to analyze due to unknown influences of socioeconomic status and environmental factors. Moreover, health data can be challenging to implement into models because of gaps in data reporting, lack of electronic health information systems, and differences in data collection formats. For these reasons, it is essential to account for contingency plans. In Barbados, the health sector noted that hurricanes and floods had impacted the continued collection of health data. The health sector also reported that COVID-19 virtually stopped dengue testing for roughly two years exposing the greater need for data risk management.

Finally, using socio-economic data can help strengthen model predictions and public health outcomes [28]. The Barbados Ministry of Health reported that some social and economic data are collected for inpatient visits. Factors such as income, education level, occupation, and access to healthcare all have a significant impact on a person's health status and should not be overlooked. By collecting and analyzing these data, public health officials can better understand the needs of different populations and tailor interventions accordingly. Funding schemes must, therefore, prioritize socio-economic data collection and usage. Investing in new technologies or workflows to make it easier for providers to collect and enter socio-economic data, as well as offering training on data intake, will help providers address social determinants of health.

Finally, it is important to note that there is a need for critical mass, and staff dedicated to these roles [Fig 5, section 2].

Addressing data gaps: Barbados has standardized disease surveillance reporting forms and standard operating procedures (SOPs). However, gaps in data reporting could stem from different issues; sometimes lack of sufficient personnel at frontline/sentinel sites, competing public health priorities, need for more trained personnel at different levels etc. Recommendations to address data gaps include building more human resource capacity, from ground level upwards, and shift from more manual to electronic reporting. This would require more IT infrastructure and government investment, which is a common barrier. Thus, new SOPs should be drafted and coupled with (Monitoring and Evaluation) M&E to assess performance of any newly implemented systems.

Tool outputs: Graphics and public communication: Creating an interface that is useful and manageable to help analyze model outputs is a crucial component of a decision-support tool. Understanding what graphical outputs are most useful and interpretable to decision-makers is essential and those with user-friendly interfaces that simplify model outputs will encourage use. Developers must work with decision-makers to understand the thought process behind a health intervention when building interfaces. Tools created with simple measures in which users can walk through basic steps before performing more complex analyses will ensure optimal utilization of the service [29].

Communication and dissemination of climate information and resources are critical for ensuring that decision-makers and practitioners have the information they need to respond to the impacts

of climate change on health. It is essential to develop materials and strategies that are appropriate for the population to be reached, for example, climate bulletins, brochures, and fact sheets using a diverse set of imagery and text, social media, radio, or other materials [27]. Different strategies may be needed to communicate with decision-makers versus practitioners or to communicate with different sectors of the health system. Strategies may also need to consider cultural and linguistic differences [30]. Working with a design team to relay alerts is crucial to ensure the population is informed and understands what health intervention may take place or may be implemented. Working with communities to explain how the EWS works and gain their trust will ensure that communities can be a part of the intervention at hand, therefore, increasing intervention efficacy.

Using qualitative methods such as targeted surveys and feedback collection from the stakeholders; along with focus groups and interviews with representatives from each group would provide deeper insights into the effectiveness of communication strategies and help identify any areas needing improvement. Based on the evaluation findings, platforms could be adapted and refined for better communication strategies. This iterative process would ensure communication remains effective and responsive to the needs and preferences of decision makers [Fig 7, section 3].

Health interventions: An EWS provides forecasts of disease risk to the health sector to prevent public health crises and limit overall health risks. A crucial step in developing forecasts is understanding what public health interventions will occur when an alert meets a specific threshold. It is also essential to understand how and why an intervention is suggested. This

means examining the underlying rationale and evidence supporting the proposed intervention, as well as considering its potential impact and effectiveness in addressing the issue at hand. Additionally, it is important to evaluate the feasibility of implementing the intervention, considering the resources, time and support required for successful execution. An EWS can trigger several types of interventions, including, but not limited to, community health campaigns, increased medicine and supply chains to hospitals and clinics, increased capacity training for health professionals, increased vector control such as fogging and tracing the vector source and identifying other cases in the vicinity, as well as re-allocation of human resources funding to high-risk regions. When developing an EWS, it is also essential to know which agency is activated in the response plan, what defines the threshold, what committee is responsible for enacting an intervention, and the branching logic for emergency dissemination. Finally, it is key to establish a thorough monitoring and evaluation plan for each health intervention implemented [Fig 5, section 4].

Servers, storage, and management: The maintenance and management of an EWS is a critical task that requires specialized knowledge and expertise. It is essential to identify who will oversee maintaining the EWS to ensure it functions properly. This includes managing the servers and storage systems that are needed to collect and store observed and modeled data (e.g., forecasts), as well as overseeing other technical aspects of the system to ensure smooth operation.

Regional partnerships can be instrumental in hosting servers and providing technical assistance to smaller countries. For example, small island states can benefit from a similar setup to that of a Regional Climate Centre, which can provide them with access to climate forecasts and other

critical data. By partnering with larger, more established institutions, smaller countries can leverage their expertise and human resources. This can help to ensure that the EWS will be managed effectively and that it is providing accurate and valuable information to decision-makers in the health sector [Fig 7, section 5].

Human resources and technical capacity: Technical capacity refers to the knowledge, skills, and infrastructure necessary to operate and maintain climate tools (i.e., EWS), such as computing systems, software, and data management. Many low-income countries lack the financial resources to hire or create new positions that are essential to running, maintaining, and operating an EWS. The more automated the processes, the better, as human resources do not have to add to an already extended workload. Automated processes can help alleviate the strain on human resources and improve the sustainability of the EWS. It can reduce the need for manual data entry and oversight, freeing up staff time for other tasks. However, it is important to note that even an automated system needs someone responsible for maintenance to perform updates as data systems change. The Barbados Meteorological Services advocated that one way to ensure a more sustainable implementation of the EWS was to ensure the automatic feeding of climate data into the models, with limited need for human oversight. Stakeholders emphasized that in countries with limited resources, automating, and streamlining inputs and outputs as much as possible will help ensure the usage of tools. Stakeholders further indicated that, due to the large volume of national projects, human resources are limited. To make the EWS tool viable and sustainable, maintenance of the system should be conducted by those who have the technical capacity, time, and funding to best support the project. Continued training is particularly vital for maintaining and enhancing technical capacity, as it ensures that employees stay up to date with

rapidly evolving systems and can effectively adapt to emerging challenges in the field [Fig 5, section 6].

It is also essential that health sector professionals have the training and capacity to understand and respond to climate impacts. One way to address training and capacity building is through the development of tailored programs starting with a needs assessment to identify skill gaps and areas of improvement. Another aspect of capacity building is fostering a culture of continuous learning and professional development. Encouraging employees to participate in workshops, conferences and online courses can help staff to keep up with best practices [31–33]. One example of this is the Global Consortium for Climate and Health Education (GCCHE) open access course *Pan American Climate Resilience Health Systems*, with its goal to equip the health sector with the knowledge and tools needed to address climate change [34].

Moreover, developing formal high school and university curricula focused on climate change and variability and/or climate services would help to produce professionals in-country and eliminate or reduce the need to outsource professionals residing in the Global North. This could help ensure that experts on the ground could develop and manage early warning information system components such as research, monitoring and prediction tools, or awareness, education and outreach, reducing the economic burden on countries to outsource work and improving on sustainable climate services operations. Creating pipeline pathways for postgraduate students to enter the workforce would also increase the demand for creation of climate and health curriculum in universities. Ongoing training and capacity building can also help strengthen professional development on the job. An excellent example of this is the Pan American Health

Organization (PAHO) Climate and Health Fellowship program, which first launched in 2021 and created a cohort of inter-sectorial, multidisciplinary leaders with the necessary skills to sustainably turn plans and policy into action [35] [Fig 7, section 6].

Monitoring and evaluation: Effective monitoring and evaluation of the use of climate tools and resources is critical to ensure that decision-makers and practitioners in the health sector have the information they need to respond to the impacts of climate on health. Ongoing monitoring and evaluation, including the identification of areas for improvement and adjustments, and regular reporting on progress and impact, are key steps in this process. Reporting the evaluation updates helps to keep relevant stakeholders informed and engaged and promotes positive health outcomes [36].

Monitoring and evaluation of communication and dissemination efforts can help to ensure that resources are reaching the intended audiences and that they are being used successfully. There are a variety of methods that can be used including surveys, interviews, and focus groups to gather feedback from practitioners and decision-makers, as well as quantitative metrics such as website traffic, the number of downloads of specific resources, or social media engagement statistics [37] [Fig 5, section 7].

Funding and resource mobilization: Funding and continuous resource mobilization is needed for implementation initiatives that are broad and far-reaching. One key area that requires funding is long-term data capture and storage. This includes developing the infrastructure needed to collect, store, and analyze data related to climate, climate(-related) hazards and their impact on

public health. Without these data, it is difficult to identify patterns and trends, impossible to model them, and a missed opportunity to develop evidence-based interventions to protect public health. Another important area that requires funding is capacity building of the current workforce as well as the development of formal university curricula for climate and health specialties for future generations. This is critical to building a workforce that is capacitated to become competent in developing, coordinating and implementing appropriate mitigation and adaptation plans and strategies that are informed by the risk information. Additionally, funding is needed for the integration of electronic health information systems into climate-health informatics, to include hiring software developers for user interface creation, as well as social scientists and communication specialists to co-design and co-evaluate associated health intervention effectiveness. All of these are crucial professional roles in developing and implementing climate services for the health sector, thus, without adequate sustained funding, progress in this area may be limited. There are plans to join forces with DHIS2 to develop a CARPHA level platform that will integrate national level systems funded by 11th EDF EU/CARIFORUM Project, “Strengthening Climate Resilient Health Systems in the Caribbean". DHIS2 is an open source, web-based platform used as a health management information system (HMIS) used in more than 100 countries. DHIS2 software development is a global collaboration managed by the HISP Centre at the University of Oslo (UiO). HISP is a global network of 17 in-country and regional organizations, providing support to ministries and local implementers of DHIS2 [38].

The system is being designed in collaboration with Barbados Government and other national agencies. It is being built taking into account current national resources infrastructure and future

expected input from these bodies to support long-term in-country sustainability [Fig 7, section 8].

1.4 Discussion/Conclusion

The integration of climate information into health sector planning and decision-making is essential to ensure the continued health and well-being of populations [23,25]. Developing guidelines and protocols, as well as testing, monitoring, and evaluation, are critical steps in this process [6]. The implementation questions proposed here (S1 Annex) can guide readers on how to access, use, and interpret climate data and models in a way that supports real-time decision-making in the health sector.

Creating and implementing climate services for health is challenging [6], as for many sectors (i.e. Goddard et al 2020 and references therein). In the beginning stages of the EWS development, we faced the challenge of aligning the diverse interests and priorities of various stakeholders, including health and environment professionals. In these projects, stakeholders include a range of roles from implementing partners to recipient decision-makers, to scientific partners, to the funders and agency personnel directing projects. Traditionally, stakeholders tend to be the recipients of information (i.e. department of health, department of conservation, special interest groups, etc.), whereas true co-development and co-production methods think about equity, hierarchy and power dynamics. Input and decisions from various stakeholders on co-design or deliverable formats and co-development engagements are not static, and often rotate and remain dynamic. However, we facilitated open discussions and provided key information and technical expertise to all parties involved. One key strategy we employed, developed through

prior projects, was using an interview guide for in-person inquiry and data auditing during the early stages of the work [39]. This established a relationship with key stakeholders in the data collection and recording realms, while allowing for investigation of the structure and distribution of those key data pipelines amongst the project partners and supporting ministries, sectors, and agencies. The development and implementation of the current framework was tailored for the Caribbean, and potential challenges of adapting this EWS framework more broadly span many of the limitations outlined in earlier sections, such as establishing partnerships, and discrepancies in minimum technical capacity and human resources requirements. Publishing this tool for users to adapt to future projects and discussions is crucial. It serves as a central part of the overall process, acting as a catalyst for interactions and discussions, rather than just being a technical tool in the larger toolkit'.

Keeping stakeholders continuously engaged and motivated throughout the project is also challenging. Therefore, we implement regular feedback mechanisms and progress updates and acknowledge the contributions of stakeholders to keep them actively involved and invested in the project's success. Progress readouts, online and in-person stakeholder engagement meetings on specific components (e.g. syntheses of interview themes, database development, discussions of alert system styles across sectors), provide ongoing, yet dynamic opportunities for co-development and co-design. Future efforts could also include periodic reviews of original goals, and collaborative mapping of shifts or redesign of pathways might provide a reflection tool, particularly in the inevitable scenario of protracted timelines due to externalities (e.g. global pandemics, bureaucratic changes, political unrest). While implementation of climate-health tools, by its very nature, does not have an endpoint, there will be endpoints in the process, and

similarly, novel starting points may arise during the undertaking. Another future consideration is to celebrate and appreciate a rotating organogram of stakeholders and roles, e.g. when personnel from different sectors change their role in the implementation, in their organization, or encounter shifting responsibilities. For specific implementations of climate-health services, there may indeed be a fundamental minimum network of roles, or size of network of personnel, needed to promote success of the overall implementation. This remains to be seen, as we are still in nascent stages of full implementations, globally.

The Caribbean has set regional cooperation on health and climate change as a top priority [40,41]. Having the political will and mandate ensures this pressing issue remains at the top of the agenda for key government sectors. Within the larger Caribbean context, Barbados has taken on a leading role on climate and health initiatives, pioneering these approaches within the region. Barbados is providing a template and a roadmap for additional partners and some major takeaways from this work in Barbados includes the following: 1) equity must be at the heart of every climate adaptation strategy—academic institutions must support research and development in the region and encourage long term sustainability through education and funding opportunities; 2) partnerships need to be developed and built on trust—and this process cannot be rushed as it involves shifting mindsets away from historic colonial approaches; 3) in order to advance in climate tool development, it is critical to invest in basic infrastructure including new weather stations, servers, data capture, storage and electronic health information systems; 4) there is still a need to sensitize the general public to climate variability and change, as well as to empower communities to take action now; 5) decision-makers need simple user interfaces that can help them to understand the risks at hand and communicate them effectively to the general

public; and 6) climate services need to be as automated as possible to reduce the workload in human resource limited areas.

Implementing climate services for the health sector is a critical step in protecting public health in the face of climate change [42–44]. Further research must be conducted on the return on investment of climate-driven disease early warning systems to showcase their impact. Defining what the return on investment may look like is important and may differ between countries and projects, i.e. number of lives saved, illness prevented, or monetary cost saved. Moreover, future work for climate-and-health EWS development and research may include demand-driven forecasting to predict monetary resources needed in prevention, control, and outbreak scenarios which would help low- and middle-income countries (LMICs) to allocate public health funds accordingly. Moving forward, promoting funding initiatives and supporting the professional development of stakeholders in the Global South will bolster capacity building and address critical skill gaps that may limit EWS implementation in the Caribbean and beyond. Finally, the authors of this paper recommend that these guidelines could be used to implement the climate-driven dengue EWS sustainably into the Barbados health sector and guide future implementation work across the LAC region.

S1 Checklist. Inclusivity in global research.

https://doi.org/10.1371/journal.pclm.0000282.s001

S1 Annex. Implementation framework and guiding questions.

https://doi.org/10.1371/journal.pclm.0000282.s002

S1 Data. Strengthening climate resilient health systems in the Caribbean.

https://doi.org/10.1371/journal.pclm.0000282.s003

Interlude: Chapter 1 → Chapter 2

Chapter 1 established that climate variability provides a meaningful and, in many cases, predictable signal relevant to dengue transmission, while demonstrating that the usefulness of this information depends on how well it is aligned with decision-making contexts and institutional processes. The implementation framework derived through transdisciplinary engagement made this explicit by defining not only what information is needed, but how it should be structured, timed, and delivered to support specific health sector decisions.

These principles directly informed the design of the forecasting system presented in Chapter 2. Rather than treating model development as a separate technical exercise, the framework developed in Chapter 1 was used to guide key design choices, including the selection of predictors, the temporal structure of the model, and the form of its outputs. Chapter 2 therefore tests the implementation framework, translating climate signals—particularly rainfall variability and its lagged influence on vector ecology—into the first climate driven budget forecasting system that is explicitly aligned with planning needs and improving resource allocation and anticipatory response.

Chapter 2: PROA: Predicción de Riesgo y Optimización de Alertas *A Co-Produced Climate-to-Budget Dengue Forecasting Framework in Panama*

This first-author work is in prep to be submitted.

2.1 Introduction

Climate change is altering the environmental conditions that govern the transmission of vector-borne diseases (1). Rising temperatures, shifting precipitation, and increasing climate variability are expanding the geographic range and extending the seasonal window of *Aedes aegypti*, the primary vector of dengue, Zika, and chikungunya viruses, into regions and altitudes that were previously inhospitable to sustained transmission (2–4). *Ae. aegypti* is an ectotherm which means it is directly regulated by ambient temperature and humidity. Warmer temperatures accelerate larval development, shorten extrinsic incubation period of dengue virus, and can even increase adult vector biting rates. Climate change can also impact rainfall onset (aka the timing for when traditional dengue seasons begin), and precipitation extremes (both extremely wet and extremely dry) effectively changing the way in which we understand dengue transmission risk (5). In extremely dry conditions as well as structurally vulnerable settings (where people may lack access to piped water) water storage practice may increase leading to a greater risk of mosquito breeding habitat development. Climate extremes, for example flooding events, can lead to the displacement of populations. People who are displaced from their homes during an extreme event may seek

shelter at a refuge or move into a friend or family member's home. This can lead to overcrowding of households or the development of informal settlements. Informal settlements are usually at risk for limited governmental services like access to sanitation pick up or maintenance of urban vegetation where litter tends to pile up and increase potential breeding habitat. As the climate warms and mosquito behavior shifts to more frequent biting patterns, human health is more at risk. Thus, the projected intensification of these climate drivers under continued greenhouse gas emissions is expected to cause compounding and cascading impacts for dengue transmission risk, with the greatest impacts concentrated in tropical and subtropical regions already carrying the highest disease burden (6).

Panama represents a particularly interesting case for understanding climate-disease interactions. The country is a narrow isthmus (75,417 km²) situated between the Caribbean Sea and Pacific Ocean, positioned close to the Intertropical Convergence Zone (ITCZ). The seasonal migration of the ITCZ drives a pronounced wet season from May through November, creating sustained *Ae. aegypti* breeding conditions across most of the country. Panama's two-ocean position produces distinct ENSO teleconnections on its Caribbean and Pacific slopes, with El Niño events associated with precipitation suppression on the Pacific and enhancement on the Caribbean creating spatially heterogeneous inter-annual climate variability that influences dengue dynamics differently across provinces (7) Other climate drivers that influence Panama’s unique climate are the Caribbean Low Level Jet, the Pacific Decadal Oscillation and the Madden Julian Oscillation amongst others. This

complex climatic structure, combined with Panama's migratory corridor between North and South America, makes it an important site for understanding how large-scale climate modes interact with dengue transmission at the regional scale (8). In many parts of Latin America and the Caribbean finding long term dengue case data can be challenging and many countries in the region do not have the epidemiological data required to build meaningful and trustworthy climate driven forecasting systems. Panama however, has a dengue surveillance system that has been operating through the Ministry of Health (MINSA) since 1993 and provides continuous national case records making it possible to develop and validate climate-driven forecast systems (9).

Panama experienced its most severe multi-year dengue epidemic on record between 2023 and 2025 with its peak in 2024. A central driver was in addition to the co-circulation of DENV 1-3, the reintroduction of dengue virus serotype 4 (DENV-4) after more than two decades of absence created an immunologically naive cohort spanning the entire birth population of 2001–2022 (10). For the first time since 2000, all four dengue serotypes circulated simultaneously, compounding transmission intensity beyond what climate conditions alone may predict. The epidemic unfolded against a backdrop of accelerating structural risk: informal urban settlements, irregular water supply, large-scale migration through the Darién Gap (more than 500,000 people in 2023 alone (8,11,12), [10], [11]]), and a health system already strained by the COVID-19 pandemic (13). These intersecting pressures produced a sustained epidemic that persisted through the climatological dry season which is an historically unprecedented pattern that highlights the limits

of climate-only forecasting and motivates the multi-layer architecture of the system developed here.

Climate services offer a pathway to reframe the dengue public health planning from response to preparation and prevention (14). By providing decision-makers with advance signals months before epidemic onset, climate-driven forecasting systems can enable more targeted vector control, proactive procurement of hospital and pharmacy supplies, optimize budget allocations, and advance community education and awareness campaigns before caseloads peak (15,16). The economic argument is simple: earlier intervention is substantially cheaper than emergency response, and health systems in low- and middle-income countries are particularly exposed to the reactive cost premium that epidemic under-preparedness generates (17,18)]. Climate services for health have demonstrated case prediction lead times of 3–6 months with skill substantially exceeding baseline models (usually 5-year epidemiological averages) in dengue-endemic regions (19–22). Yet despite this potential, many climate services for health have remained research outputs rather than operational tools (23). This is in part due to several factors, including minimal interaction between climate and health sectors, tools that are built without the end user in mind (overly complex), lack of implementation and operationalization planning, lack of formal mandates, lack of in-house human resource capacity amongst many others (24). Furthermore, a persistent gap lies between probabilistic climate forecast outputs and in many cases the binary

decision contexts health decision makers need to enact quickly (i.e. procure or not, escalate or not, deploy or not etc.) (25).

The ambition to bridge this gap motivated the creation of **PROA (Predicción de Riesgo y Optimización de Alertas)—**a climate-to-budget dengue forecasting framework (translated from Spanish to English as Prediction of Risk and Optimization of Alerts). Rather than producing a research forecast validated retrospectively against historical data, we set out to co-design with MINSA and PAHO a system whose outputs would directly benefit their end-user needs. Some of these needs include better understanding evolving budget allocation schemes for preventing an outbreak and in-season procurement triggers that characterize Panama's public health operational reality (i.e. given the resource forecast– how many new hires might they need during a high or low season– or in severe cases, where a high alert is issued, notifying key response actors like PAHO or the Red Cross to prepare for a potential emergency well in advance). PROA builds on an established institutional collaboration through the AeDES Map Room project, a NOAA-funded, IRI-led climate services initiative for Aedes-borne disease risk in Latin America and the Caribbean (26). PROA's co-production process, structured through participatory workshops, systems mapping exercises, and direct engagement with Panama's dengue cost literature, ensures that PROA's design choices reflect end-user decision needs rather than data availability alone (27). The system is explicitly presented as a first-generation operational framework: validated across 15

years of out-of-sample data, with specific failure modes and a concrete enhancement roadmap supported by the results.

We present PROA as three contributions. First, a validated three-layer hybrid ensemble architecture including, climate, epidemiological and transmission momentum to monthly dengue case prediction. Second, a probabilistic budget planning framework derived from the forecast's uncertainty envelope, implemented through a three-tier commitment structure designed for use at a quarterly cycle. Third, a Dengue Vulnerability Index (DVI) budget allocation method that redistributes national budget estimates toward structurally underserved and vulnerable provinces beyond what case counts alone would justify. The three contributions address research question 2 (RQ2) (forecast skill, budget translation, and equity allocation) while the three-tier commitment structure connects to the uncertainty communication response to RQ3, and the prospective evaluation connects to the full pipeline under the operational conditions RQ1 and RQ4 are designed to sustain.

2.2 Methods

We use a transdisciplinary approach to co-produce a climate driven dengue budget forecasting system: PROA. PROA integrates a Partial Least Squares (PLS) climate model driven by rainy-day frequency (FRD) lags 1–3 from NOAA CPC observations, a serotype novelty multiplier N(t)

looking at inter-annual immunological susceptibility, and a transmission momentum amplification layer, forming a hybrid statistical-mechanistic ensemble framework. An autoregressive correction module (PROA-Monitor) provides in-season adjustment using prior-month surveillance data. All analyses were conducted in Python using Jupyter Notebook. We validate across a 15-fold (leave 3 years out) walk-forward cross-validation (2009–2025, 540 out-of-sample predictions) for epidemic threshold detection and determine skill attribution. We test the model using a prospective Q1 2026 forecast driven by a 51-member C3S SEAS5.1 seasonal climate ensemble, enabling probabilistic prediction. We then build a three-tier budget planning framework (guaranteed floor (historical P10), operational target, contingency ceiling) to communicate uncertainty and reduce budget procurement delays. Finally, we construct a Dengue Vulnerability Index (DVI) provincial budget allocation method as a complementary operational tool to address structural vulnerability gaps in surveillance reporting.

2.2.1 Transdisciplinary Co-Production

PROA's development adopted a transdisciplinary approach integrating expertise from climate science, infectious disease epidemiology, health economics, and public health operations. Partners engaged in the design process included MINSA epidemiologists, vector control, GIS and program directors, PAHO regional advisors, researchers from the Instituto Conmemorativo Gorgas de

Estudios de la Salud, and academic and private collaborators from Columbia University's Department of Earth and Environmental Sciences and Alisios Cooperation. It is important to note the use of “partners” rather than stakeholders as this work is truly built together with all those involved.

The co-production process was structured in three phases with ongoing communication through in-person meetings, email and zoom. In February 2024, initial participatory workshops characterized the current state of dengue surveillance and response, identified gaps in existing forecast capacity, and defined the decision-relevant outputs the system should produce. This phase established the two-product architecture: an advance warning signal for seasonal procurement and quarterly resource allocation (PROA-Forecast), and an in-season tracking tool for monthly resource reallocation during active outbreaks (PROA-Monitor). The second phase used a systems mapping exercise to identify both the predictands and predictors. Through co-construction, the map linked climate, environmental, social, immunological, and health-system factors to dengue incidence and budget requirements. Climate variables, specifically rainfall frequency, were consistently identified by Ministry of Health partners as the most operationally tractable predictors of inter-annual transmission risk. Other key drivers reported included social vulnerability, sanitation, and serotypes circling. The third phase engaged the lead investigator of the only published study quantifying the economic cost of dengue in Panama [24], who is a co-author of this work, to anchor the budget module in empirically derived unit costs. In June 2024 and

December 2025, data harmonization and model outputs were shared at formal in-person meetings with the Ministry of Health and PAHO for end-user feedback.

It is noted that requests to MINSA for dengue-specific institutional expenditure records were made during the co-production process but were not granted. PROA's economic burden estimates are therefore derived from literature unit costs applied to predicted case counts, not validated against verified budget lines. This is an acknowledged limitation discussed in Section 4.4.

2.2.2 Epidemiological Data

Panama is an isthmus of 75,417 km² and approximately ~4.6 million population, divided administratively into 12 provinces and 3 indigenous comarcas (28). For this paper we combine Panama North, East and West into 1 metropolis (9 provinces and 3 comarcas) in order to use the Global Data Lab Subnational Vulnerability Index outlined in section 2.9. Dengue is a nationally notifiable disease; individual case records are submitted electronically to MINSA's epidemiological surveillance system by epidemiological week. Historical case records (1999–2024) were obtained from MINSA as de-identified surveillance data assigned to epiweek, province, and year. This data is made publicly available in PDF format (https://www.minsa.gob.pa/informacion-salud/boletines-semanales). Monthly national and

provincial totals were derived by converting CDC epiweeks to calendar months using the end-date function.

For 2025, monthly national totals were reconstructed from MINSA PDF weekly epidemiological bulletins (Boletín Epidemiológico Semanal, weeks 1–52) reporting cumulative national dengue cases. Week 26 was unavailable and interpolated as the mean of weeks 25 and 27. The 2025 national total of 16,103 cases (through week 52) was verified against the week 52 cumulative total. For Q1 2026, monthly case totals were also derived from MINSA weekly epidemiological bulletins (weeks 1–11). Week 12 (ending March 28) was unavailable at time of analysis and was adjusted using the mean of weeks 9–11 (approximately 146 cases), yielding an estimated March total of 584 cases. Under plausible alternative March estimates of ±20% (range: 467–701 cases), the Q1 2026 total varies between approximately 1,699 and 1,933 cases; in all scenarios this total exceeds the epidemic threshold of 506 cases in at least two of three months and the quarterly sum remains well above the P75 threshold, confirming that the prospective evaluation outcome — PROA correctly identifying Q1 2026 as an epidemic-threshold quarter — is robust to uncertainty in the Week 12 interpolation.

2.2.3 Climate Data and Predictor Selection

Rainy-day frequency (FRD, days per month with precipitation ≥ 1 mm/day), total monthly precipitation (PR, mm/month), and temperature suitable days (FSD) were computed from the Climate Prediction Center CPC Global Unified Gauge-Based Analysis of Daily Precipitation data provided by the NOAA PSL, Boulder, Colorado, USA, from their website at https://psl.noaa.gov (0.5° × 0.5°) (29,30). Spatial averaging was performed over Panama [7°N–10°N, 84°W–77°W]. Monthly values were computed from daily fields for 1999–2025. For prospective Q1 2026 forecast months requiring future climate data (February and March 2026), FRD was derived from the Copernicus Climate Change Service (C3S) SEAS5.1 seasonal ensemble (ECMWF system 51, November 2025 initialization, leads 2–4, 51 ensemble members), which was used to drive climate forcing of PROA. Monthly mean total precipitation rate (tprate, m/s) was converted to mm/month and to FRD via a historical PR–FRD linear regression fit to the full CPC record ($FRD = 2.59 + 0.0566 \times PR$, $R^2 = 0.867$). System 51 (SEAS5.1) was required for forecasts from November 2023 onwards; system 5 (SEAS5) covers earlier hindcast periods.

Predictor selection was conducted by exhaustive lag grid search (lags 1–8 months) across FRD, PR, dry-day frequency (DDF = 30 − FRD), and FSD, followed by combination testing of all pairwise and three-way variable sets. All tests were evaluated under the walk-forward CV framework described in Section 2.6. FRD lags 1–3 outperformed all single-variable alternatives at longer lags and matched or exceeded all multi-variable combinations in pooled AUC for epidemic

threshold detection. The biological basis for this result is that the count of rainy days compared to total precipitation volume determines the availability and persistence of larval breeding habitat. For example, one single intense storm creates less sustained habitat (or can even wipe out habitat due to flushing of containers) than multiple days of moderate rainfall. FRD was selected as the climate predictor on grounds of parsimony, operational interpretability, and empirical out-of-sample performance.

2.2.4 Serotype Surveillance and the Novelty Index N(t)

Annual serotype circulation records for Panama (1995–2025) were obtained from PAHO regional surveillance reports which are made available through the Instituto Conmemorativo Gorgas, specifying which of the four dengue serotypes (DENV-1 through DENV-4) were detected each calendar year. The Serotype Novelty Index N(t) quantifies the population-level immunological susceptibility of Panama in year t:

$$N(t) = (1/4) \Sigma_{s=1}^{4} [\Sigma_{\gamma=t-5}^{t-1} \mathbb{1}[s \notin S_{\gamma}] / 5]$$

where S_{γ} is the set of serotypes detected in year y. N(t) ranges from 0 (all four serotypes recently active) to 1 (all four serotypes absent for five years). The five-year lookback captures the approximate generation time over which population-level serotype immunity is replenished. N (2026) = 0.200, reflecting recent broad serotype activity. A multiplicative rather than additive

novelty scaling is used (Section 2.5), consistent with the biological constraint that near-zero rainfall predicts near-zero transmission regardless of immunity state. This window is consistent with empirical estimates of heterotypic cross-immunity duration in dengue, which suggest protective effects wane substantially within four to six years of initial infection (31). Sensitivity to alternative lookback windows is discussed in Section 4.5.

2.2.5 PROA Model Architecture

PROA comprises four nested components (Table 1):

Table 2.1 PROA Model Architecture

Layer	Inputs	Forward-looking	Lead	Use
PROA-Climate	FRD lags 1–3 (CPC/C3S)	Yes — CPC/C3S	1–4 mo	Climate baseline
PROA-Forecast (no ampl.)	+ Novelty N(t)	Yes — annual	1–4 mo	Research only
PROA-Forecast (with ampl.)	**+ Transmission momentum**	**Yes — lagged obs**	**1–4 mo**	**Quarterly planning**
PROA-Monitor	+ AR (1) ε(t−1)	No — needs live data	1 mo	In-season tracking

PROA-Forecast (with amplification) is the primary operational product for advance planning. PROA-Monitor requires confirmed prior-month case counts and is the in-season tracking tool.

PROA-Climate fits a Partial Least Squares (PLS) regression (3 components) on standardized FRD lags 1–3 to predict log (cases + 1). PLS was selected over ordinary least squares because the three lag predictors exhibit multicollinearity, rainy months tend to cluster sequentially so FRD lags are highly intercorrelated, and PLS regularization remains stable at the effective sample sizes encountered within 10-year training windows.

PROA-Forecast scales the climate prediction by a novelty multiplier and an amplification correction:

$$\hat{y}_t = \text{PROA-Climate}_t \times (1 + \alpha \times N(t)) \times \text{Amplification}(t) \quad \alpha = 0.8$$

The amplification layer is a linear regression on transmission momentum predictors available at forecast time: $\log(\text{cases}_{t-1})$, a 3-month rolling mean of log cases, N(t), and seasonal harmonic terms (sin and cos of month/12 × 2π). It learns the historical log-scale gap between the climate-novelty prediction and observed cases, correcting for the structural inability of rainfall alone to capture active outbreak momentum. The coefficient $\alpha = 0.8$ was selected empirically as the value maximizing pooled CV AUC across $\alpha \in \{0.0, 0.2, ..., 1.5\}$. The amplification layer is refit annually as part of the standard operational update, incorporating the confirmed prior year's case record into the training data before issuing each Q1 forecast. This ensures correction factors remain calibrated to the most recent epidemic conditions.

PROA-Monitor applies an autoregressive correction:

$$\text{Monitor}_t = \text{PROA-Forecast}_t \times \exp(\gamma \times \varphi \times \varepsilon(t-1)) \quad \gamma = 0.15$$

where $\varepsilon(t-1)$ is the log-scale residual between observed and forecast cases in the prior month, $\varphi = 0.897$ is the empirical residual autocorrelation fitted per training window, and $\gamma = 0.15$ is a damping factor preventing over-correction during noisy surveillance periods. PROA-Monitor requires confirmed prior-month case data and is an in-season tracking tool rather than a forward forecast.

2.2.6 Cross-Validation Framework

Model skill was evaluated using a 15-fold rolling walk-forward cross-validation. Each fold trains on 10 consecutive years and tests on the subsequent 3 years, advancing by one year per fold. Fold 1 trains on 1999–2008 and tests on 2009–2011; fold 15 trains on 2013–2022 and tests on 2023–2025. This yields 540 out-of-sample monthly predictions covering 2009–2025. The CV loop implements a sequential residual, updating actual case counts which are then incorporated into the residual map before predicting the next month, correctly simulating operational PROA-Monitor deployment. No test month ever appears in its own training window. All skill metrics (r(log), R^2, signal-to-noise ratio (SNR = $R^2/(1-R^2)$), AUC, Heidke Skill Score (HSS), and forecast bias) are computed exclusively on out-of-sample predictions. Correlation metrics are computed on log-transformed case counts (log1p) to stabilize and reflect multiplicative error structure. Epidemic metrics like AUC and HSS are evaluated relative to a fixed outbreak threshold (≥ 506

cases/month), with AUC computed using log-transformed forecast values as continuous scores. Performance is summarized across folds (mean ± standard deviation) and as pooled out-of-sample estimates across all predictions. Uncertainty in pooled metrics is quantified using bootstrap resampling (Section 2.7).

2.2.7 Uncertainty Quantification

Two distinct sources of uncertainty are considered: model evaluation uncertainty (2.6) and forecast uncertainty, which is quantified through the prediction intervals described here. Prediction intervals were generated by bootstrapping (n = 2,000 draws per forecast month). Each draw samples (1) C3S ensemble members directly for lag months requiring seasonal forecast input, thereby propagating SEAS5.1 inter-member climate uncertainty; (2) Gaussian noise on the PLS prediction ($\sigma = 0.626$, derived from the empirical standard deviation of CV log-residuals); and (3) Gaussian noise on the amplification gap ($\sigma = 0.590$, derived from CV amplification residuals).

2.2.8 Budget Planning Framework

Forecast case counts are converted to economic burden estimates:

$$\text{Burden}(t) = \hat{y}_t \times \lambda \times c$$

where $\lambda = 3.0$ is the conservative under-reporting multiplier and c = $1,940 USD per case (Armién et al. 2008 [24], adjusted to 2024 USD using the Panama CPI). This unit cost represents the full societal burden including hospitalization, outpatient treatment, vector control, and household productivity loss. It is important to note that for the purpose of this paper, all economic outputs are planning-scale approximations.

A three-tier decision framework is derived from PROA's probabilistic output. Tier 1 (guaranteed floor) uses the historical P10 of quarterly burden from the CV record intended to be a minimum commitment regardless of the current forecast. Tier 2 (operational target) uses the PROA P75 as the primary procurement budget. Tier 3 (contingency ceiling) uses the PROA P95 as a pre-authorized ceiling released upon AR (1) monitor confirmation of epidemic escalation. This structure is designed to map onto Panama's vector control procurement cycle, which requires 4–8 weeks of lead time for supplies and surge staffing.

2.2.9 Dengue Vulnerability Index and Provincial Allocation

The Dengue Vulnerability Index (DVI) provides a provincial-level equity weighting for budget disaggregation:

$$DVI = 0.5 \times \text{norm}(SGVI) + 0.5 \times \text{norm}(1 - \text{piped water coverage})$$

where SGVI is the Subnational Global Vulnerability Index (capturing socioeconomic fragility) and piped water coverage is sourced from INEC household survey data compiled and retrieved from the Global Data Lab, https://globaldatalab.org/gvi/, version v1.1. The inverse of piped water coverage serves as a proxy for larval habitat persistence and household-level vector control capacity. National budget estimates are disaggregated to 12 provinces and comarcas using a weighted allocation index: 60% proportional to recent case burden (12-month PAHO lookback) and 40% proportional to DVI. This 60/40 weighting ensures that provinces with high structural vulnerability but lower reported case counts (which may reflect surveillance deficits rather than genuinely lower burden) receive equitable resource consideration. The allocation is a disaggregation of the national forecast rather than a separate provincial model; the limitations of this approach are discussed in Section 4.

2.3 Results

2.3.1 Epidemiological and Climate Context

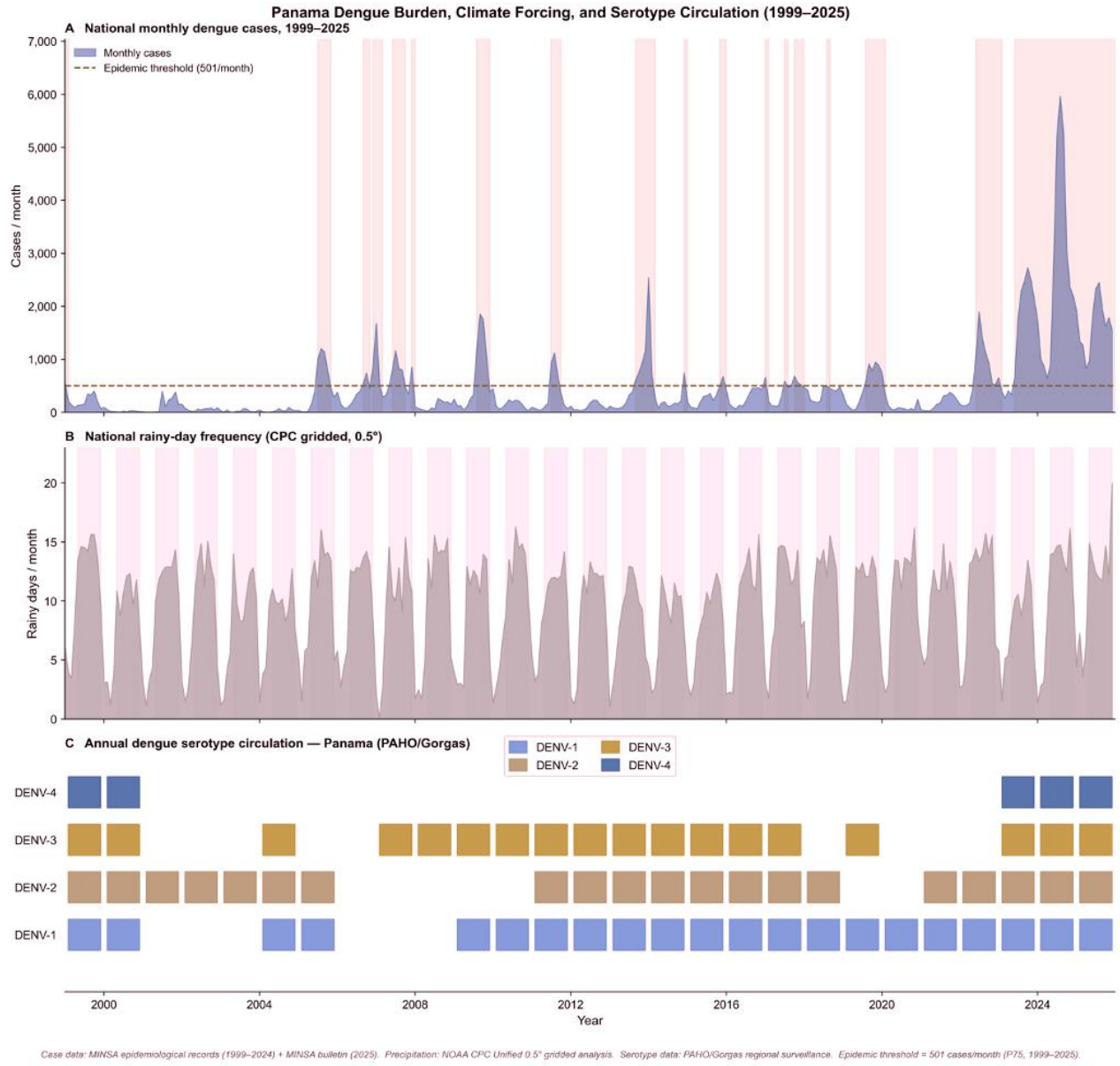

Figure 2.1. Panama Dengue Burden, Climate Forcing, and Serotype Circulation (1999–2025). Panel A: national monthly dengue cases (MINSA 1999–2024; MINSA bulletin 2025) with epidemic threshold (506 cases/month, P75 of 1999–2025 distribution) and shading of epidemic periods. Panel B: national rainy-day frequency (FRD, days/month) from NOAA CPC 0.5° gridded product, with wet season shading (May–November). Panel C: annual dengue serotype circulation (DENV-1 through DENV-4) from PAHO/Gorgas surveillance records, showing the 22-year absence and 2023 return of DENV-4.

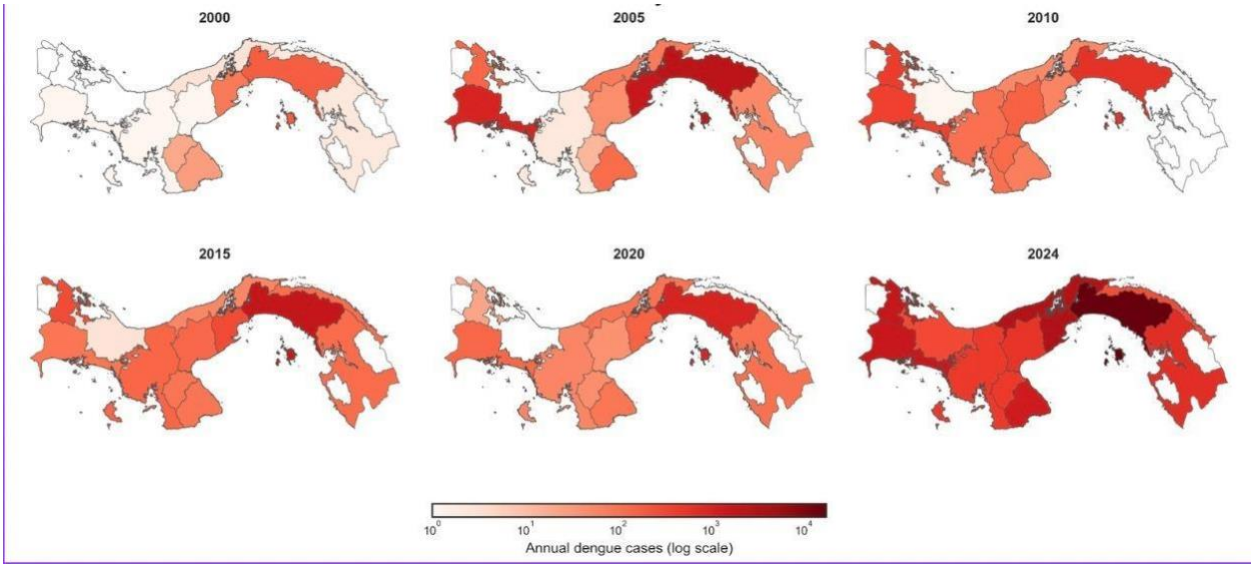

Figure 2.2. Panama's dengue case progression over 25 years.

Panama's dengue cases have increased over the last 25 years (Figure 2). Panama recorded 16,103 dengue cases in 2025 (MINSA bulletin, weeks 1–52), extending an unprecedented three-year epidemic sequence that began in 2023. The 2023–2025 period represents the highest sustained dengue burden in Panama's 26-year surveillance record, driven by the simultaneous circulation of all four serotypes for the first time since 1999–2000. DENV-4 re-entered national circulation in 2023 after a 22-year absence, creating an immunologically naive cohort spanning the birth population of 2001–2022. The Serotype Novelty Index peaked at N = 0.550 in 2012 and again at N = 0.500 in 2023, reflecting the compounding effect of serotype absence on population susceptibility (Figure 1). By 2026, N(t) had declined to 0.200 as all four serotypes entered the recent circulation window.

December 2025 recorded anomalously elevated rainfall (FRD = 20.0 days, z = +2.43 standard deviations above the historical December mean of 7.7 days), providing an unusually strong late-season climate forcing signal entering Q1 2026. The juxtaposition of high FRD and ongoing multi-year epidemic dynamics illustrates the core challenge PROA is designed to address translating a climate signal that is anomalously strong into a forecast that appropriately weights both the climate and epidemiological drivers.

2.3.2 Predictor Selection

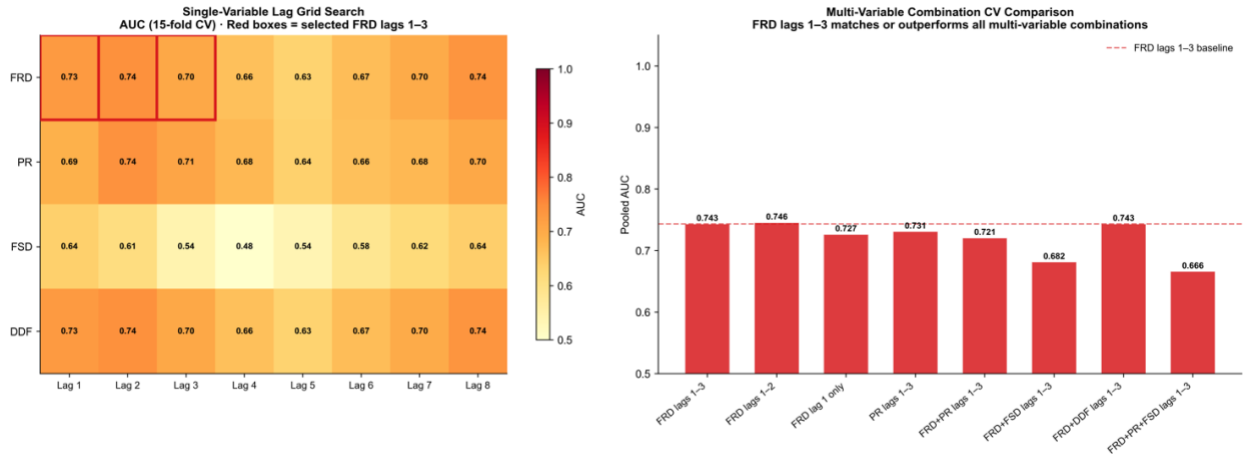

Figure 2.3. Predictor selection results. Left: AUC single variable lag grid search heatmap across all climate variables and lag lengths (1–8 months). Right: AUC for all multi-variable combinations, showing FRD lags 1–3 baseline and no improvement from adding PR, FSD, or DDF.

FRD lags 1–3 emerged as the optimal predictor configuration across the 15-fold CV, achieving higher pooled AUC than all single-variable alternatives at lags 4–8 and matching or exceeding all multi-variable combinations including FRD+PR, FRD+FSD, and FRD+PR+FSD (Figure 3). The

multiplicative novelty scaling was confirmed as superior to additive formulation across all tested α values; α = 0.8 was selected as the coefficient maximizing CV AUC (Figure S1). This result supports the mechanistic interpretation that rainfall frequency rather than precipitation volume or temperature suitability is the minimum sufficient climate predictor for monthly dengue risk in Panama, and that novelty amplifies an existing climate signal rather than adding independently to the case count.

2.3.3 Cross-Validation Skill

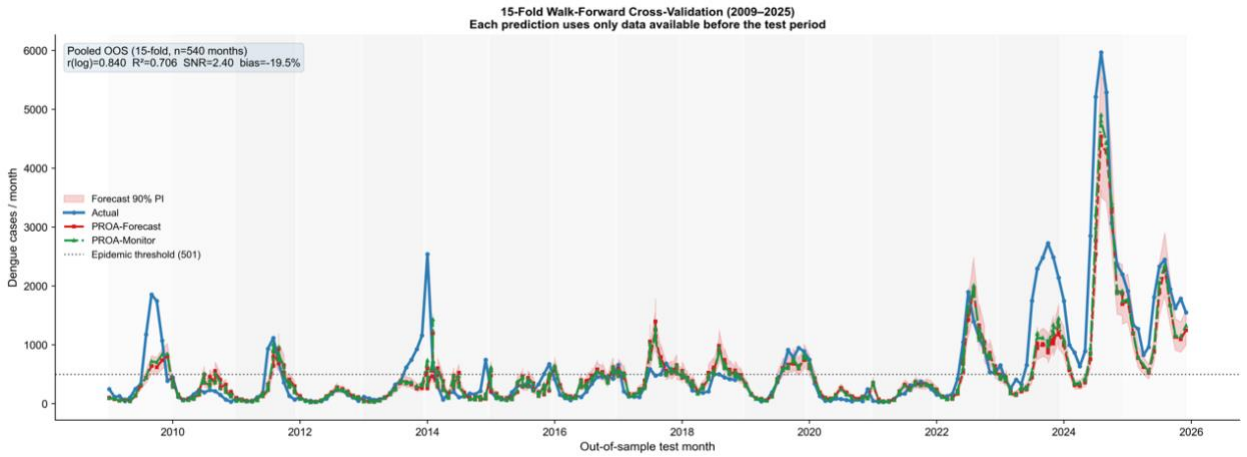

Figure 2.4. 15-Fold Walk-Forward Cross-Validation Time Series. Out-of-sample PROA-Forecast (dashed) and PROA-Monitor (dash-dot) against actual monthly cases (solid) across all 540 out-of-sample predictions, 2009–2025. Shading indicates 90% prediction intervals. Fold boundaries are indicated by vertical dashed lines.

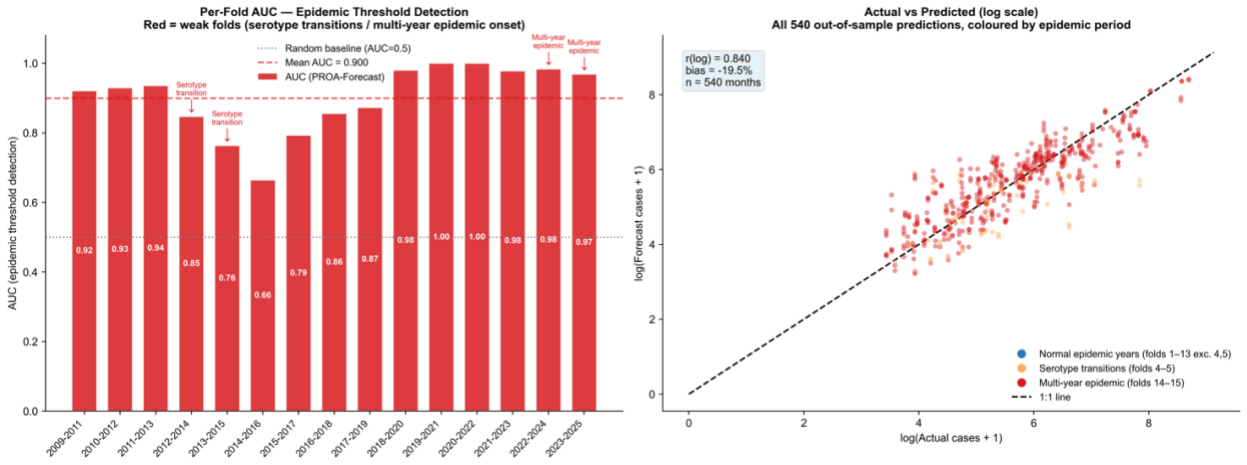

Figure 2.5. Per-Fold CV Skill. Left: AUC by fold with folds 4, 5, 14, 15 annotated with their identified failure mode. Horizontal dashed line indicates random baseline (AUC = 0.5). Right: scatter plot of all 540 out-of-sample predictions vs actual cases (log scale), colored by epidemic period.

Pooled across 540 out-of-sample predictions, PROA-Forecast achieved r(log) = 0.839 (95%CI: 0.809-0.864, AUC = 0.899 (95% CI: 0.869-0.925), HSS = 0.631 (95% CI 0.556-0.701), and HR = 0.72 with a FAR of 0.10 meaning the system correctly identified 72% of epidemic months while generating false alarms in only 10% of non-epidemic months (Table 2). Performance was stable across folds (mean AUC= 0.900 ± 0.099; mean r(log)=0.809 ± 0.109). Skill was strong and consistent across 11 of 15 folds, with AUC exceeding 0.850 and HSS exceeding 0.300 in all folds except (folds 4–5) and (folds 14–15) (Figure 4). Folds 11 and 12 achieved near perfect epidemic detection (HSS = 1.000, HR = 1.00, FAR = 0.00). Notably, folds 14 and 15, which include the unprecedented 2022–2025 multi-year epidemic, achieve the highest r(log) values in the entire CV record (0.897 and 0.905 respectively), confirming that PROA can identify the directional outbreak signal and its trajectory even within the most challenging epidemic regime in Panama's surveillance history (Figure 4).

Table 2.2 15-Fold Walk-Forward CV Per-Fold Summary

Table 2: r(log) = Pearson correlation on log-transformed case counts. AUC = area under ROC curve for epidemic threshold detection (506 cases/month, P75 of 1999–2025). Bias = (forecast − actual)/actual × 100%. HSS = Heidke Skill Score. HR = hit rate = TP/(TP+FN). FAR = false alarm rate = FP/(FP+TN). Blue shading = pooled totals (TP=113, FP=37, FN=44, TN=346). All metrics on out-of-sample predictions only. 540 OOS predictions

Fold	Test years	r(log)	AUC	Bias	HSS	HR	FAR
1	2009–2011	0.783	0.921	−29.2%	0.719	0.71	0.03
2	2010–2012	0.782	0.929	+27.2%	0.526	0.67	0.06
3	2011–2013	0.842	0.936	−28.4%	0.321	0.29	0.03
4	2012–2014	0.693	0.847	−48.2%	0.000	0.00	0.00
5	2013–2015	0.611	0.763	−47.0%	0.158	0.11	0.00
6	2014–2016	0.553	0.665	+5.0%	0.204	0.40	0.16
7	2015–2017	0.816	0.793	+30.7%	0.331	0.71	0.28
8	2016–2018	0.868	0.856	+35.6%	0.333	1.00	0.40
9	2017–2019	0.904	0.873	+11.1%	0.644	0.91	0.20
10	2018–2020	0.889	0.980	+5.9%	0.771	1.00	0.10
11	2019–2021	0.874	1.000	+0.6%	1.000	1.00	0.00

12	**2020–2022**	**0.881**	**1.000**	**+5.6%**	**1.000**	**1.00**	**0.00**
13	**2021–2023**	**0.875**	**0.978**	**−31.8%**	**0.824**	**0.80**	**0.00**
14	**2022–2024**	**0.897**	**0.984**	**−35.2%**	**0.636**	**0.78**	**0.00**
15	**2023–2025**	**0.868**	**0.969**	**−30.6%**	**0.491**	**0.81**	**0.00**
Pooled	**2009–2025**	**0.839 (0.809 - 0.864)**	**0.899 (0.869 - 0.925)**	**−18.5%**	**0.631 (0.556 - 0.701)**	**0.72**	**0.10**

Below we present a single fold attribution analysis for the final validation period (2023- 2025)

(Table 3) intended to illustrate relative component contributions rather than statistical variability.

Table 2.3 PROA Skill Attribution (final CV fold: train 2013–2022, test 2023–2025)

SNR = $R^2/(1-R^2)$. All metrics computed on the test period 2023–2025 (36 months). PROA-Monitor requires confirmed prior-month case data and is not a forward forecast.

Layer	r(log)	R^2	SNR	Bias	RMSE	Note
PROA-Climate	0.769	0.591	1.45	−85.1%	2037	FRD lags 1–3 only
PROA-Forecast (no ampl.)	0.760	0.578	1.37	−79.9%	1939	+ Novelty N(t)
PROA-Forecast (with ampl.)	**0.905**	**0.818**	**4.51**	**−34.3%**	**888**	**◄ primary**

PROA-Monitor	0.905	0.820	4.55	−34.4%	888	+ AR (1) ε(t−1)

For the 2023-2025 test fold, the amplification layer produced the largest single skill gain in the attribution analysis ($\Delta r = +0.145$, from 0.760 to 0.905; R^2 from 0.578 to 0.818; SNR from 1.37 to 4.51). This result establishes transmission momentum which is captured by lagged case trajectories and seasonal harmonics as the dominant within-season predictor once an epidemic is underway. The amplification layer's bias reduction (from −79.9% to −34.3%) is equally substantial, demonstrating that the climate-novelty foundation systematically underestimates outbreak scale in the absence of momentum correction. PROA-Monitor achieved marginal additional improvement under batch evaluation ($\Delta r < 0.001$, Δbias = −0.1 pp), consistent with the known limitation of batch CV for evaluating AR (1) corrections: sequential residual updating (the mechanism through which PROA-Monitor operates) cannot be fully replicated in a retrospective framework.

The skill decomposition reveals a two-regime structure in PROA's architecture. Before an outbreak begins, the climate signal and novelty index provide the only available advance warning and their combination explains $R^2 = 0.578$ of outcome variance. Once an outbreak is underway, transmission momentum dominates, and the amplification layer lifts explained variance to $R^2 = 0.818$. These two regimes are temporally complementary across the operational planning cycle: climate and novelty drive the pre-season budget signal Q1–Q2, while amplification drives the in-season reallocation signal expected to see in Q2–Q4.

2.3.4 Q1 2026 Prospective Forecast

PROA was applied prospectively to Q1 2026 with the operational model trained on the full 1999–2025 record (312 months, φ = 0.897, N(2026) = 0.200). January 2026 lags used CPC observed FRD (December 2025: FRD = 20.0 days, z = +2.43). February and March 2026 lags incorporated C3S SEAS5.1 ensemble FRD estimates (January 2026: 11.2 ± 2.3 days from 51 members; February 2026: 8.5 ± 1.9 days; March 2026: 7.3 ± 1.6 days). Results are presented as a test of the operational pipeline rather than as a primary validation result (Table 4).

Table 4. Q1 2026 Prospective Forecast with Model Layer Decomposition

*Jan 2026 forcing: CPC observed. Feb–Mar 2026 forcing: C3S SEAS5.1 system 51, 51-member ensemble, November 2025 initialization. Actual cases from PAHO Q1 2026 epidemiological updates. Bias(F) = forecast bias; Bias(M) = monitor bias. PI calibrated from CV residuals (σ_PLS = 0.626, σ_amp = 0.590). *March = wks 9–11 confirmed + wk12 imputed ~146 cases. Source: MINSA weekly bulletins. All actual values fell within the 90% prediction interval.*

Month	Climate	+Novelty	+Ampl	+Monitor	Actual	Bias(F)	Bias(M)	90% PI
Jan 2026	46	53	212	250	637	−66.7%	−60.7%	[51–857]
Feb 2026	43	50	160	186	595	−73.1%	−68.8%	[37–665]
Mar 2026	38	44	180	215	584	−69.2%	−63.2%	[44–770]
Q1 Total	**127**	**147**	**552**	**651**	**1816**	−69.6%	−64.2%	—

2.3.5 Three-Tier Budget Planning Framework

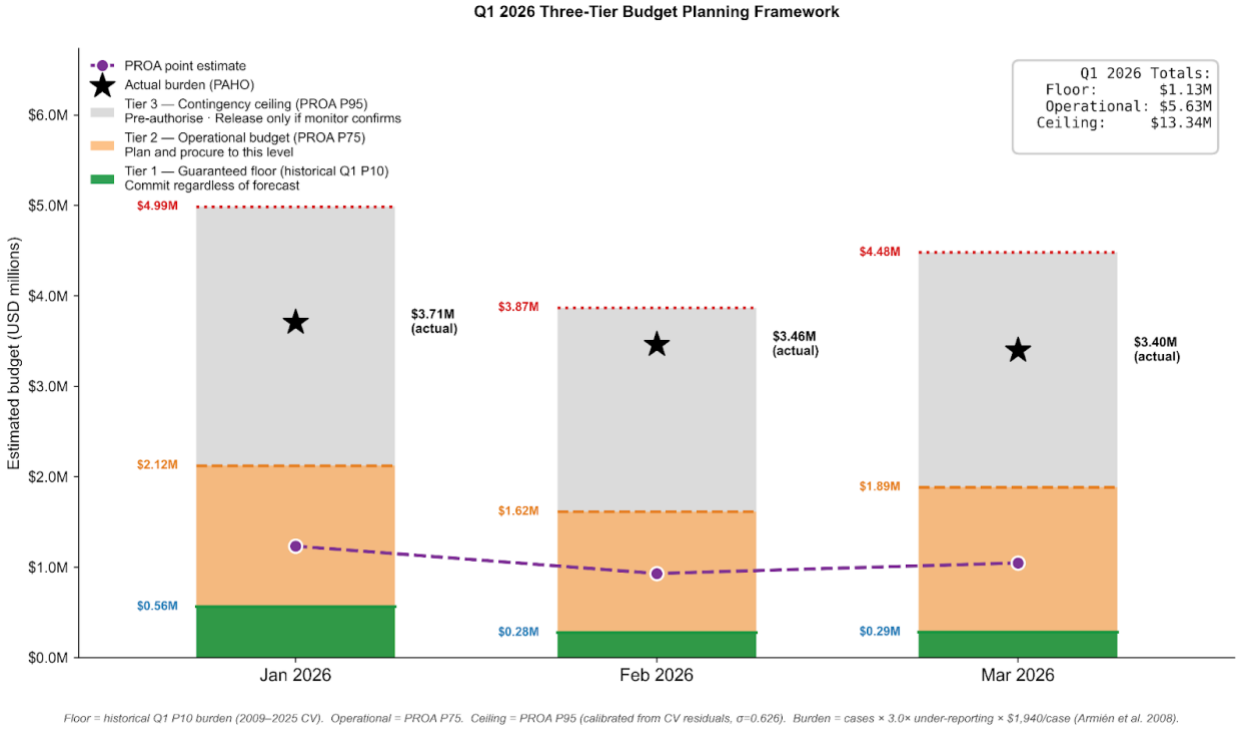

Figure 2.6. Q1 2026 Three-Tier Budget Planning Framework. Panel A: monthly forecast with model layer decomposition (climate, novelty, amplification, monitor) and actual cases (★). Panel B: risk tier probabilities with 90% PI by month. Panel C: national budget tiers (floor $3.39M (historic), operational $5.63M, contingency $13.34M) with actual Q1 burden ($10.57M) indicated. Panel D: provincial allocation with forecast and P95 contingency scenarios.

The Q1 2026-point estimates show a forecast bias of −69.6% (651 forecast vs 1,816 actual cases) (Table 4). The hypothesized mechanisms driving this underprediction are detailed in Section 4.2. Despite the point estimate shortfall, the empirically calibrated 90% prediction interval captured actual monthly cases in 3 of 3 forecast months, and the Q1 total actual burden ($10.57M) fell within the quarterly budget envelope ($0.76–$13.34M), representing 79% utilization of the pre-authorized contingency ceiling (Figure 6)The three-tier budget framework derived from PROA's

Q1 2026 probabilistic output yielded: Tier 1 (guaranteed floor) = $3.39M (historical Q1 P10 from 2009–2025 CV record, committed regardless of forecast); Tier 2 (operational target) = $5.63M (PROA P75, primary procurement driver); Tier 3 (contingency ceiling) = $13.34M (PROA P95, pre-authorized). The Q1 2026 actual burden of $10.57M represents 79% utilization of the contingency ceiling, demonstrating that a MOH operating under this framework would have had sufficient pre-authorized resources to cover the actual Q1 demand, contingent on timely release of the contingency reserve upon AR (1) monitor confirmation of January 2026 escalation (ε_{Jan} = +1.427 log-scale). Crucially, this result would have been operationally sufficient without requiring an ad hoc emergency budget process mid-quarter — the primary operational value of the forecast envelope.

2.3.6 Provincial DVI Allocation

The DVI equity weighting redistributed Q1 2026 resources substantially toward structurally underserved provinces and comarcas (Table 5). Panama province, accounting for 66.1% of recent case burden, received 39.6% of the DVI-adjusted allocation — a reduction of $0.967M relative to a cases-only baseline. Ngöbe-Buglé comarca (DVI = 0.922, 0.5% case share) received $0.362M — an increase of +1,748% relative to the cases-only baseline, reflecting its low piped water coverage and high SGVI vulnerability score. Emberá-Wounaan (DVI = 0.905, 0.0% recorded case share) received $0.344M entirely through the DVI equity channel, an allocation that correctly identifies this comarca's structural vulnerability despite surveillance gaps that suppress its reported case count.

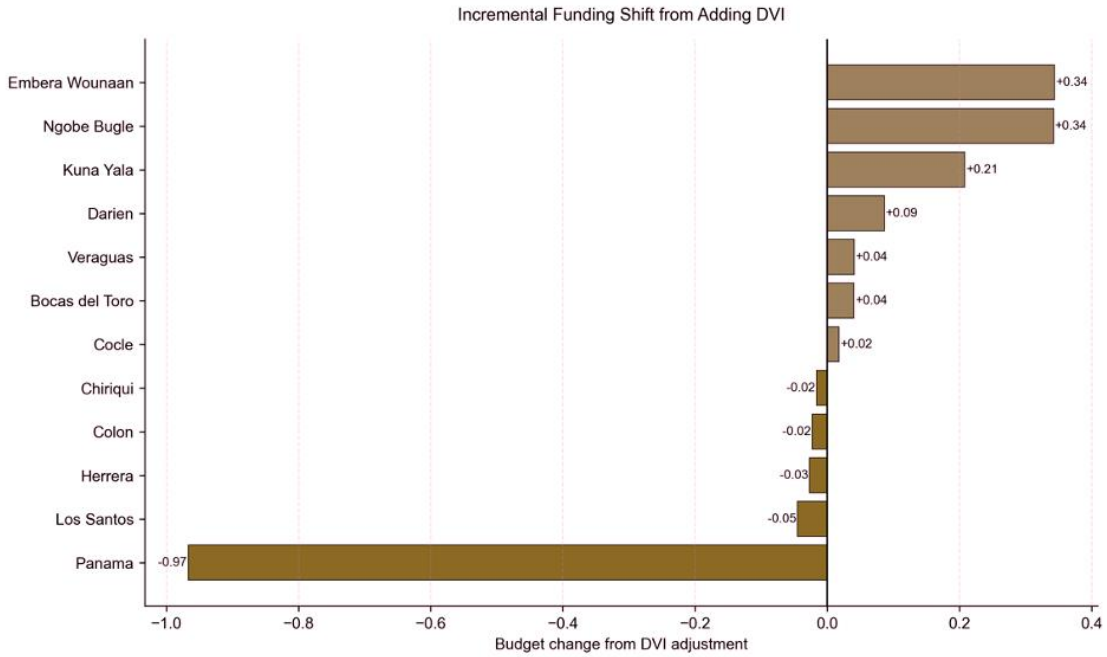

Figure 2.7. Provincial budget redistribution under DVI adjustment, Q1 2026. Bars show the change in allocated budget (USD millions) relative to a cases-only baseline. Green bars indicate provinces and comarcas receiving additional resources through the DVI equity channel; red bars indicate provinces where allocation is reduced relative to their case-count share. Panama province accounts for 66% of reported cases but absorbs the largest reduction (−$0.97M), while structurally vulnerable comarcas with low or zero reported case counts (Emberá Wounaan, Ngöbe Buglé, and Guna Yala) receive the largest proportional increases

Table 2.5 Provincial DVI Budget Allocation, Q1 2026 *DVI = 0.5 × norm(SGVI) + 0.5 × norm(1 − piped water coverage). Allocation = 60% cases share + 40% DVI share. Baseline = cases-only allocation. Provincial ranking is stable across the full budget envelope (floor $3.39M to P95 ceiling $13.34M). Large percentage increases in low-case provinces reflect small baseline allocations and should be interpreted alongside absolute changes.*

Province	DVI	Cases share	Baseline ($M)	DVI-adj ($M)	Δ ($M)	Δ (%)
Panama	0.000	66.1%	$2.417	$1.450	−0.967	−40.0%
Ngobe Bugle	0.922	0.5%	$0.020	$0.362	+0.342	+1,748%
Embera Wounaan	0.905	0.0%	$0.000	$0.344	+0.344	—
Bocas del Toro	0.297	4.9%	$0.181	$0.221	+0.040	+22.2%

Kuna Yala	0.552	0.1%	$0.004	$0.212	+0.208	+5,356%
Darien	0.350	3.2%	$0.116	$0.203	+0.086	+74.2%
Veraguas	0.275	4.4%	$0.160	$0.200	+0.040	+25.3%
Chiriqui	0.157	5.2%	$0.191	$0.174	−0.016	−8.6%
Los Santos	0.081	5.2%	$0.189	$0.144	−0.045	−23.8%
Cocle	0.158	2.9%	$0.106	$0.124	+0.018	+16.6%
Herrera	0.082	3.9%	$0.144	$0.118	−0.027	−18.5%
Colon	0.078	3.6%	$0.131	$0.108	−0.023	−17.6%
National total			**$3.659M**	**$3.659M**	—	—

2.4 Discussion

2.4.1 A Framework for Climate-to-Budget Forecasting

PROA demonstrates that a parsimonious, operationally interpretable hybrid statistical-mechanistic framework can achieve strong out-of-sample skill for dengue prediction at national scale. With a pooled AUC of 0.899 (95% CI: 0.869 - 0.925) across 540 out-of-sample predictions and r(log) = 0.839 (95% CI 0.808 - 0.864) spanning 15 years of varied epidemic conditions, PROA performs

well in its epidemic detection, using only rainy-day frequency lag 1-3 and two epidemiological inputs. This set up is not incidental; it is a design choice motivated by the end-user context (32). We wanted to produce a system with the Ministry of Health that was transparent enough to audit, simple enough to retrain annually, and robust enough to generalize across epidemic regimes that differ from those in the training record.

The skill attribution analysis reveals an insight that carries implications beyond PROA. The amplification layer which uses lagged case counts and seasonal harmonics rather than climate data contributes the largest single gain in the decomposition ($\Delta r = +0.145$ over the climate-novelty baseline). This finding does not diminish the role of climate: the climate signal provides the only forward-looking component in the model, and it is the source of the 1–3-month lead time that gives PROA its operational value. But it establishes that once an outbreak is underway, transmission momentum is the dominant near-term predictor. For the design of climate services for health, this suggests a two-stage architecture is generally appropriate: a climate-driven early warning signal for advance planning, followed by an epidemiological momentum layer for in-season tracking. PROA-Forecast and PROA-Monitor implement exactly this structure.

The finding that FRD rainfall frequency rather than total precipitation volume outperforms all multi-variable alternatives is consistent with the mechanistic biology of *Ae. aegypti*. What matters for larval breeding is not how much rain falls in a storm but how many days of standing water result. A single intense rainfall event creates less persistent habitat than multiple days of moderate

rainfall at the same total volume. FRD captures this threshold-exceedance structure directly; PR does not. This result supports a growing body of evidence in the climate-health literature that physically motivated, biologically interpretable predictors may outperform data-driven variable selection at the national scale when training records are moderate in length.

The co-production methodology underlying PROA's development produced design choices that would not have emerged from a data-driven process alone. The two-product architecture (Forecast and Monitor), the quarterly budget framework, the three-tier commitment structure, and the DVI equity weighting all originated from the participatory workshops and causal loop diagramming rather than from statistical optimization. This illustrates the central argument for transdisciplinary co-production in climate services: that the gap between technically sophisticated forecast outputs and operationally useful decision support is fundamentally a design gap, not just a technical one (21,24,25).

2.4.2 Boundary Conditions and Failure Modes

PROA's reduced skill in four folds (4, 5, 14, 15) and its substantial point-estimate bias in Q1 2026 are consistent with the literature that dengue is oftentimes harder to forecast and can produce worse predictive performance for high incidence seasons(33). We hypothesize four mechanisms that may contribute to the Q1 2026 underprediction, each addressable through targeted enhancements:

ENSO-transmission decoupling. Folds 4–5 (test 2012–2015) and folds 14–15 (test 2022–2025) share a common mechanism: strong El Niño events (ONI = +2.3 in 2015; ONI ≥ +1.5 in 2023–2024) which suppress Pacific-slope rainfall in Panama, driving FRD lags low and pulling the climate forecast downward. When serotype dynamics simultaneously sustain transmission above what the rainfall signal would predict (which occurred during both periods) the model correctly reads the climate but cannot compensate for the suspected immunity-driven transmission that decouples from it. Future research could explore incorporating the ENSO Oceanic Niño Index (ONI) in relation to other large scale teleconnections to adjust how rainfall signals are used during El Nino or La Nina years (34). This perhaps would better reflect the non-stationary nature of the system and adjust for the changes over time that the model would need to stay accurate. The PROA architecture can accommodate this extension without structural change.

Novelty index limitation. The five-year window causes the index to drop quickly when a serotype returns even though the large susceptible population built up over many years would not disappear after one outbreak. N(2026) = 0.200 reflects recent serotype activity without capturing the age-cohort susceptibility gaps created by three consecutive epidemic years of different magnitudes. A susceptible pool depletion model tracking $S(t) = S(t-1) - \text{cases}(t)/\text{population}$ by serotype would perhaps more accurately represent ongoing vulnerability and is a priority enhancement for PROA v2 (35). Serotype circulation and susceptibility were one of the reported key factors in Panama

dengue dynamics during the systems mapping exercise. This update would be technically feasible within the existing modelling framework.

Amplification layer regime extrapolation. The amplification layer's correction factors were calibrated to outbreak magnitudes present in the 1999–2025 training record. The 2023–2026 four-consecutive-quarter epidemic including the historically unprecedented persistence of transmission through Panama's dry season in Q1 2026 has no training analogue. The model correctly identified declining momentum (the Q1 2026 forecast is appropriately lower than Q4 2025) but could not extrapolate amplification factors to the scale required. This seems to be a training-data boundary condition; future renditions should retrain the models with 2023–2026 data which may improve calibration for similar future events.

Dry-season outbreak persistence. Q1 2026 (January–March) is Panama's climatological dry season, with mean FRD of 5–8 days per month. The model correctly identified low rainfall and forecast low-to-moderate cases. However, the actual Q1 2026 outbreak persisted at levels well above any historical Q1 in the 1999–2025 record hypothesized to be driven by serotype dynamics sustaining transmission independently of vector breeding conditions. This failure mode is specific to sustained multi-year epidemics entering their fourth consecutive quarter: a boundary condition that had never occurred in the training data. The three-tier budget framework which would have pre-authorized $13.34M against an actual burden of $10.57M demonstrates that the probabilistic

uncertainty envelope could successfully contain this unprecedented scenario even when the point estimate could not.

2.4.3 The Operational Value of Probabilistic Budget Envelopes

A central finding of this study is that probabilistic budget envelopes provide operational value even when point estimates are substantially biased. The Q1 2026 total actual burden of $10.57M fell within PROA's ensemble budget interval ($1.13M–$13.34M) and represented 79% utilization of the pre-authorized P95 contingency ceiling. The calibrated bootstrap uncertainty derived from the observed distribution of CV residuals ($\sigma_PLS = 0.626$, $\sigma_amp = 0.590$) rather than arbitrary noise parameters is essential to this result. Prior hardcoded intervals ($\sigma = 0.15, 0.05$) failed to capture any of the three Q1 2026 months. Empirical calibration from CV residuals ensures that the uncertainty intervals reflect the actual out-of-sample forecast error distribution, including both parameter uncertainty and structural uncertainty from regime shifts and serotype dynamics. Empirical calibration from CV residuals ($\sigma_PLS = 0.625$, $\sigma_amp = 0.590$) achieves 3/3 PI coverage.

This result argues for a fundamental reorientation in how dengue forecast systems are evaluated. Point forecast bias penalizes systems for systematic underprediction without crediting the uncertainty interval's coverage of actual outcomes. For budget planning, coverage of the actual

requirement by the pre-authorized envelope is the operationally relevant criterion, not point forecast accuracy. Additionally, it is important to discuss the theory of decision maker "paralysis". Forecasts that include wide uncertainty envelopes may not be considered particularly useful to decision makers when concrete action is needed immediately. Forecasters must be able to communicate the uncertainty without stalling the decision-making process.

The three-tier framework makes this argument concrete. A MINSA finance office operating under the framework would have committed $3.39M as a guaranteed floor (always sufficient for non-epidemic Q1 conditions), planned procurement to $5.631M (the P75 operational target), and pre-authorized $13.34M as a contingency ceiling. The actual Q1 2026 burden of $10.57M would have been covered by the pre-authorized ceiling without requiring emergency budget processes or ad hoc authorization. This is precisely how the operational scenario framework is designed to prevent decision fatigue. This finding is robust and demonstrates that planning for probabilistic uncertainty quantification is one way to design climate services intended for health budget planning.

2.4.4 The DVI Allocation and Health Equity

The DVI equity weighting makes explicit that only including case-counts for resource allocation is introduced bias and systematically introduces provinces with the worst surveillance and structural capacity to receive the least resources. Oftentimes, low reported counts are

misinterpreted as low burden rather than low detection; the DVI was added to reduce this misrepresentation. Emberá-Wounaan's allocation of $0.344M entirely through the DVI equity channel (with zero recorded recent cases) directly addresses this structural inequity. Ngöbe-Buglé's 1,748% increase relative to the cases-only baseline reflects genuine structural vulnerability (DVI = 0.922) that surveillance data alone cannot reveal.

The stability of provincial rankings across the full budget envelope (floor $3.39M to P95 ceiling $13.34M) is an important property for institutional adoption. If relative allocation changed substantially with the budget level, provincial directors would face unstable planning signals. The stability result which follows directly from the fixed provincial shares applied to a variable national total means that PROA provides a consistent equity signal regardless of whether the national forecast triggers a conservative or contingency-level response.

The allocation is a disaggregation rather than a separate provincial forecast and should be used accordingly. The assumption that outbreak burden distributes proportionally to structural vulnerability may not hold during a highly localized epidemic concentrated in one province. The path to true provincial forecasting hierarchical models that borrow statistical strength across provinces, similar to the approach of Fletcher (36), requires approximately 10 years of consistent monthly reporting per province, currently feasible for Panama City, Colón, and Chiriquí. This is another area of research designated for the next phase of PROA's development. Furthermore, a limitation is the updating of social vulnerability data which is usually compiled during census

years. This could lead to issues in structural vulnerability determination as some areas in Panama have undergone rapid development over the last 10 years and will continue to do so in the future. More research is needed to understand how to better incorporate vulnerability, which plays a major role in dengue risk, control and prevention.

2.4.5 Limitations

Several limitations constrain the current version of PROA. First, we build the economic burden using literature-derived unit costs from a 2008 study adjusted by Consumer Price Index (CPI); the current cost structure may differ following changes in administration, protocols and overall health system costs. Institutional budget data from MINSA were requested but not available for validation. Second, the amplification layer uses a fixed linear model fit to the full training period; a time-varying or regime-switching formulation may better capture the transition between inter-epidemic and sustained epidemic states. Third, the system currently operates at national scale and disaggregates to provinces via the DVI method; it does not yet produce province-specific forecasts with independent uncertainty characterization. This data also comes from the GDL though Panama census data which is only performed every 10 years.

The economic burden estimates rely on literature - derived unit costs from a single 2008 study adjusted by Consumer Price Index to 2024 USD. The current cost structure may differ substantially

as health system protocols and operations have evolved over the last ~20 years. Institutional budget expenditures were requested from MINSA but were not made available for validation purposes. Thus, PROAs budget figures cannot be verified against the actual Ministry expenditures. This is an acknowledged gap and is the top priority for PROA version 2.0. As the models improve, the financial data must be secured to validate the system before use in any operational matter.

The amplification layer uses a fixed linear model fit from 1999 to 2025. A time varying formulation may help to better capture transition between inter-epidemic and sustained epidemic periods (i.e., 2023-2025). Similarly, the 5 year look back window of serotype novelty index N(t) may not capture susceptibility built up over prolonged absence. When a new strand enters the population after over 10 years of absence, the index will underestimate population-level naivety because it does not track age-cohort immunity. Thus, a susceptible pool depletion model is proposed as an enhancement for PROA 2.0. The serotype novelty index currently depends on annual PAHO data surveillance which has a lag anywhere from 3-15 months. During times of rapid serotype change this lag could create delays in representation of the true population immunological state. We propose a formal data sharing agreement to provide near-real time serotype data sharing from El Instituto Memorial Gorgas as another top priority for PROA 2.0.

The social vulnerability component of the DVI is derived from the Global Data Lab which in part receives its data from the Panama Census. The census is updated on a 10-year cycle. Provinces that have undergone rapid urbanization and built-up infrastructure (i.e., new housing

developments, hospitals, roads etc.) may not be accounted for or mischaracterized. This is a limitation as directing resources towards areas whose vulnerability has changed could lead to inaccurate distribution of resources.

Lastly, rainy day frequency from Q1 February and March 2026 was derived from SEAS5.1 precipitation via a PR-FRD regression (R2= 0.867). This conversion adds an additional source of uncertainty that is not explicitly propagated into prediction intervals, meaning forecast uncertainty for SEAS5.1 forced months may be slightly underestimated.

2.4.6 Implications for Climate Services Design

PROA illustrates both the potential and the many challenges of operational climate services for health. The system achieves demonstrated skill across 15 years of out-of-sample validation, provides a probabilistic budget envelope that contains the Q1 2026 actual burden, and delivers a provincial allocation framework with an explicit equity mechanism.

At the same time, the Q1 2026 boundary condition demonstrates that even a well-designed climate service reaches the limits of its predictive utility when the epidemiological system transitions outside its training distribution. The annual amplification refit is a key mechanism for progressive system improvement. As the 2023–2025 epidemic data accumulates in the training record,

correction factors will recalibrate toward the larger-scale outbreak dynamics that characterized this period without requiring structural model changes.

The characterization of PROA's failure modes and proposed enhancement pathways for each, is presented as an integral scientific contribution alongside the skill metrics. A climate service that is honest about what it cannot do, and provides a clear roadmap for extending its capabilities, is more likely to achieve sustained institutional adoption than one that overstates its current performance. Partnerships rooted in trust and transparency are ultimately more successful. The process of co-production can be messy and challenging but to build sustainable climate services for health it is a must. Using a transdisciplinary approach is not a one-time design exercise but a continuous cycle of co-production. PROA future research must include forecast performance evaluated against actual outcomes, model limitations documented transparently, and system enhancements prioritized based on the decision contexts where failures have the greatest operational consequence. PROA's documentation of the Q1 2026 boundary condition, its causes, its magnitude, and the specific enhancements that would address it is as important to this cycle as the CV skill metrics.

2.4.7 Next steps and future research

The next generation of model development should target PROA's two proposed failure modes before operational deployment is attempted. For ENSO-serotype decoupling, testing the Oceanic

Niño Index as a conditioning predictor can be evaluated within the existing 15-fold CV framework by comparing pooled AUC and per-fold bias with and without the ONI term, with particular attention to folds 4, 5, 14, and 15 where we suspect decoupling identified. For the novelty index limitation, a susceptible pool depletion model tracking S(t) by serotype can be run in parallel with the current N(t) formulation and compared on out-of-sample skill during serotype re-entry years (2023 being the strongest available test case). A prospective evaluation of Q2–Q4 2026 using the same operational pipeline applied to Q1 will provide the first genuinely multi-quarter prospective test of PROA under live conditions, including the first wet-season forecast produced with full SEAS5.1 integration and the first opportunity to observe whether the model's wet-season skill (which the CV record confirms is strong) translates under operational conditions. These model improvements represent the minimum necessary foundation before institutional deployment is discussed.

Transitioning the improved system toward operational status requires substantial work that goes beyond model performance, and it is important to be explicit about what that entails. The system as presented is a validated research prototype and it has demonstrated skill under historical and prospective test conditions, but it has not yet been embedded in an institutional workflow, stress-tested under live operational conditions, or evaluated for its effect on actual budget decisions. Critical steps toward operationalization include establishing a formal data agreement with MINSA for timely access to monthly surveillance data, stabilizing and automating the C3S

SEAS5.1 climate data pipeline so that seasonal forecast inputs are ingested without manual intervention, and developing a clear decision protocol specifying when PROA output is produced, who reviews it, what evidence threshold triggers a tier escalation, and how the contingency release mechanism is activated. Alongside these technical requirements, capacity development within MINSA is essential. Training for epidemiologists and budget officers to ensure that probabilistic outputs are correctly interpreted, that the P95 ceiling is understood as a pre-authorization target rather than an expected cost, and that tier escalation should trigger procurement action rather than a wait-and-see posture are all areas for focus. The development of a decision-support interface, one that makes the complete forecast output accessible to MINSA health economists, provincial directors, and PAHO regional advisors through a shared dashboard updated monthly, is a further priority, with the design of that interface itself requiring co-production to ensure that uncertainty is communicated in ways that support rather than complicate planning decisions. These institutional steps are as consequential as the model enhancements, and none of them can be completed without sustained engagement with MINSA and PAHO beyond what was possible within this study.

Looking further ahead, two research directions would substantially strengthen the evidence base for PROA's formal adoption. The first is the application and testing of the monitoring and evaluation framework developed to assess operational climate services for health in this context, which is currently in preparation for publication (Diaz et al., in preparation). That framework

will track not only forecast accuracy but decision uptake, whether PROA's tier signals are acted upon, whether the contingency mechanism is used, and whether resource allocation shifts in the direction the DVI weighting recommends, providing the behavioral evidence that forecast skill alone cannot supply. The second is a formal return-on-investment analysis quantifying the economic value of the advance warning signal: the difference between what a Ministry of Health operating under the three-tier framework would have spent and what it would have spent under reactive response, across the historical CV record. The data required for this analysis is PROA's retrospective budget envelope for each CV year and a literature-derived reactive cost premium are available and the methodology is tractable, but the analysis was not possible within this study because institutional expenditure data from MINSA could not be obtained. Securing access to those records or identifying a proxy measure of reactive response cost from PAHO regional reports, is a priority for the next co-production phase and would provide the economic evidence needed to support PROA's adoption within Panama's national dengue response framework.

2.5 Conclusions

PROA is amongst the first climate-to-budget dengue forecasting and resource allocation system co-produced with Panama's Ministry of Health and PAHO. It demonstrates that a parsimonious, operationally interpretable framework can achieve strong and consistent out-of-sample epidemic

detection skill. The amplification layer is identified as the dominant contributor to skill during active outbreak periods, establishing transmission momentum as the critical complement to climate forcing in dengue forecasting. A probabilistic three-tier budget framework derived from PROA's uncertainty envelope contained the unprecedented Q1 2026 actual burden within its pre-authorized contingency ceiling at 79% utilization. While point-estimate bias remains a documented limitation during multi-year epidemic conditions, the calibrated uncertainty envelope demonstrates that probabilistic uncertainty quantification is the better design criterion for climate services intended for budget planning. The DVI provincial allocation method provides a structurally grounded equity mechanism that correctly identifies surveillance-deficient provinces as resource priorities. PROA's documented boundary conditions provide a specific and technically grounded enhancement roadmap for PROA v2. This study establishes a replicable co-produced framework for climate-to-budget health planning that can be adapted to dengue-endemic countries across Latin America and the Caribbean.

2.6 Supplementary

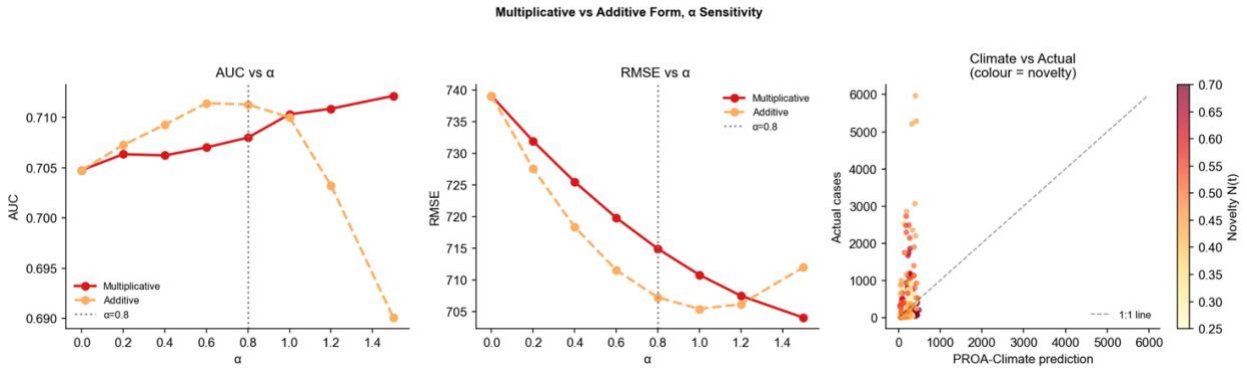

Figure S1 (Supplementary). Alpha coefficient sweep. AUC and RMSE as a function of novelty scaling coefficient α ∈ {0.0, 0.2, ..., 1.5} for multiplicative and additive novelty formulations, evaluated under 15-fold walk-forward CV.

Interlude: Chapter 2 → Chapter 3

Chapter 2 demonstrated how climate-informed forecasting systems can be structured to align with decision-making needs, producing outputs that translate environmental conditions into anticipated disease burden and associated resource requirements. In doing so, it incorporated probabilistic climate information directly into the modelling framework, ensuring that uncertainty is retained as an inherent feature of the system.

However, the development process also revealed that embedding uncertainty within model outputs does not, on its own, ensure that it can be effectively interpreted or acted upon. During engagement with decision-makers, it became clear that the way uncertainty was presented influenced not only understanding, but willingness to act. This insight, which emerged directly from the application of the forecasting system, motivates the focus of Chapter 3. Building on the outputs and user interactions from Chapter 2, it examines how uncertainty can be structured and communicated in ways that support interpretation and decision-making in practice.

Chapter 3: From Ensemble to Action: Communicating Forecast Uncertainty Across the Climate-to-Health Chain

This first-author work is in prep to be submitted.

3.1 Introduction

Seasonal climate forecasts have demonstrated skill for a range of climate-sensitive health outcomes, and the scientific case for climate-informed health early warning has strengthened considerably over the past two decades [1], [2], [3]. Despite this progress, a substantial proportion of climate services developed for health applications remain in the academic literature rather than reaching operational use within health systems[4], [5], [6]. The reasons are multiple and well-documented: limited institutional capacity within health ministries to run and maintain forecast systems, weak cross-sectoral linkages between climate and health agencies, absence of formal mandates, inadequate funding for sustained operation, tools built without sufficient engagement with end users, and translating model outputs into interpretable alerts that decision makers can use to take action [7] [8]. This paper focuses on the last challenge: translating model outputs into action by focusing on what usually makes it challenging to do so– communicating and interpreting forecast uncertainty.

Probabilistic forecast outputs (i.e., ensemble spread, exceedance probabilities, prediction intervals) are standard and important tools in forecast verification and appropriate for technically trained audiences. Health decision-makers, however, operate within fixed procurement cycles, budget authorization structures, and administrative accountability requirements that demand concrete commitments: whether to pre-position supplies, how much to budget for a coming quarter, when to escalate a response [9]. Bridging this gap requires understanding how

uncertainty accumulates across the full climate-to-health forecast chain and designing outputs whose format reflects the decision being made, not only the forecast being issued [10].

This paper addresses that challenge for vector-borne disease applications, where the scientific evidence base for seasonal forecast skill is strongest and the diversity of operational experience is richest. We trace how uncertainty accumulates across the climate-to-health forecast chain (Figure 1), identify where within the chain the dominant uncertainty sources tend to lie and why this matters for communication design, and illustrate these principles through a dengue budget forecasting framework co-produced with Panama's Ministry of Health. A full description of that system, PROA (Díaz et al. In prep.), is presented as a worked illustration in Box 1; this paper focuses on the uncertainty communication challenge and the design principles that follow from it. Here, we discuss the mismatch between how forecast uncertainty is expressed and what health institutions need to make decisions [11]. This paper draws on targeted literature across climate science, public health, and decision science, combined with insights from the development of a climate-driven dengue budget forecasting system.

3.2 Uncertainty Across the Climate-to-Health Forecast Chain

3.2.1 The chain and where uncertainty enters

The climate-to-health forecast chain spans five steps: climate model → climate variable extraction → epidemiological translation → health output → institutional decision. Uncertainty compounds at each step, and the total uncertainty reaching the decision layer reflects contributions from all preceding steps. Identifying which step contributes most to total forecast or implementation error in a given application is a prerequisite for both improving the system

and communicating its limitations honestly to health partners [12]. This dominant source is not fixed, it varies by geographic setting, disease ecology, and forecast lead time, and failing to identify it can lead forecast developers to optimize the wrong layer while the actual bottleneck remains unaddressed.

3.2.2 Climate model uncertainty

Structural uncertainty across Global Climate Models (GCMs) in tropical precipitation arises from differences in how models represent convection, land-surface feedbacks, and large-scale circulation responses to SST forcing [13], [14]. Major operational seasonal forecast systems , including ECMWF's Copernicus Climate Change Service (C3S), the North American Multi-Model Ensemble (NMME), the UK Met Office GloSea system, and the Australian Bureau of Meteorology's ACCESS-S show divergence in regional precipitation skill that is particularly marked in the tropics and subtropics where the vector-borne disease burden is highest [15], [16], [17], [18]. Multi-model ensembles partially reduce this structural uncertainty by pooling across systems, and comparative assessments have shown multi-model approaches to outperform individual GCMs for health-relevant climate variables in several tropical settings [19].

Forecast skill at seasonal lead times is shaped by multiple large-scale modes of climate variability. Beyond ENSO (which provides the strongest and most widely exploited source of seasonal predictability in many tropical regions [20], [21], [22]) there are many other climate phenomena including but not limited to, the Indian Ocean Dipole, the Madden-Julian Oscillation at sub-seasonal timescales, the Pacific Decadal Oscillation, and the Atlantic Multidecadal Oscillation each contribute to regional precipitation predictability in ways that are geography- and season-dependent [23], [24], [25]. The relative importance of these modes for any given

health application should be assessed empirically; assuming ENSO dominates in all tropical settings risks mischaracterizing the forecast skill available in a particular region.

The temporal structure of skill within the year is directly decision-relevant and is often underreported in health applications [26]. In many tropical and subtropical regions, seasonal transition periods like the wet-season onset are associated with stronger and more reliable forecast skill than dry-season conditions, because wet-season onset is linked to large-scale circulation shifts that current forecast systems capture with meaningful lead times [27] . Health early warning systems whose planning cycles align with these more predictable seasonal windows can exploit stronger climate signals than those requiring prediction during periods of lower atmospheric predictability [28]. This alignment between institutional planning cycles and forecast skill windows has been explicitly recognized as a design principle in operational climate services for health [29].

Statistical downscaling and bias correction introduce further uncertainty and rest on an assumption of stationarity believing that the statistical relationship between large-scale climate drivers and local conditions remains stable over time [30]. Under non-stationary climate conditions driven by long-term climate change, shifting climate regimes, or land use change, this assumption weakens and can potentially introduce systematic errors into health forecast systems that depend on historically derived transfer functions [31]. A statistical model trained on a 20-year historical record may perform well in the training period but degrade as the underlying climate-disease relationship shifts which is a limitation that must be acknowledged in system documentation and communicated honestly to health partners.

Temperature projections across GCMs show lower inter-model spread relative to their forced signal than precipitation projections models and tend to agree more closely on the direction and magnitude of temperature change than on precipitation change at regional scales [13]. For vector-borne disease applications that incorporate temperature suitability components such as the thermal performance curves for *Aedes aegypti* and *Anopheles* mosquitoes this relative consistency in the temperature signal is relevant, though uncertainty in the disease outcome depends on the full chain and not on any single layer [32], [33].

3.2.3 Epidemiological translation uncertainty

The step from climate variable to health outcome introduces uncertainty through model structure, training data length and quality, predictor variable selection and temporal aggregation, and the representativeness of training conditions for future epidemic states [34]. This step is frequently where total forecast error is largest in vector-borne disease applications, yet it receives less systematic attention in climate-health publications than the climate forcing layer [35].

Statistical models trained on historical data extrapolate poorly when epidemic conditions fall outside the training distribution. This in hand is a structural property of data-driven approaches regardless of model complexity [36]. This can be particularly challenging in countries that have limited historical health data to train on. Mechanistic models partially address this by embedding biological structure, but introduce parameter uncertainty and require assumptions about transmission dynamics that may not transfer across settings or time periods [37], [38]. Neither approach eliminates translation uncertainty; both require honest characterization of the conditions under which the model may be limited or fail.

Predictor selection introduces its own uncertainty. For vector-borne disease, published systems have used various predictors, for example total precipitation, sea surface temperature indices, temperature suitability indices , and rainy-day frequency or additive/multiplicative interactions [39], [40], [41]. The choice of climate variable and its temporal aggregation reflects both biological hypotheses about transmission mechanisms and empirical constraints from available data and carries direct implications for how forecast skill can be characterized and communicated to health partners. A system whose skill depends on a predictor with limited forecast lead time in each region should communicate that limitation explicitly rather than reporting overall skill metrics that may obscure it.

In vector-borne disease systems with complex immunological dynamics, i.e., dengue which has ecological and biological factors which can go beyond the reach of the climate model it may be challenging to forecast the magnitude of epidemics. Strain circulation dynamics, population immunity, urbanization trends, and vector control program intensity can each drive case burdens that climate forcing alone cannot fully predict [42]. When these factors like a novel serotype entering circulation (i.e., the historical 2023-2025 massive global dengue outbreaks in Latin America), a large immunologically naive cohort, a major change in vector control coverage, decision-makers should be explicitly informed that the climate-based forecast may systematically under- or overestimate burden, and that the uncertainty interval should be interpreted and explained accordingly.

3.2.4 Decision-context and health output constraints

Health institutions impose structural constraints on whether a forecast signal can reach a decision. Fixed procurement cycles, budget authorization structures, hiring, public outreach

campaigns and administrative reporting requirements determine what form of output is institutionally compatible [43]. A forecast that arrives after the procurement window has closed, or whose outputs require approvals that do not yet exist, provides no operational benefit regardless of its technical quality.

Surveillance data that arrives weeks to months after the events it describes (i.e., serotype reports delayed by months or administrative expenditure records inaccessible for validation) is a form of operational uncertainty that does not appear in standard skill metrics but is frequently consequential for system performance [44]. In several operational dengue early warning systems, the lag between case occurrence and confirmed surveillance reporting has been identified as a greater practical constraint on forecast utility than the quality of the climate forcing [45]. This category of uncertainty should be documented explicitly alongside model-based skill assessments when reporting on operational or near-operational forecast systems.

3.3 Case Study: Designing Uncertainty Communication for Actionable Health Decisions

Box 1: Case Study- Translating Seasonal Climate Forecast Uncertainty into a Health Budget Decision

The system: *PROA* is a climate-driven dengue budget forecasting research prototype co-produced with Panama's Ministry of Health (MINSA), Pan American Health Organization (PAHO), Gorgas Memorial Institute, Alisios Corporation and Columbia University. It translates seasonal rainfall forecasts and disease surveillance into a quarterly budget recommendation for operational health planning.

Forecasting approach: PROA uses a hybrid statistical-mechanistic architecture comprising four nested layers. A Partial Least Squares (PLS) regression on observed rainy-day frequency (FRD) at lags 1–3 months from NOAA CPC provides the climate baseline, with SEAS5.1 51-member ensemble output substituted for months beyond the observed record. A serotype novelty multiplier N(t) scales the climate prediction by population-level immunological susceptibility. A transmission momentum amplification layer using lagged case counts and seasonal harmonics that captures in-season epidemic dynamics. An autoregressive correction module (PROA-Monitor) applies a residual bias correction once confirmed prior-month surveillance data are available.

Where uncertainty dominates: The dominant residual uncertainty in PROA is epidemiological (strain circulation dynamics, population immunity gaps, and a 3–15-month lag in serotype surveillance data) rather than climatological. The transmission momentum amplification layer contributes the largest single skill gain in the system (signal-to-noise ratio: 1.37 → 4.51), using lagged case counts and seasonal harmonics.

Uncertainty metrics and what they show: Validated across 540 out-of-sample monthly predictions using walk-forward cross-validation (2009–2025), PROA-Forecast achieved pooled r(log) = 0.839 (95% CI: 0.809–0.864) and AUC = 0.899 (95% CI: 0.869–0.925) for epidemic threshold detection, with HSS = 0.631 (95% CI: 0.556–0.701), hit rate = 0.72, and false alarm rate = 0.10. The r(log) of 0.839 indicates the system correctly ranks epidemic severity across months with strong consistency; the AUC of 0.899 indicates it correctly identifies epidemic months approximately nine times out of ten; the false alarm rate of 0.10 means only one in ten non-epidemic months triggers a spurious alert. Pooled forecast bias was −18.5%, reflecting systematic underprediction, a known structural limitation documented in full in Díaz et al. (in prep). Prediction intervals are derived from bootstrap resampling of CV residuals: $\sigma_PLS = 0.626$ and $\sigma_amp = 0.590$ on the log scale empirically calibrated, not assumed.

Calibration and its operational consequence: In a prospective Q1 2026 test, the point estimate was 70% below actual cases, driven by an unprecedented dry-season epidemic outside the training distribution. Despite this, all three forecast months fell inside the 90% prediction interval and the actual Q1 burden fell within the pre-authorized budget ceiling. An earlier version using hardcoded intervals failed to capture any of the three months: demonstrating that empirical calibration is operationally decisive, not a refinement. This finding is consistent with established forecast verification principles: a calibrated probabilistic forecast that accurately represents its own uncertainty is more operationally valuable than an overconfident point estimate.

Translating uncertainty into a budget decision: The central communication challenge in PROA is converting a probabilistic forecast distribution, which a health finance office cannot directly act on into pre-authorized spending commitments that map onto Panama's quarterly procurement cycle. This was addressed through a three-tier budget framework derived directly from the empirically calibrated forecast distribution: a guaranteed floor based on the historical Q1 P10 (committed regardless of forecast), an operational target at the PROA P75 (the primary procurement figure), and a contingency ceiling at the PROA P95 (pre-authorized but not committed). The contingency ceiling is released only upon confirmation from PROA-Monitor that observed cases are tracking above forecast converting a wide probabilistic interval into a conditional institutional trigger. This structure means the forecast's uncertainty is not presented to decision-makers as a problem to interpret but as a set of pre-agreed actions: at what point does escalation occur, who authorizes it, and what resources are already in place when it does. The Q1 2026 prospective test demonstrated the operational consequence of this design: despite a point estimate ~70% below actual cases, the pre-authorized ceiling covered the actual burden without requiring an emergency budget process. PROA remains a validated research prototype; its documented failure modes are reported in full in Díaz et al. (in prep).

3.3.1 Diagnose the dominant uncertainty source before designing the output

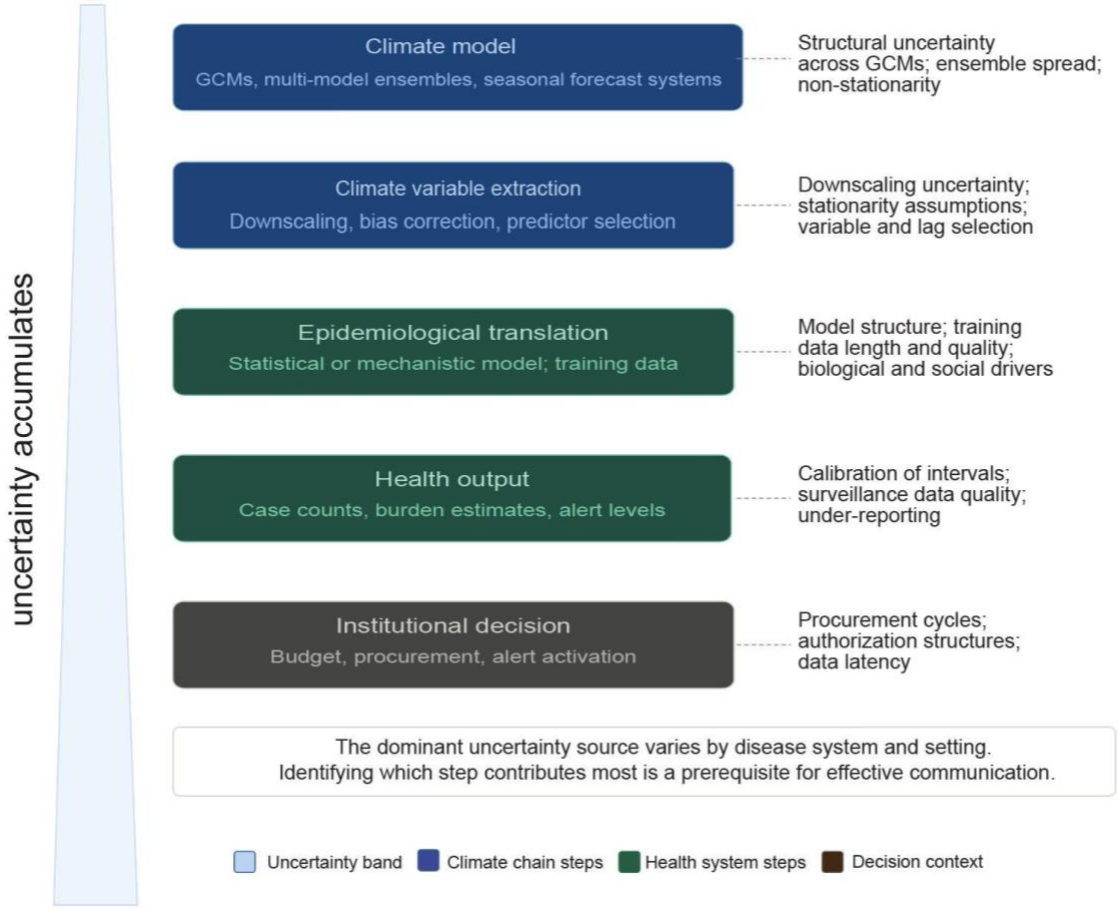

Figure 3.1. Uncertainty across the climate-to-health forecast chain. The chain spans five sequential steps from climate model to institutional decision. Uncertainty compounds at each step, as represented by the expanding band on the left. Annotations describe the dominant sources of uncertainty introduced at each layer: structural divergence across GCMs and ensemble spread at the climate model step; downscaling assumptions and predictor selection at the climate variable extraction step; model structure, training data quality, and biological and social drivers at the epidemiological translation step; calibration of intervals, surveillance quality, and under-reporting at the health output step; and procurement cycles, authorization structures, and data latency at the institutional decision step. Color distinguishes the nature of each step: climate chain steps (navy), health system steps (green), and decision context (dark gray). The dominant uncertainty source varies by disease system and setting — identifying which step contributes most to total forecast error is a prerequisite for effective uncertainty communication and output design.

Before selecting an output format, researchers should locate where uncertainty is largest in the specific forecast chain being developed (Figure 1). A practical diagnostic approach is being able to decompose total out-of-sample forecast error into contributions from the climate model, the epidemiological translation layer, data latency and so forth to reveal which step is driving the

most error and where further effort is most warranted - an example of this is is presented Box 1. This diagnosis should be revisited as systems mature. As surveillance coverage improves, forecast systems are updated, or epidemic dynamics shift, the dominant uncertainty source can change and the communication design should be updated accordingly.

3.3.2 Measure and report uncertainty rigorously — for all audiences

Rigorous uncertainty quantification is a scientific obligation independent of whether the primary audience for any given system is technically trained. It is the foundation on which operationally useful communication is built. Without honest, empirically grounded uncertainty characterization, no output format, however well designed, can deliver reliable decision support.

Here we discuss some core metrics for characterizing forecast uncertainty in climate-health applications which fall into several categories. The first concerns forecast skill: how well does the model perform against observations? From here we will draw on the case study in Box 1, person correlation coefficient measures how well the system ranks months or seasons in order of disease burden; values above 0.7 are generally considered strong for seasonal dengue forecasting [46], [47] . The Area Under the Receiver Operating Characteristic Curve (AUC) measures the system's ability to distinguish epidemic from non-epidemic periods regardless of the threshold chosen; AUC = 0.5 indicates no skill above chance, AUC = 1.0 indicates perfect separation, and values above 0.8 are considered operationally useful for health alert systems [28], [48], [49]. The Heidke Skill Score (HSS) measures categorical forecast performance (the ability to correctly classify periods as epidemic or non-epidemic) adjusted for what chance alone would achieve;

HSS = 0 indicates no skill over random, HSS = 1 indicates perfect skill [50]. Hit rate and false alarm rate together characterize the trade-off between correctly flagging epidemics and generating spurious alerts, a trade-off that health systems must weigh explicitly given the operational costs of both missed warnings and unnecessary mobilizations.

The second category concerns calibration and whether the stated uncertainty accurately reflects the true uncertainty. A 90% prediction interval that covers actual outcomes only 60% of the time is overconfident and will systematically fail health planners who rely on it for example in budget authorization initiatives. Calibration can be assessed through reliability diagrams that compare stated probability to observed frequency, and through coverage diagnostics that report the proportion of actual outcomes falling within stated prediction intervals [51]. These calibration diagnostics are as important as skill metrics for operational systems and should be reported as standard practice.

The third category looks at prediction intervals. Prediction intervals and skill metrics answer different questions and should not be conflated. Skill metrics for example (r(log), AUC, HSS, etc.) summarize how well the model has performed historically against observed outcomes across many predictions. They describe the track record. Prediction intervals describe the forward-looking uncertainty around a specific future forecast: given what this model produces for the next quarter, what is the plausible range of outcomes? In PROA, prediction intervals are constructed by bootstrap resampling (n = 2,000 draws per forecast month) that simultaneously propagates three sources of uncertainty: the spread across seasonal forecast ensemble members for months requiring seasonal climate input, the empirical standard deviation of the PLS model residuals from the cross-validation record ($\sigma_PLS = 0.626$ on the log scale), and the empirical

standard deviation of amplification layer residuals ($\sigma_{amp} = 0.590$ on the log scale). Both σ values are derived directly from 540 out-of-sample predictions rather than assumed which is what makes them calibrated rather than nominal. The resulting intervals are asymmetric on the case count scale because the uncertainty is multiplicative on the log scale: a wide interval does not mean the model is uninformative, it means the model is being honest about the range of plausible outcomes given genuine structural uncertainty in the epidemiological translation layer. Reporting the source decomposition of prediction interval width for example how much comes from climate ensemble spread versus model residual uncertainty versus amplification error, is a practice that should become standard in climate-health forecast publications, because it tells health partners and reviewers where the uncertainty is coming from and therefore which improvements would most reduce it.

For technically trained audiences like climate scientists, epidemiologists, and health system analysts with capacity to engage with probabilistic outputs, full reporting of these metrics provides the evidence base needed to evaluate system performance, identify failure modes, and guide iterative improvement. Communicating what these numbers mean in plain terms is itself a skill worth developing: $r(\log) = 0.84$ tells a technically trained reader that the system ranks epidemic severity correctly about 84% of the time; AUC = 0.90 tells them the system correctly identifies epidemic months nine times out of ten; a bias of −18% tells them the system tends to underpredict, so the lower bound of the budget envelope should not be treated as the most likely outcome. The $\sigma_{PLS} = 0.626$ and $\sigma_{amp} = 0.590$ on the log scale tell them that the model's typical prediction error corresponds to a multiplicative uncertainty of roughly 1.9× in either direction on the case count scale meaning a point estimate of 500 cases carries a plausible range of approximately 260 to 950 cases before climate ensemble spread is added. Critically, the skill

attribution analysis reveals where that uncertainty is concentrated: the climate layer alone explains approximately 59% of outcome variance, while the transmission momentum amplification layer which uses lagged case counts and seasonal harmonics contributes the largest single skill gain in the system, more than tripling the signal-to-noise ratio from 1.37 to 4.51. This decomposition tells the technically trained reader something that neither full model skill scores nor prediction intervals alone can convey: in the case of PROA, the dominant uncertainty is epidemiological, not climatological, and further investment in the climate forcing layer may contribute less to forecast improvement than closing the serotype surveillance lag or improving the immunity tracking component. Rigorous uncertainty measurement is what makes this diagnosis possible and it is why reporting the full suite of metrics, including the source decomposition of forecast error, should be standard practice in climate-health forecast publications. Thus, building this technical literacy among health system analysts through training, documentation, and joint interpretation sessions is as important as improving the forecast itself.

3.3.3 From uncertainty to action: co-designing institutional decision structures

Rigorous reporting of uncertainty metrics is necessary but not sufficient for operational climate services. A technically complete uncertainty characterization that health decision-makers cannot act on delivers no operational value. The additional step is to be able to translate calibrated uncertainty into institutional action structures; it is also where many climate services for health have fallen short [52], [53].

Different institutional decisions require different output formats. In the case of PROA, seasonal budget commitments require spending ranges with pre-authorization logic tied to defined trigger

conditions. In other systems used for monthly procurement adjustments may require point estimates with monitoring signals. Weekly alert activations may require exceedance probabilities with agreed response thresholds. A single probabilistic output format will not serve all three, and applying one universally is a documented source of poor uptake in operational climate services [54].

A critical challenge in this translation is the risk of decision-maker paralysis, which is the tendency for wide uncertainty envelopes to inhibit rather than enable action when concrete decisions are needed under time pressure [55]. When a forecast presents a large range of plausible outcomes without specifying what institutional action follows from each, decision-makers facing accountability constraints may default to inaction, or to acting on the point estimate alone while ignoring the uncertainty [56]. Experimental research in forecast communication has demonstrated that how uncertainty is framed and whether it is accompanied by explicit decision guidance substantially affects whether probabilistic information improves or degrades decision quality [57], [58],[59]. WMO guidance reflects the same operational finding: probability information without linked action thresholds is insufficient for decision support [60].

The design response proposed is to co-design the interval into a set of agreed institutional actions before the forecast is issued, so that a wide interval activates a pre-agreed decision rule rather than requiring real-time deliberation under uncertainty [61]. The three-tier budget framework in Box 1 converts the probabilistic forecast distribution into three pre-authorized spending commitments, each tied to a specific trigger condition. In both cases, uncertainty is not hidden from decision-makers, it is discussed and converted in advance into a structure they can act

within. The full uncertainty metrics remain available to technically trained users; the institutional decision layer sits on top of that foundation rather than replacing it.

3.3.4 Build iterative refinement into the process from the outset

One practical starting point for climate-health teams is to map the health institution's decision cycle before designing any output: what decisions are made, by whom, at what frequency, and within what authorization structure, understanding that these timelines are subject to change. This mapping, conducted jointly with health institution partners, frequently reveals that the output format initially planned on by forecast scientists is often incompatible with the decision formats the health system actually uses [62].

The translation from probabilistic forecast to institutional action is not solved once but rather it is refined continuously as forecasts are tested against real decisions, failure modes become visible, and institutional contexts evolve [63]. Practical mechanisms for building iterative refinement into a climate-health forecast system include documenting forecast performance against actual health outcomes each season and reviewing findings jointly with health partners; examining cases where forecast signals were available but institutional action did not follow, whether due to format mismatch, timing, or authorization gaps; and committing to revising the output format when institutional decision cycles change. Forecast scientists who treat uncertainty communication as an ongoing scientific and institutional commitment alongside forecast skill improvement will build the system literacy and institutional trust that makes climate services durable.

3.4 Conclusion

Translating uncertainty metrics into operational health decisions requires equal attention to how uncertainty is structured, measured, communicated, and pre-translated into institutional action across a forecast chain in which the climate model is only one of several uncertainty-generating steps.

The example presented here points to several concrete directions for the field. The dominant source of forecast uncertainty should be identified before output formats are designed. Uncertainty metrics like correlation, AUC, HSS, calibration diagnostics should be reported rigorously and interpreted transparently for technically trained audiences, building the system literacy that supports long-term operational trust. Calibrated uncertainty intervals should accompany forecast skill metrics, and coverage of actual outcomes should be treated as a primary performance criterion for systems intended for budget and resource planning. It is equally important to distinguish between retrospective skill (what the model has achieved against historical observations) and forward-looking prediction intervals (which characterize the plausible range of outcomes for a specific future forecast) and reflect the compounded uncertainty of climate forcing, epidemiological translation, and data latency at the moment the forecast is issued. Both need to be reported, and both need to be communicated in terms that health partners can understand and act on. To reduce the risk of decision-maker paralysis means that wide uncertainty envelopes must be translated into agreed institutional action structures converted in advance into decision rules that health institutions can act within rather than interpret in real time. Communicating uncertainty honestly and designing for action are not competing objectives. The climate service field is best served by systems that deliver both

together. PROA, illustrated in Box 1, demonstrates one approach to this challenge in a budget planning context. The most consequential design decisions were made at the translation layer between probabilistic forecast output and institutional action. That translation deserves the same scientific rigor, empirical grounding, and iterative commitment to improvement that forecast scientists bring to the climate driven model itself.

Interlude: Chapter 3 → Chapter 4

Chapter 3 showed that the usability of climate-informed forecasts depends on how uncertainty is structured relative to decisions, demonstrating that probabilistic information becomes more actionable when translated into formats aligned with operational needs. These findings, grounded in interactions with health system actors, clarified how forecast information can support decision-making in the short term.

At the same time, these engagements highlight a further gap: while forecasts can be interpreted and used, oftentimes there is no systematic way to assess whether their use is improving decision-making or contributing to public health outcomes over time. This limitation becomes particularly evident in the absence of agreed-upon indicators for success beyond model performance. Chapter 4 builds directly on these insights, presenting the co-development of a monitoring and evaluation framework designed to track system use, assess effectiveness, and support the longer-term integration of climate-informed early warning systems within health systems.

Chapter 4: Monitoring and Evaluation Framework for a Climate-Driven Dengue Early Warning System in the Caribbean: A Transdisciplinary Approach

This first-author work is in prep to be submitted.

4.1. Introduction

The relationship between climate variability and vector-borne disease dynamics represents one of the most tractable problems in applied climate science: it is mechanistically grounded, epidemiologically consequential, and it operates on seasonal timescales that fall within the skillful range of probabilistic forecast systems [3]. *Aedes aegypti*-transmitted dengue fever is an exemplary case. The vector's extrinsic incubation period and gonotrophic cycle are strongly temperature-dependent, exhibiting nonlinear acceleration in the 24–32°C range; oviposition habitat expands rapidly with rainfall-driven surface water accumulation; and drought-induced household water storage practice creates breeding reservoirs that persist independently of precipitation [4]. These three hydroclimatological pathways (thermal forcing, rainfall-driven habitat expansion, and drought-induced behavioral adaptation) operate at distinct temporal lags, producing a compound climate signal that is detectable months ahead of outbreak onset and is therefore in principle forecastable [5]. The scientific challenge is therefore two-fold. On one hand, we must continue to improve model skill and forecasting tools, and we must also focus on building operational systems capable of translating outputs into timely, actionable risk information for public health decision-makers and develop rigorous frameworks for evaluating whether these forecasting systems are actually improving public health.

The Caribbean is among the most climate-vulnerable environments on Earth and thus an important region for examining the climate-disease system under conditions of compound forcing and constrained adaptive capacity [6]. Caribbean Small Island Developing States (SIDS) are subject to sea level rise (SLR), extreme sea level events (ESL) (i.e., storm surges and flooding), North Atlantic hurricane forcing, compound drought-flood sequences driven by ENSO teleconnections (teleconnections are like global seesaws where a change in weather or air pressure in one part of the world triggers an opposite reaction thousands of miles away) [7]. They are also subject to other types of variability like the Atlantic Multidecadal Oscillation (long-term cycle of sea surface temperature (SST) fluctuations in the North Atlantic Ocean that occur every 50 to 70 years with warm and cool phases; warm phase resulting in more frequent hurricanes and higher rainfall and cool phase in more frequent droughts in the Caribbean), and progressive thermal intensification superimposed on pre-existing high *Aedes aegypti* habitat suitability [8], [9]. Moreover, these climate phenomena are happening on different timescales and when they interact it can lead to more extreme events; identifying these alignments (i.e. when the Madden Julian Oscillation MJO will overlap with a strong ENSO event) is thus important for climate service development [10]. Furthermore, these intersecting climate stressors (i.e., moisture, temperature and wind etc.) create precisely the kind of multi-pathway, lagged hydroclimatological forcing structure that compound climate predictors are designed to capture. At the same time, Caribbean SIDS operate under constraints on epidemiological surveillance infrastructure, meteorological service capacity, and human resources [11]. These constraints make the operational implementation of any new climate service challenging and supports the claim that long-term service sustainability is as scientifically important as model skill [2].

A decade of transdisciplinary research in the Eastern Caribbean has produced a suite of interlocking scientific products that together constitute a complete operational climate service framework for dengue: the foundational modelling work documenting nonlinear and delayed climate-dengue relationships in Barbados [5]; followed by a co-produced impact-based Early Warning System (EWS) that uses a Bayesian hierarchical framework with compound and cascading hydroclimatological predictors [1]; and a demand-driven implementation roadmap for operationalizing the EWS in SIDS contexts [2]. With that, there is one big piece of the puzzle missing from this suite of climate service products: a systematic, empirically grounded framework for evaluating whether the EWS is generating its intended outcomes across the full causal pathway from hydroclimatological signal detection through institutional response to community health impact. This paper provides that framework.

The EWS model in Barbados employs a three-way interaction between long-lag drought (SPI-6 at 5-month lag), mean temperature anomaly (3-month average, 3-month lag), and short-lag excess rainfall (SPI-6 at 1-month lag), plus log-transformed lagged dengue incidence. The model achieves an Area Under the Receiver Operating Characteristic (ROC) Curve AUC of 0.80 and True Positive Rate (TPR) of 81% under rolling-origin cross-validation, performance substantially outperforms a seasonal baseline. The model was validated during the International Cricket Council (ICC) Men's T20 World Cup where it successfully predicted a 95% outbreak probability for Barbados three months ahead of the event [1]. The central scientific question motivating this study is the decoupling of forecast skill from climate service effectiveness. Verification statistics (AUC, True Positive Rate, Brier Skill Score) characterize the input-output behavior of the forecast model: whether probabilistic output co-varies with observed outcomes under cross-validation. While these metrics are critical in providing the evidence behind model outputs and building trust with health

decision makers, they do not tell us about whether an alert actually reached a decision-maker in time to trigger a response, whether that decision-maker had an established response protocol, or whether a community received actionable risk communication before outbreak onset. Dilling and Lemos [2011] demonstrate that information quality and decision-making quality are separated by institutional, organizational, and cognitive factors invisible to verification metrics [12]. This suite of work has thus looked to provide not only high skill models but embed them in a system with action pathways that will generate maximum health benefit. However, closing this gap between model production and system operationalization requires an evaluation framework that is explicitly multi-level: assessing both whether the climate signal is being detected, and whether the detection is generating timely alerts, whether alerts are activating responses, and whether responses are reaching and mobilizing communities.

Despite this theoretical foundation, operational monitoring and evaluation (M&E) frameworks for climate-health EWS remain underdeveloped and underutilized [13]. Where M&E is discussed (i.e., WHO's Early Warning, Alert and Response System framework [14] it offers some broad guidance but nothing in terms of vector borne disease early warning. The 2023 WMO State of Climate Services: Health report identifies the absence of systematic evaluation architecture as a critical gap in the climate-health service chain, noting that the growth in climate tools has not been matched by rigorous assessment of whether those tools translate into health benefits [15]. The report also touches on how many teams tend to focus on forecast verification metrics without addressing whether alerts generate timely institutional responses, reach communities in actionable form, or sustain multi-sector engagement across successive operational cycles and where they do talk about these elements there is little guidance on how to measure them. This narrow framing conflates model performance with system effectiveness, which is a distinction with direct scientific

consequences for how we understand the value and limits of climate services for health in SIDS and beyond [16].

Three theoretical areas inform the evaluation architecture developed here. 1) The WMO End-to-End Early Warning System framework defines EWS effectiveness across four linked components (risk knowledge, monitoring and warning, dissemination and communication, and response capability) and is adopted as the primary organizing principle, since it maps directly onto the operational structure of the Caribbean climate-health service [17]. No single metric, including forecast accuracy, can substitute for assessment of the full chain. 2) The Donabedian structure-process-outcome model [18], drawn from health systems evaluation theory, is incorporated as a complementary lens: structural indicators (governance, data systems, institutional sustainability) describe the conditions that enable the chain to function; process indicators (alert timeliness, response activation, community engagement) describe what the system does; and outcome indicators (case reduction, cost per case averted) describe what results. Applied together, these frameworks generate an evaluation architecture in which hydroclimatological forecast verification occupies its correct position (as one measurable piece of a multi-level causal chain) rather than as a summary metric of overall EWS performance. 3) The co-production methodology through which the framework was developed [19], is constitutive of its scientific quality: transdisciplinary co-production with the institutions responsible for EWS implementation is the mechanism through which climate information is translated into actionable decision support, and an evaluation framework that lacks this institutional grounding will not be implemented regardless of its technical rigor [20]

Here, we present a co-produced, transdisciplinary M&E framework for climate-informed dengue Early Warning Systems for Barbados, Grenada, and St. Lucia including selected key performance indicators and a complete operational tool kit. Operationalization of the prospective M&E is planned for 2027; this paper presents the framework as a prospective evaluation architecture and advances three distinct scientific contributions: (1) a theoretically grounded argument that forecast verification and climate service evaluation are fundamentally different scientific problems requiring different methodological approaches; (2) a replicable co-production methodology for generating evaluation frameworks with built-in institutional ownership in SIDS climate service contexts; and (3) an operational toolkit calibrated to the human resource constraints of small island health and meteorological systems, filling the gap between high-level WMO M&E guidance and the granular implementation detail needed for sustainable operationalization. This chapter addresses RQ3 by co-developing a Monitoring and Evaluation (M&E) framework to assess the performance, usability, and real-world impact of climate-informed early warning systems. It evaluates how effectively these systems support decision-making and identifies pathways to strengthen their operational sustainability.

4.2. Methods

4.2.1 Overview

The M&E framework was completed in two phases. First, ten semi-structured expert interviews (n=10; 45–90 minutes each) and second, a structured half-day co-production workshop (Bridgetown, Barbados, April 2025; n=36) engaging climate scientists, mathematical modellers, hydroclimatologists, epidemiologists, vector control specialists, national meteorological services, and regional institutions including the Caribbean Public Health Agency (CARPHA), Pan American Health Organization (PAHO), and Caribbean Institute for Meteorology and Hydrology (CIMH) from Barbados, Grenada, and Saint Lucia. We produce 10 Key Performance Indicators (KPIs) spanning the full causal pathway from hydroclimatological data governance through alert generation, institutional response capacity, community engagement, and long-term service sustainability. The framework is accompanied by a complete operational toolkit (Annex 1) comprising thirteen instruments for governance, data collection, reporting, and annual evaluation, designed for direct use by national oversight committees without requiring ongoing external technical support.

4.2.2 Ethical Approval and Consent

All interviews and workshops were conducted under an approved Institutional Review Board (IRB) protocol AAAV1147(M00Y01). Participants provided informed consent prior to participation. Interview notes were anonymized before analysis; identifiers are not reported. Workshop discussions were facilitated as public engagement activities; findings are attributed to country-level groups throughout this paper. All participants were informed of the purpose of data collection and the planned publication of aggregated findings.

4.2.3 Phase 1: Expert Interviews

We conducted ten semi-structured interviews with experts purposively selected to represent the disciplinary breadth required for a multi-dimensional M&E framework [21]. Purposive rather than random sampling was appropriate because the target population (individuals with direct expertise in Caribbean climate-health EWS design, implementation, or evaluation) is small and geographically concentrated, and because the goal was theoretical coverage of relevant domains rather than statistical representativeness. Disciplines represented were climate modelling and forecast systems (n=2), mathematical epidemiology (n=2), social and behavioral science (n=2), vector-borne disease epidemiology (n=2), and regional public health systems (n=2). This configuration was designed to ensure that no single disciplinary perspective dominated the resulting KPI framework. Each interview lasted 45 to 90 minutes and was conducted by the lead author using an IRB-approved semi-structured guide. Per IRB protocol, sessions were not audio-recorded; detailed notes were taken in real time by the interviewer and subsequently expanded into full interview records within 24 hours while recall was intact.

The interview guide was organized into five thematic domains: (1) EWS model responsiveness and accuracy; (2) KPI identification and data needs; (3) stakeholder roles and engagement strategies; (4) public health impact measurement including cost-effectiveness; and (5) planning for sustainable M&E cycles. Questions were semi-structured to allow participants to introduce priorities not anticipated in the guide, consistent with the principle that qualitative inquiry should remain open to emergent themes [22]. The guide is reproduced in full as Supporting Information S1.

Thematic analysis of interview notes followed a hybrid deductive-inductive approach [22]. The deductive coding frame was structured around the WHO Early Warning 4 All framework and the

Donabedian structure-process-outcome model applied to organize candidate KPIs into three tiers: structural inputs (governance, resources, data systems), process indicators (alert pipeline, response activation, community engagement), and health outcomes (case reduction, cost-effectiveness). Inductive codes emerged from participant responses and were iteratively refined through re-reading of interview records, generating themes not anticipated in the a priori framework. Credibility of the analysis was strengthened through member-checking: preliminary KPI categories and definitions were shared with three interview participants for review prior to the workshop, and their feedback was incorporated into the workshop materials. The resulting preliminary framework, 10 candidate KPIs organized across five conceptual domains, served as the primary input into Phase 2.

A note on researcher positionality: the lead author has been embedded in the Caribbean climate-health EWS collaboration since its early stages and facilitated both the interviews and the workshop. This insider positioning is an epistemological asset, enabling the depth of trust, contextual understanding, and institutional access that the research required, but it also introduces potential risks of bias and confirmatory interpretation [23], [24]. To mitigate these risks, interview questions were designed to actively elicit critical perspectives and implementation barriers rather than validating existing plans; the workshop included structured small-group work with country specific and cross-sector groupings specifically to surface divergent views; and the thematic analysis was reviewed by collaborators before finalization. These are recognized as partial rather than complete mitigations and are acknowledged in the Limitations section.

4.2.4 Phase 2: Co-Production Workshop

A structured half-day co-production workshop was held in Bridgetown, Barbados in April 2025 as a dedicated module within the regional training event "Operationalization of Climate-Informed Early Warning Systems for Vector-Borne Diseases in the Caribbean." The workshop involved 36 participants from Barbados, Grenada, and Saint Lucia, representing national meteorological services; Ministries of Health (epidemiology, environmental health, vector control, health promotion, GIS); disaster management agencies; water and sewage authorities; and regional bodies including CARPHA, PAHO, and CIMH. All three countries were represented in each of the workshop's collaborative activities.

The workshop was designed and facilitated by the lead author and comprised four structured sequential activities. First, participants were divided into eight small groups of four to five people, cross-sector representation in each group. Each group was assigned one of the 10 candidate KPIs derived from Phase 1 interviews (two groups were assigned to the two highest-priority KPIs). Groups completed a structured worksheet that required them to: (1) critically evaluate the KPI definition; (2) identify the specific department responsible for data collection and reporting; (3) specify data inputs and outputs; (4) identify available tools and systems; (5) name anticipated implementation challenges; (6) propose context-specific success criteria; and (7) describe local factors that would require adaptation of the KPI. Groups presented findings in oral summaries to the full workshop.

Second, a facilitated plenary synthesis session integrated across-group findings and resolved points of inter-country divergence. Third, participants voted anonymously via an online tool on the question of whether country-level EWS oversight committees would be useful and feasible. Fourth, country teams convened independently for a 30-minute structured planning exercise to

outline proposed committee composition, meeting frequency, feedback mechanisms, and first-quarter priorities.

Workshop outputs were documented in real time by the facilitation team and compiled into a formal workshop outcomes report reviewed by a subset of participants for accuracy prior to finalization. The workshop design incorporated several features to support the quality and credibility of outputs. First, small groups were deliberately composed to include cross-sector representation, minimizing the risk that any single institutional perspective would dominate KPI refinement. Second, structured worksheets with specific prompts, including explicit questions about local barriers, required adaptations, and success criteria, were used to generate comparable data across groups rather than open-ended discussion that might be more susceptible to group conformity effects. Third, plenary presentations by group spokespersons enabled peer scrutiny of preliminary findings before synthesis. Notwithstanding these design features, the workshop context carries inherent social desirability risks in a setting where participants know the facilitator and are invested in the success of the project; this limitation is discussed in Section 4.5.

4.2.5 Framework Synthesis and M&E Tool Development

Following the workshop, the lead author synthesized interview and workshop data to produce the final M&E framework and accompanying M&E toolkit. Synthesis proceeded in three steps: (1) integration of interview-derived KPI definitions with workshop refinements; (2) compiling of workshop narratives to identify cross-country patterns, shared challenges, and country-specific adaptations; and (3) development of two annexes: Annex I, a structured national M&E tracking tool specifying, for each priority KPI, the indicator definition, required data, collection method,

responsible entity, monitoring frequency, reporting mechanism, and success targets; and Part 2, a complete ten-instrument M&E toolkit designed for direct use by oversight committees. Toolkit instruments cover governance (Terms of Reference, inter-agency MOU, focal point role description), data collection (monthly KPI submission form, field intervention logbook, community awareness survey), reporting and communication (KPI scorecard, annual M&E report template), and evaluation and learning (stakeholder satisfaction survey, annual performance review protocol). All instruments were designed for low-burden operational use and adapted to the capacity constraints of Small Island Developing States health systems. Deferred KPIs (Accuracy of Alerts, Cost per Case Averted, System Scalability) are documented in the framework but excluded from the immediate tracking tool pending data infrastructure improvements and resource mobilization.

The full study design is summarized in Table 1.

Table 4.1. Study design, phases, activities, and participants.

Phase	Activity	Participants	Primary Output
Phase 1 Expert Interviews (Pre-workshop)	Ten semi-structured interviews (45–90 min each) using IRB-approved guide covering model performance, KPI identification, stakeholder roles, health impact measurement, and M&E sustainability	10 experts: climate modelling (n=2), mathematical epidemiology (n=2), social & behavioral science (n=2), vector-borne disease epidemiology (n=2), regional public health systems (n=2)	10 candidate KPIs; draft M&E framework structure; priority domains for workshop
Phase 2 Co-Production Workshop (Bridgetown, April 2025)	Half-day structured workshop embedded within a week-long EWS training event: (1) small-group KPI refinement, (2) plenary synthesis, (3) oversight committee vote, (4) country team planning	36 participants across Barbados, Grenada, and Saint Lucia: MOH epidemiology, environmental health, vector control, health promotion, GIS; national meteorological services; CARPHA, PAHO, CIMH; disaster management agencies	Refined KPI definitions; country-specific implementation priorities; oversight committee structures; final M&E framework
Phase 3 Synthesis	Thematic analysis of interview notes and workshop documentation; iterative review with collaborators	Lead author and project team	Finalized M&E framework with 10 KPIs, governance structure, and national M&E tracking tool (Annex, Part 1)

4.3 Results

4.3.1 EWS Model Technical Performance

We briefly discuss the (Fletcher 2025) model evaluation and connect the outcomes to operational flow and design. The selected EWS model, a Bayesian hierarchical framework with a three-way compound climate interaction plus lagged dengue incidence rate achieved an Area Under the ROC Curve (AUC) of 0.80 (95% CI: 0.72–0.88), a True Positive Rate (TPR) of 81%, and a False Positive Rate (FPR) of 29% under rolling-origin cross-validation, substantially outperforming the seasonal baseline model (AUC 0.60, TPR 68%, FPR 48%) and an additive model without interaction terms (AUC 0.75, TPR 77%, FPR 37%) [4]. The selected model explained 69% of

variation in the dengue incidence rate, compared with 17% for the baseline. The compound climate predictor, capturing the synergistic pathway from long-lag drought through mid-lag heat to short-lag excess rainfall, provides incremental discriminatory value over the sum of individual climate signals, consistent with the biological mechanism of drought-driven water storage, heat-accelerated vector development, and rainfall-expanded breeding sites. As a prospective demonstration, the model predicted a 95% outbreak probability (very-high risk) for the Inter-Continental Cricket (ICC) Men's T20 World Cup in Barbados in June 2024, issued three months ahead; this forecast was shared with the Barbados Ministry of Health and Wellness and informed pre-tournament vector control operations.

These metrics constitute the model evaluation layer of the EWS. Several areas bear directly on the design of the operational M&E framework that follows. The TPR of 81% was achieved with retrospective confirmed case data; in operational deployment, case counts arrive with sometimes week long or multi-week lags and laboratory confirmation can underrepresent true incidence. Qualitatively, the Ministry of Health confirmed they received the alert and noted its value for situational awareness. However, due to a lack of formal protocols for monitoring and evaluation, we were unable to quantitatively track whether this information translated into specific vector control actions or shifts in community behavior. These gaps directly motivate the multi-domain M&E framework detailed in Sections 3.3–3.5.

4.3.2 Phase 1: Expert Interviews — Candidate KPIs and Conceptual Framework

Ten expert interviews yielded 10 candidate KPIs organized across five conceptual domains. Figure 1 illustrates the full causal pathway, from climate data governance through alert generation, institutional response, and community engagement to health outcomes with KPI

numbers annotating each evaluation layer and Donabedian structure-process-outcome tiers indicated. Technical performance KPIs (Accuracy of Alerts, Timeliness of Alerts) address the quality and speed of the alert pipeline itself. The operational response domain (Response Activation Time) measures whether alerts translate into timely public health interventions. Epidemiological impact KPIs (Reduction in Dengue Cases, Cost per Case Averted) capture downstream health and economic outcomes. Social and behavioral KPIs (Community Awareness, Community Participation) assess whether the EWS reaches and mobilizes communities. Institutional sustainability KPIs (Stakeholder Participation, Sustainability Metrics, System Scalability) track the governance and resource conditions that determine long-term EWS function.

Several cross-cutting themes emerged across interviews. First, interviewees consistently distinguished leading indicators (those measurable before health outcomes are observed, such as timeliness and community awareness) from lagging indicators (outcome measures such as case reduction), recommending that the M&E framework prioritize leading indicators for early operational feedback. Second, experts raised substantial concern that forecast accuracy, while scientifically important, is frequently unmeasurable in operational settings due to surveillance data delays, spatial aggregation, and the absence of standardized alert validation protocols. Third, every interviewee emphasized that the most consequential gap in existing EWS evaluations is the failure to trace the causal chain from alert to response to outcome: a system can produce an accurate forecast that generates no health benefit if the institutional pathway is broken at any point downstream. Fourth, interviewees stressed that long-term M&E sustainability requires a standing governance mechanism, not just an indicator list, to ensure data are reviewed, interpreted, and fed back into system improvements.

4.3.3 Phase 2: Workshop — KPI Refinement by Domain

4.3.3.1 Accuracy of Alerts (KPI 1)

Stakeholders from all three countries affirmed the conceptual importance of this KPI but reached consensus that it cannot serve as a primary operational monitoring metric at present. Barbados noted incremental improvements in health-climate data system alignment but confirmed that epidemiological reporting delays make near-real-time forecast validation impractical. Saint Lucia observed that passive surveillance systems lack the spatial granularity required to compare predicted risk areas against actual outbreak locations with meaningful precision. Grenada highlighted that low endemic-period case counts mean that even one or two unexpected cases can be epidemiologically significant without being detectable through probabilistic model outputs. Participants agreed that the definition of what constitutes an "accurate" alert is itself contested, requiring decisions about lead time, spatial resolution, and threshold levels, and that stakeholder expectations around accuracy must be carefully managed during EWS rollout. The workshop consensus was to designate Accuracy of Alerts as a medium-term research priority, with pilot evaluation methodology to be developed during the first two EWS operational cycles. The structural constraints described in Section 2.3 apply directly here: the cross-validation TPR of 81% reported by Fletcher et al. [4] was achieved with complete retrospective case data, and prospective accuracy estimation in any of the three countries will require near-real-time surveillance improvements before it can be meaningfully assessed.

4.3.3.2 Timeliness of Alerts (KPI 2)

This KPI was rated as the most immediately actionable metric across all three country groups. Timeliness measures elapsed time from submission of epidemiological and climate data to

issuance of a formal EWS alert to the Ministry of Health. Barbados proposed automated reminder notifications to data-submitting departments if key inputs are not received by the 15th of each month, with escalation protocols for persistent delays. Grenada recommended integrating a visual dashboard with color-coded delay indicators that flags when any link in the alert pipeline has exceeded acceptable thresholds. Saint Lucia proposed timestamp metadata captured at each stage (data receipt, model run, alert dispatch) with automated internal review triggers when delays exceed five days. All three countries identified dual institutional points of contact in both the Ministry of Health and the national meteorological service as a structural requirement for continuity in the event of staff absence.

4.3.3.3 Response Activation Time (KPI 3)

This KPI, the number of days between a HIGH-RISK EWS alert and the first documented vector control intervention, surfaced concrete institutional bottlenecks that the M&E framework must track. Barbados identified a structural lag in communication between epidemiological surveillance and environmental health units and proposed establishing a formal inter-departmental communication chain codified in a standard operating procedure. Grenada advocated for pre-defined response time benchmarks (≤7 days from alert to first intervention) integrated into vector control reporting requirements, with compliance tracked quarterly. Saint Lucia proposed response trigger checklists with automated push notifications to Environmental Health Officers when an alert crosses the HIGH threshold, even before laboratory case confirmation, given that delayed lab confirmation was identified by all three countries as a major impediment to swift action. The importance of logging intervention start dates, types, and completion times as a routine data practice was universally endorsed.

4.3.3.4 Reduction in Dengue Cases (KPI 4)

All three country groups acknowledged this long-term outcome KPI as the ultimate measure of EWS value while cautioning strongly against treating it as a direct performance metric without appropriate epidemiological framing. Dengue case counts are influenced by multiple simultaneous factors (viral serotype circulation, rainfall, urbanization, intervention coverage, and surveillance capacity) making attribution of case changes to the EWS inherently complex. Grenada proposed using three-year rolling seasonal averages as a dynamic baseline for comparison, enabling detection of divergence from expected patterns while accounting for interannual climate variability. Barbados recommended systematic triangulation of case data with climate anomaly records and intervention timelines to contextualize any observed trends. Saint Lucia proposed integrating entomological indices into GIS-based dashboards to visualize the relationship between vector presence, climate conditions, and case trajectories. The group agreed that this KPI should be assessed annually in the M&E report and should always be reported alongside the other KPIs to avoid misleading causal inferences.

4.3.3.5 Cost per Case Averted (KPI 5)

This economic indicator was recognized as critical for long-term EWS funding justification and was rated as a high-priority domain in expert interviews. Workshop participants were unanimous, however, that the technical and resource requirements for calculating this KPI exceed what is currently available in all three countries. Calculating cost per case averted requires: a baseline treatment cost per dengue case (including hospitalization, outpatient visits, and vector control expenditures); an estimate of cases averted attributable to the EWS; and accounting for indirect costs such as lost productivity and effects on health-seeking behavior.

Grenada's planning unit proposed a collaboration pathway with ministries of finance and regional health economists; Barbados suggested outbreak simulation modeling as an approach to estimating avoided costs. Saint Lucia advocated explicitly for including indirect economic impacts such as work absenteeism and effects on tourism revenue (economically significant for small island economies) in any costing framework. All three countries agreed that donor support is necessary for tool development and that this KPI should be treated as a medium-to-long-term goal, targeted for the third year of EWS operations.

4.3.3.6 Community Awareness (KPI 6) and Community Participation (KPI 7)

These two KPIs address distinct but causally linked processes in the EWS-to-health-outcome pathway. Community Awareness measures whether the target population knows that the EWS exists, understands the meaning of alert levels, and can identify recommended preventive actions. Community Participation measures active engagement in EWS-triggered interventions, including attendance at clean-up campaigns, household source inspections, and larval surveys. Workshop groups treated these as a pair but were clear that awareness does not automatically translate into participation, and that each requires distinct measurement strategies.

For Awareness, Barbados proposed seasonal mobile surveys administered at community events and health facility visits, supplemented by social media analytics where applicable. Grenada discussed designing a pre/post questionnaire instrument for distribution at community gatherings before and after peak dengue season. Saint Lucia identified schools, churches, and community health workers as primary dissemination nodes for awareness measurement. For Participation, Barbados proposed developing a participation index aggregated from Environmental Health Officer campaign reports and entomological outcome data. Grenada emphasized the role of

Environmental Health Officers as community focal points responsible for attendance tracking. Saint Lucia proposed training youth as "mosquito rangers" who conduct household inspections and report findings via mobile applications, providing both community engagement and a data stream for the Participation KPI. All groups agreed on the need for culturally adapted messaging in awareness campaigns and seasonal timing aligned with the pre-peak period (typically March–May in the Eastern Caribbean).

4.3.3.7 Stakeholder Participation (KPI 8)

This institutional KPI assesses the degree of multi-sector engagement in EWS governance. Workshop groups across all three countries linked it directly to the oversight committee structure discussed in Section 3.4. Measurement approaches included: meeting attendance logs; MOU documentation tracking formalization of inter-agency data-sharing agreements; cross-training workshop participation records; and annual stakeholder satisfaction surveys administered anonymously. Barbados recommended that each participating department designate a named KPI focal point with explicit responsibility for data reporting to the oversight committee. Success criteria proposed included ≥80% of designated agencies represented at ≥75% of quarterly committee meetings and a formalized inter-agency MOU within 12 months of EWS activation.

4.3.3.8 Sustainability Metrics (KPI 9) and System Scalability (KPI 10)

Sustainability Metrics captures whether the EWS is becoming genuinely embedded in national health systems, measured through presence of budget line items, permanent staffing designations, integration in national health strategic plans, and adoption of open-source platform tools that reduce long-term cost dependency. Barbados committed to including explicit EWS language in the next national health strategy review. Grenada proposed formalizing at least one

EWS coordination role as a permanent civil service position. Saint Lucia emphasized succession planning and structured knowledge-transfer protocols to reduce disruption from the staff turnover common in small public health systems. Use of open-source platforms and regional partnerships with CIMH and CARPHA were cited across all three countries as structural ways to reduce unit costs.

System Scalability, i.e. the EWS capacity to adapt to additional climate-sensitive diseases or expand geographically, was framed both as a future aspiration and as a current funding argument. Barbados expressed interest in extending the model framework to chikungunya given shared *Aedes aegypti* transmission dynamics. Grenada proposed exploring application to heat-related illness, an emerging priority with non-communicable disease implications. Saint Lucia identified leptospirosis and waterborne disease tracking as regional priorities following the flooding events of recent years. All groups agreed that systematic documentation of adaptations, challenges, and implementation lessons is a prerequisite for justifying geographic or disease-scope expansion.

Table 4.2 Ten co-produced KPIs: domain, interview priority, and workshop status.

No.	KPI	Domain	Interview Priority (pre-workshop)	Workshop Status & Approach
1	Accuracy of Alerts	Technical Performance	HIGH — primary model quality metric	Deferred to medium-term research priority. Current data infrastructure insufficient for near-real-time accuracy assessments across all three countries. Designated as an aspirational benchmark; pilot methodology testing recommended.
2	Timeliness of Alerts	Technical Performance	HIGH — identified as most operational metric	Immediate implementation priority (all 3 countries). Metric: days from data submission to alert issuance. Automated timestamp tracking, 15th-of-month submission deadline, dual institutional points of contact.
3	Response Activation Time	Operational Response	HIGH	Immediate priority. Metric: days from alert issuance to first documented vector control deployment. Requires standardized SOPs and intervention logging protocols across MOH and environmental health units.
4	Reduction in Dengue Cases	Epidemiological Impact	HIGH — long-term outcome measure	Medium-term outcome KPI. Baseline: 3-year rolling seasonal averages. Caution against direct attribution without triangulation across climate anomaly records and intervention logs.
5	Cost per Case Averted	Economic Impact	MEDIUM — important but technically demanding	Longer-term KPI requiring health economics support. Donor funding recommended for tool development. Indirect costs (absenteeism, tourism impact) to be included in the full model.
6	Community Awareness	Social & Behavioral	HIGH — essential for behavior change	Operational via seasonal surveys and social media monitoring. Pre/post questionnaire design to be harmonized regionally. Culturally adapted messaging emphasized across all countries.
7	Community Participation	Social & Behavioral	HIGH — directly linked to vector control	Tracked via event attendance, Environmental Health Officer reports, community focal point data. Youth engagement programs proposed (Saint Lucia). Participation index development in progress.

No.	KPI	Domain	Interview Priority (pre-workshop)	Workshop Status & Approach
1	Accuracy of Alerts	Technical Performance	HIGH — primary model quality metric	Deferred to medium-term research priority. Current data infrastructure insufficient for near-real-time accuracy assessments across all three countries. Designated as an aspirational benchmark; pilot methodology testing recommended.
8	Stakeholder Participation	Institutional Governance	HIGH	Oversight committee attendance logs, MOU documentation, inter-agency drill records, annual satisfaction surveys. Formal departmental KPI focal points recommended.
9	Sustainability Metrics	Sustainability	MEDIUM-HIGH — critical for long-term function	Indicators: budget line items, permanent staffing designations, integration in national health strategic plans, use of open-source tools. Each country developing country-specific sustainability roadmap.
10	System Scalability	Scalability & Expansion	MEDIUM — future orientation	Tracked through documented adaptations for additional diseases (chikungunya, heat illness, leptospirosis). Regional partnerships with CIMH and CARPHA cited as enabling infrastructure.

4.3.4 Oversight Committee Formation

Prior to the country team planning exercise, the workshop facilitated an anonymous plenary vote on the question: "Would developing a country-level EWS oversight committee be useful and important in your work environment?" All 36 participants voted affirmatively (100%). This unanimous response was notable given the diversity of institutional roles represented, including officials from small meteorological offices with constrained capacity, and reflects a shared recognition that no single institution can sustain EWS M&E oversight in isolation.

Country teams then worked independently to outline oversight committee structures. All three proposals reflected the same core principle: that committee membership must span the meteorological-health institutional divide that has historically limited integration of climate services into public health decision-making. Table 3 summarizes the agreed configurations.

Table 4.3 Proposed national EWS oversight committee structures.

Country	Committee Composition	Meeting Cadence	Initial Priorities (0–6 months)
Barbados	Barbados Meteorological Services; Epidemiology Unit; Health Promotion Unit; Environmental Health Department; Planning & Research Unit; Public Health Laboratory	Quarterly + semi-annual; annual in-person M&E review	Establish KPI baseline targets; pilot dashboard for KPI tracking; integrate EWS indicators into national health strategic plan; formalize inter-agency feedback loops
Grenada	Ministry of Health (Epidemiology, Environmental Health, Planning); NaDMA; Ministry of Agriculture; NaWASA; Met Office; GIS Unit	Quarterly; ad hoc convening during declared health emergencies	Finalize SOPs with institutional leads per KPI; draft 12-month implementation roadmap; establish standard protocols for intervention logging
Saint Lucia	Disaster Officer for Health (Chair); Epidemiology Unit; Environmental Health; Bureau of Health Education; Met Office; NEMO; Public Health Laboratory; Water & Sewage Authority	Quarterly reporting to Ministry of Health	Develop committee TORs and draft inter-agency MOU; integrate KPIs into routine epidemiological reporting; launch pilot community awareness surveys

All three committees proposed quarterly meetings as the minimum governance cadence, with annual in-person reviews to assess M&E progress and update KPI targets. Key first-quarter priorities across all countries focused on institutional formalization: developing terms of reference, assigning departmental KPI focal points, and drafting inter-agency MOUs to establish data-sharing agreements and accountability structures. The oversight committees are positioned

within national health governance structures but maintain technical links to the regional EWS development team and to CARPHA as a coordinating body.

4.3.5 Cross-Cutting Themes

Five themes emerged consistently across both interview and workshop phases, transcending country-specific differences in institutional capacity and data infrastructure:

First, M&E must be embedded in national systems rather than maintained as an externally driven project requirement. Workshop participants (particularly those from Ministries of Health planning departments) repeatedly emphasized that indicators not integrated into routine epidemiological reporting cycles will not be sustained beyond project funding. Integration requires that EWS M&E outputs are legible in the language and format of existing national health planning instruments.

Second, operationalization of any KPI requires institutional mandates, standard operating procedures, and staff training before meaningful data collection can begin. Several groups noted that regional SOPs could provide a starting template but must be adapted to each country's existing infrastructure, human resource situation, and data system architecture.

Third, stakeholder engagement is a dynamic process that requires ongoing relationship maintenance, not a static input that can be secured through one-time consultation. M&E frameworks must therefore include mechanisms for stakeholder feedback on the framework itself, not only on EWS outputs.

Fourth, communities are active agents in outbreak prevention, not passive recipients of alerts. Community Awareness and Participation KPIs reflect a systems understanding in which community engagement is both an outcome indicator (demonstrating that the EWS is reaching its

intended beneficiaries) and a process indicator (contributing to the vector control activities that drive epidemiological outcomes).

Fifth, sustainability and scalability are interdependent. Systems that demonstrate adaptability to additional diseases or geographic expansion are more likely to attract sustained government and donor investment. Documenting and communicating EWS value (including through this M&E framework) is itself a sustainability strategy.

4.3.6 M&E Framework and Toolkit Outputs

The synthesis process produced two primary deliverables, together constituting a single combined Annex. Part 1 of the Annex contains the National M&E Tracking Tool (based on KPIs), specifying data requirements, collection methods, responsible entities, monitoring frequencies, and success targets for the seven priority KPIs, along with an annual reporting calendar, country-specific implementation notes for Barbados, Grenada, and Saint Lucia, and conditions for activating the three deferred KPIs. Part 2 presents a complete ten-instrument M&E toolkit (Tools B-1 through B-10) designed for direct use by oversight committees without requiring external technical support. The toolkit is organized to follow the natural M&E workflow: governance establishment (Tools B-1 to B-3), monthly and seasonal data collection (Tools B-4 to B-6), annual reporting and communication to ministry leadership (Tools B-7 and B-8), and annual evaluation and learning (Tools B-9 and B-10). Each instrument includes explicit instructions, fill-in-the-blank fields, illustrative examples, and adaptation guidance for country-specific institutional contexts. Together, Parts 1 and 2 constitute a self-contained operational M&E package that oversight committees can begin using from the first day of the M&E cycle. Furthermore, these tools can be adapted by other SIDS that are working towards

developing and implementing climate informed dengue early warning systems (i.e. The Bahamas and Trinidad & Tobago).

4.4. Discussion

4.4.1 Theoretical Positioning: Structure, Process, and Outcome in EWS Evaluation

The 10-KPI framework developed here maps naturally onto the Donabedian structure-process-outcome (SPO) triad, a framework originally developed for hospital quality assessment but widely applied in health systems evaluation [25]. **Structural KPIs**: Stakeholder Participation (KPI 8), Sustainability Metrics (KPI 9), and System Scalability (KPI 10), capture the institutional conditions that enable the EWS to function: governance arrangements, resource allocation, and inter-agency data-sharing agreements. **Process KPIs**: Timeliness of Alerts (KPI 2), Response Activation Time (KPI 3), Community Awareness (KPI 6), and Community Participation (KPI 7), measure what the system actually does: how quickly alerts are issued, whether interventions follow, and whether communities are reached and engaged. **Outcome KPIs**: Accuracy of Alerts (KPI 1), Reduction in Dengue Cases (KPI 4), and Cost per Case Averted (KPI 5), capture the health and economic results the system is intended to produce.

This three-party structure has direct practical implications. The deferred status of Accuracy of Alerts (KPI 1), Reduction in Dengue Cases (KPI 4 as a primary attribution metric), and Cost per Case Averted (KPI 5) is not simply a data availability problem; it reflects the appropriate sequencing of a health systems evaluation: structural and process conditions must be established and documented before outcome claims can be credibly made. An EWS that cannot yet demonstrate consistent timeliness or response activation cannot meaningfully attribute case reductions to its function, the causal pathway is broken upstream. The phased KPI activation

structure in Annex Part 1 operationalizes this sequencing explicitly, requiring structural and process KPIs to reach target thresholds as a prerequisite for outcome evaluation. This represents a methodological advance over existing EWS evaluation approaches that treat forecast accuracy as the primary (sometimes sole) performance metric, despite the fact that accuracy is the outcome of a long causal chain beginning with data governance and ending with community behavior [26].

The framework also extends the WHO Early Warning 4 All in a direction particularly relevant to climate-health applications in low-resource settings. The WHO framework defines effectiveness across four linked components: risk knowledge, monitoring and warning, dissemination and communication, and response capability. Our KPI structure covers all four but adds a fifth dimension (institutional sustainability) that the WHO framework treats as more of a background condition rather than a measurable indicator. In small island states with constrained public sector capacity and project-cycle funding, sustainability is not a background condition; it is the central challenge. Budget line items, permanent staffing designations, and integration in national strategic plans (KPI 9) are leading indicators of whether the EWS will function in Year 3 as it did in Year 1. Making sustainability explicitly measurable, rather than assumed is a substantive contribution of this framework.

4.4.2 Technical Performance and the Limits of Forecast Accuracy as a Primary KPI

The EWS model achieves an AUC of 0.80 and TPR of 81% under retrospective cross-validation [1], substantially outperforming the seasonal baseline and confirming that compound climatic predictors carry genuine information about dengue outbreak risk in Barbados at a 3-month lead time. The central finding of this study, anticipated in expert interviews and confirmed

unanimously by workshop participants with direct operational responsibility, is that this statistical performance, while critical, is not sufficient to evaluate whether the EWS is functioning as a public health tool.

This finding is consistent with a growing body of evidence in climate services evaluation. Dilling and Lemos 2011 demonstrate that information quality and decision-making quality are decoupled by institutional, organizational, and cognitive factors that statistical verification cannot capture[12]. The 'usability gap' in climate services arises primarily from failures in the dissemination-to-response pathway rather than from inadequate forecast skill [27]. In the Caribbean specifically, even well-validated climate-dengue models fail to generate operational uptake until stakeholder engagement processes establish the institutional trust and procedural clarity needed to connect forecasts to intervention decisions[28]. These precedents suggest that the deference of Accuracy of Alerts to research-track status in our framework is not a methodological concession but a theoretically grounded choice: measuring accuracy before structural and process conditions are established would generate misleading assessments that could undermine political support for the EWS. KPI 1 (Accuracy of Alerts), when operationalized, will generate country-specific performance data that allow genuine cross-country comparison for the first time. The framework thus creates the data infrastructure needed to answer the transferability question empirically rather than by assumption.

4.4.3 Transdisciplinary Co-Production as a Methodological Contribution

The disciplinary composition of this study's participant pool, spanning climate physics, mathematical epidemiology, social science, vector control, environmental health, disaster management, and regional governance was indicative of the framework's quality. This reflects a broader finding in the transdisciplinary co-production literature: that for problems defined by complexity, uncertainty, and multi-actor governance, knowledge quality is inseparable from the process through which it is generated[29], [30], [31]. Norström et al. 2020 identifies five principles of co-production for sustainability: context-based, goal-oriented, pluralistic, and interactive[32]. All four are operative in this study: context-sensitivity through country-specific KPI adaptation; inclusion through deliberate cross-sector workshop design; transdisciplinarity through the range of disciplines represented; goal orientation through the explicit focus on operational utility; and trust through a decade of relationship-building within the collaboration.

The disciplinary breadth produced substantive improvements that expert-only design cannot replicate. The decision to defer Accuracy of Alerts was reached not through theoretical argument alone but through testimony from operational health officials that their surveillance systems would produce misleading accuracy estimates. The 15th-of-month data submission deadline for KPI 2 (Timeliness) came from MOH epidemiology staff with direct knowledge of their reporting workflows. The youth mosquito ranger proposal for KPI 7 (Community Participation) came from a Saint Lucia environmental health officer drawing on an existing community program. These specifics, the operational texture of the framework, are unreachable by desk review or expert consultation alone.

Co-production also generates a form of durable institutional ownership distinct from consultation. The unanimous vote for national oversight committees and the immediately productive country team planning sessions are evidence of genuine investment rather than

compliance. This distinction matters for sustainability: frameworks that institutions co-designed are monitored; frameworks delivered to them for adoption frequently are not [33]. The oversight committee model, multi-sector, nationally anchored, with defined reporting obligations to the Ministry of Health is itself a governance innovation that emerged from the co-production process rather than being imposed upon it. No amount of technical M&E design would have generated that result without the participatory process that preceded it.

4.4.4 Governance as a Structural Prerequisite

The unanimous endorsement of national oversight committees and the immediately productive country team planning exercises reflect a finding that emerged independently in multiple expert interviews: KPI frameworks without standing governance mechanisms produce data that are collected, filed, and never acted upon. This finding resonates with implementation science literature on the 'know-do gap' in health systems [34]: the challenge is rarely generating good evidence, but ensuring that evidence is reviewed by people with the authority and motivation to act on it. The oversight committee model addresses this by creating a standing institutional forum with defined accountability, quarterly meetings, attendance logs, annual reporting to the Ministry, and a formal decision protocol for when the M&E plan itself needs revision (Tool B-10, Annex).

The multi-sector composition of all three proposed committees, spanning meteorological services, epidemiology, environmental health, GIS, and disaster management, reflects a systems understanding of EWS governance: forecasts are generated by Met Services and acted upon by health and emergency management institutions, and neither can perform its function without the other. The absence of formal mechanisms connecting these institutional domains has been

identified as a primary barrier to EWS operationalization in the Caribbean and globally [35] . Formalizing this interdependence through a committee with defined terms of reference, quorum requirements, and reporting obligations is a structural prerequisite for M&E sustainability, not an administrative add-on.

4.4.5 Situating the Framework in the Broader Climate Services for Health Literature

This framework contributes to a small but growing body of literature on operationalizing climate services for health in low-and-middle-income and small island settings. This study goes beyond reporting KPIs to providing the institutional architecture, oversight committees, inter-agency MOUs, data submission forms, annual report templates needed to sustain evaluation over multiple operational cycles.

Compared with PAHO's regional M&E guidance for disease surveillance systems [36], our framework adds two dimensions that existing guidance does not address: (1) the explicit integration of climate-model technical performance into the M&E architecture, situating forecast accuracy as one layer in a multi-level evaluation rather than the sole success criterion; and (2) the co-production process itself as a documented methodological approach, generating frameworks with built-in institutional ownership rather than frameworks requiring adoption. Compared with the WMO/WHO Climate Services for Health guidelines, our framework is more operationally granular, specifying not just what to measure but who collects it, how, with what instrument, and at what frequency, reflecting the view that evaluation frameworks that do not reach the level of data collection protocols will not be implemented in resource-constrained settings.

The framework also speaks to the implementation science literature on sustainability of health innovations in LMIC contexts [37], [38], [39]. Sustainability requires not just funding but

institutional embedding, the routinization of a new practice into existing workflows, planning cycles, and reporting structures. The tools in Annex Part 2 are designed explicitly for this purpose: the Monthly KPI Data Submission Form (Tool B-4) is designed to be completed by existing staff in 25 minutes; the Annual M&E Report Template (Tool B-8) uses the structure already required for Ministry of Health annual reporting; the KPI Scorecard (Tool B-7) is designed for presentation by existing committee chairs in existing ministerial briefings. Reducing the marginal burden of M&E participation is a sustainability strategy, not merely a design preference.

4.4.6 M&E Operationalization Timeline and Phased Implementation

The framework is designed for operationalization beginning Q1 of 2027 following the first EWS implementation cycle in Barbados, with extension to Saint Lucia and Grenada as those EWS implementations reach operational readiness. This timeline allows for: development and piloting of KPI data collection instruments during the 2026 dengue season; finalization of oversight committee Terms of Reference and inter-agency MOUs; baseline data collection for leading indicators prior to formal M&E reporting; and training of KPI focal points in each participating department. The phased KPI implementation horizon—near-term (KPIs 2, 3, 6, 7, 8, 9), medium-term (KPIs 1, 4, 5), and aspirational (KPI 10)—reflects the sequenced nature of EWS institutional development and the data infrastructure improvements needed for full evaluation.

An important question for future research is whether the framework as designed is feasible within the human resource constraints of small island health systems. The Monthly KPI Data Submission Form (Tool B-4) requires designated focal points in five to seven departments; the quarterly committee meetings require protected time from senior officials in multiple agencies;

the Community Awareness Survey (Tool B-6) requires field enumerator capacity twice per year. Feasibility testing during the first M&E cycle should generate data on the actual time burden per focal point and per agency—data that will be used to revise the toolkit for the second cycle. The framework is explicitly a living document in this sense: its first operational use will be an evaluation of the framework itself.

4.4.7 Limitations

Several limitations should be acknowledged transparently. First, the interview sample (n=10), while purposively designed for disciplinary coverage, is small. Perspectives from district-level health officers, community health workers, and patients, the public receiving most directly affected by EWS alerts were not directly represented in Phase 1. While the workshop addressed this gap through environmental health and health promotion officers with community-facing roles, it cannot be assumed that the KPI framework fully reflects frontline operational realities. Future iterations should incorporate structured community-level consultation.

Second, the workshop context carries inherent group conformity risks. The workshop was facilitated by the lead author, who is known to participants as a long-standing collaborator and whose research success depends in part on the EWS being perceived as valuable. Despite the mitigation strategies described in Section 2.4 (cross-sector groupings, structured worksheets, plenary scrutiny), the unanimous committee endorsement vote and the convergent KPI prioritization may partly reflect facilitated consensus rather than genuinely independent perspectives. This is an honest methodological limitation of co-production research in embedded contexts that cannot be fully resolved and should be acknowledged rather than minimized.

Third, the framework was developed for three countries with meaningful differences in institutional capacity, surveillance infrastructure, and meteorological service organization. Grenada's smaller public health workforce, Saint Lucia's disaster-officer-led governance structure, and Barbados's more developed data systems mean that a single set of KPI targets and data collection protocols will require more substantial adaptation than the country-specific notes in Annex Part 1 can fully anticipate. Iterative adaptation during the first M&E cycle will be essential.

Fourth, the Cost per Case Averted KPI (KPI 5) lacks a standardized dengue cost-of-illness methodology for any of the three countries. The Armien et al. 2008 Panama cost study and the Shepard et al. 2016 global economic burden analysis provide useful reference points, but Caribbean-specific cost data, which should account for healthcare system structure, tourism-related indirect costs, and the small-population dynamics of island epidemics, does not yet exist in usable form[40], [41]. This limits the economic evaluation dimension of the framework until dedicated health economics work is completed.

Fifth, causal attribution of dengue case reductions to EWS function remains a fundamental epidemiological challenge. Multiple simultaneous determinants of dengue transmission, serotype circulation, rainfall patterns, urbanization, intervention coverage, surveillance capacity make it difficult to isolate EWS contribution even with rich longitudinal data. The triangulation approach recommended for KPI 4 (combining case trends with climate anomaly records and intervention timelines) is the best available strategy under these constraints but does not constitute causal identification in the econometric sense. This limitation is inherent to the evaluation of complex public health interventions and cannot be resolved by improved M&E design alone.

4.5 Conclusion

This study presents a co-produced, transdisciplinary Monitoring and Evaluation framework for a climate-informed dengue Early Warning System in Barbados, Grenada, and Saint Lucia, the third in a suite of interlocking products that together constitute a complete climate service for health in the Caribbean. Developed through ten expert interviews and a 36-participant co-production workshop, the framework applies the Donabedian structure-process-outcome model and the WHO End-to-End EWS framework as organizing principles, producing 10 KPIs that span the full causal pathway from alert generation through community health impact and an operational toolkit of 10 instruments, including a national KPI tracking tool, governance templates, data collection forms, field logbooks, reporting templates, and evaluation protocols designed for direct use by national oversight committees without requiring ongoing external technical support. Operationalization is scheduled to begin in late 2026. The framework is explicitly prospective and has not yet been tested; its first operational use will be as much an evaluation of the framework itself as an evaluation of the EWS. Future work should focus on feasibility testing of data collection instruments in the first cycle, iterative adaptation of KPI targets based on baseline data, activation of deferred KPIs as data infrastructure improves, and ultimately a comparative analysis of EWS M&E performance across the three countries that this framework, for the first time, makes possible. The broader ambition is that a framework designed and tested in the Eastern Caribbean can inform the development of climate-health EWS evaluation approaches across the wider Caribbean and other small island developing state regions where climate services for health are urgently needed and chronically under-evaluated.

4.6 Annex

M&E Framework, Tracking Tool, and Complete Toolkit for Climate-Informed Dengue Early Warning System

Countries: Barbados | Grenada | Saint Lucia
EWS Model Reference: Fletcher et al., Lancet Planetary Health, 2025
M&E Operationalization Target: Late 2026
Oversight Body: National EWS Oversight Committee (per country)
Annual Review: Q4 of each calendar year
Framework Version: 1.0 (2025) — Living Document

Scope note: This tool covers the seven KPIs prioritized for immediate operationalization (KPIs 2, 3, 4, 6, 7, 8, 9).
Three KPIs are deferred:

- Accuracy of Alerts (KPI 1) — medium-term research priority pending data infrastructure improvements;
- Cost per Case Averted (KPI 5) — requires health economics support and dedicated funding;
- System Scalability (KPI 10) — aspirational, to be addressed following ≥2 full EWS operational cycles.
- Country teams should adapt the responsible entity column to their specific institutional structures.
- All entries are to be reviewed and updated annually by the national oversight committee.

How to use this tool:
(1) Each oversight committee meeting should begin with review of data reported against each active KPI since the last meeting.
(2) The 'Data Required' column defines the minimum dataset needed before any KPI can be meaningfully assessed — committees should audit data availability as a first step.
(3) 'Responsible Entity' designations should be formalized in departmental terms of reference and inter-agency MOUs.
(4) 'Success Targets' are indicative benchmarks; committees may adjust these to reflect national baseline conditions.

(5) KPIs marked as 'medium-term' should be revisited at each annual review for readiness to activate.

Part 1: KPIs & Reporting Schedule

Table A1. National M&E Tracking Tool — Priority KPIs (ordered by implementation timeline)

KPI	Indicator & Definition	Data Required	Collection Method	Responsible Entity	Frequency	Reporting Mechanism	Success Target
2	**Timeliness of Alerts** *Time (days) elapsed from submission of monthly epidemiological and climate data to issuance of an EWS alert to the Ministry of Health*	Timestamp logs for: (1) data receipt from surveillance and Met Office, (2) model run date, (3) alert dispatch date	Automated timestamp metadata captured in EWS platform; manual log if platform unavailable	Technical EWS team (model operator); oversight committee monitors	Monthly	Monthly report to oversight committee; flagged in dashboard if >5-day delay from 15th-of-month deadline	≤5 days from data submission to alert; <10% of months exceeding threshold
3	**Response Activation Time** *Days between issuance of a HIGH-RISK EWS alert and deployment of the first documented vector control intervention (e.g., fogging, larviciding, community clean-up campaign)*	Alert dispatch date (from EWS platform); intervention start date and type (from environmental health logs); intervention completion date	Intervention logbooks maintained by Environmental Health / Vector Control units; cross-referenced with alert records	Environmental Health / Vector Control Department (data collection); Epidemiology Unit (cross-referencing); oversight committee (review)	Per alert event (not fixed schedule); reviewed quarterly	Quarterly summary table to oversight committee; annual trend analysis; include in national health ministry report	≤7 days from HIGH-RISK alert to first intervention; documented response for ≥90% of HIGH alerts
4	**Reduction in Dengue Cases** *Change in confirmed dengue case counts relative to a rolling 3-year seasonal baseline,*	Monthly confirmed dengue case counts from passive surveillance (MOH epidemiology);	National passive surveillance reporting system; monthly epidemiological	Epidemiology Unit (primary); Meteorological Service (climate triangulation);	Monthly case data collection; annual comparative	Annual M&E report to Ministry of Health; presented at oversight committee annual in-person review;	Statistically significant downward trend over 3+ EWS operational years compared to pre-EWS baseline; or maintained low

KPI	Indicator & Definition	Data Required	Collection Method	Responsible Entity	Frequency	Reporting Mechanism	Success Target
	measured annually and in post-outbreak reviews	rainfall and temperature records; intervention timeline log	bulletin; quarterly triangulation with climate data and intervention logs	Environmental Health (intervention records)	analysis against 3-year rolling baseline	regional comparison through CARPHA	case counts relative to expected climate-driven risk
6	**Community Awareness** *Proportion of target population who are aware of the dengue EWS, understand the meaning of an alert level, and can name at least one recommended preventive action*	Survey responses: EWS awareness (yes/no); ability to explain alert meaning; preventive actions cited; demographic data (district, age group)	Pre/post seasonal questionnaire administered at community events, health facilities, or via mobile survey tool; social media reach analytics (where applicable)	Bureau of Health Education / Health Promotion Unit (survey design and administration); oversight committee (data review)	Bi-annually (before and after peak dengue season); social media monitoring monthly where tools available	Bi-annual summary report to oversight committee; public-facing infographic on awareness levels; aggregated in annual M&E report	≥50% awareness in target communities in Year 1; ≥70% by Year 3; culturally adapted messaging reaching ≥2 community-level distribution channels per district
7	**Community Participation** *Level of active community engagement in EWS-triggered vector control activities (clean-up campaigns, source reduction inspections, larval surveys)*	Event attendance records; number of households inspected; number and type of breeding sites identified and eliminated; community focal point reports	Environmental Health Officer field reports; community event attendance sheets; mobile reporting app (Saint Lucia youth monitor program); parish-level campaign logs	Environmental Health Officers (primary field data); community focal points / youth monitors; Epidemiology Unit (consolidation)	Per campaign event; monthly summary from Environmental Health	Monthly brief to oversight committee during dengue season; annual participation index report; geographic mapping of participation rates	≥1 documented community-level intervention per HIGH alert; participation trend increasing year-on-year; ≥30% of target communities with active focal point
8	**Stakeholder Participation** *Degree of multi-institutional engagement in EWS governance, measured through*	Committee meeting attendance records; MOU status; cross-	Oversight committee secretariat	Committee Chair / Secretariat (attendance	Quarterly (attendance and meeting	Quarterly committee meeting minutes distributed to all	≥80% of designated agencies represented at ≥75% of quarterly

KPI	Indicator & Definition	Data Required	Collection Method	Responsible Entity	Frequency	Reporting Mechanism	Success Target
	oversight committee attendance, inter-agency data sharing, and cross-sectoral collaboration activities	training participation logs; inter-agency data sharing frequency; stakeholder satisfaction survey results	maintains attendance and agenda records; annual online satisfaction survey (anonymous); documentation of MOUs and formal agreements	tracking); oversight committee (survey coordination); lead agency (MOU management)	records); Annually (satisfaction survey and MOU review)	members; annual governance report to Ministry of Health; inter-agency scorecard	meetings; at least one inter-agency MOU formalized within 12 months; annual satisfaction score ≥3.5/5.0
9	**Sustainability Metrics** *Evidence that the EWS is institutionally embedded in national health systems, including designated funding, permanent human resources, and integration in health strategic plans*	Budget line item status (confirmed/pending); staffing records (permanent vs. contract); EWS reference in national strategic health plan; open-source platform adoption status	Review of Ministry of Health budget documentation (annual); review of national strategic health plan; HR records; platform sustainability audit	Planning & Research Unit / Finance (budget review); Human Resources Department (staffing); oversight committee (annual institutional audit)	Annually (sustainability audit); budget review tied to national health planning cycle	Annual sustainability report to oversight committee and Ministry of Health; included in CARPHA regional EWS progress update	EWS explicitly referenced in national health strategic plan by Year 2; ≥1 permanent staff position designated for EWS coordination; confirmed budget line item by Year 3

Annual M&E Reporting Schedule

Table A2. Annual M&E reporting calendar (all three countries).

Period	Activity	Output	Responsible
January	Annual M&E synthesis: compile all KPI data from prior year; compare against success targets; assess oversight committee function	Annual M&E Report (submitted to Ministry of Health by 28 February)	Oversight committee secretariat + Epidemiology Unit
March–April	Pre-season preparation: confirm data collection protocols active; brief KPI focal points; schedule community awareness surveys	Readiness confirmation memo; survey instruments finalized	Committee Chair + departmental KPI focal points
April–May	Baseline community awareness survey (pre-peak season)	Pre-season awareness survey report	Health Promotion / Bureau of Health Education
June–October	Peak dengue season active monitoring: monthly KPI data capture; alert pipeline monitoring (Timeliness KPI); real-time intervention logging (Response Activation Time)	Monthly KPI data entries; flagged exceptions reported to committee within 5 days	Technical EWS team + Environmental Health + Epidemiology
October–November	Post-season community awareness survey; post-season community participation review; entomological index assessment	Post-season survey report; participation index update	Health Promotion / Environmental Health Officers
November–December	Annual oversight committee in-person review: KPI performance review; lessons learned; framework updates; planning for next cycle	Updated M&E framework (if revisions needed); next-cycle work plan	Full oversight committee; regional report to CARPHA

Period	Activity	Output	Responsible
Quarterly (all months)	Oversight committee regular meeting: KPI data review; data gap identification; intervention logging audit; stakeholder engagement check	Quarterly meeting minutes; action register	Oversight committee secretariat

Deferred KPIs: Conditions for Activation

Three KPIs were excluded from the immediate tracking tool following expert interview and workshop consensus. The following conditions should be reviewed at each annual committee meeting to determine readiness for activation:

KPI 1 — Accuracy of Alerts

- Activation condition: Near-real-time (≤2-week lag) confirmed dengue case data available in all three countries; standardized alert validation protocol developed and agreed across the three national systems; pilot methodology for accuracy calculation tested and validated on at least 12 months of prospective data.
- Responsible for readiness review: Technical EWS team in coordination with Epidemiology Units and CARPHA.
- Target: Activate as operational KPI by Year 3 (2029) pending data infrastructure improvement.

KPI 5 — Cost per Case Averted

- Activation condition: Standardized dengue cost-of-illness methodology developed and agreed; baseline treatment cost data (hospitalization, outpatient, vector control expenditure) available for all three countries; health economics technical support secured (in-country or regional).
- Responsible for readiness review: Planning & Research Units with support from CARPHA health economics team.
- Target: Activate by Year 3 (2029) with donor co-funding; indirect cost (absenteeism, tourism impact) component to be added in subsequent cycle.

KPI 10 — System Scalability

- Activation condition: EWS has completed ≥2 full operational cycles; at least one disease-expansion feasibility study initiated; regional replication interest formally expressed by ≥1 additional Caribbean country.
- Responsible for readiness review: Full oversight committee with CARPHA regional coordination.
- Target: Designate as active KPI in Year 4+ planning cycle (2030 onwards).

PART 2 — OPERATIONAL M&E TOOLKIT (Tools B-1 to B-10)

The ten tools below are designed for direct operational use by oversight committees and KPI focal points. They are ordered to follow the natural M&E workflow: establish governance first, then collect data monthly, then report and communicate annually, then evaluate and improve. Each tool includes instructions, fillable fields, and where relevant, illustrative example entries. Country teams should adapt field labels and deadlines to their national context. This toolkit is built as a guide and should be catered to each country's individual needs and priorities.

Tool B-1 — National EWS Oversight Committee: Terms of Reference Template

Instructions: Complete all fields. Present for committee approval at the inaugural meeting. File signed copy with the Ministry of Health and with CARPHA. Review annually at Q4 meeting.

Country: _____

Committee name: EWS Oversight Committee for Climate-Informed Dengue Early Warning System

Established: _____ (date of inaugural meeting)

Host institution: _____ (Ministry of Health, [Country])

Committee Chair: _____ (name, title, department)

Committee Secretariat: _____ (name, title, department)

1. Mandate

The Committee is established to provide multi-sector oversight, governance, and accountability for the national climate-informed dengue Early Warning System. The Committee is responsible for: reviewing M&E data and assessing EWS performance against agreed Key Performance Indicators; identifying data gaps, institutional barriers, and required system improvements; ensuring inter-agency data-sharing obligations are met; reporting EWS performance to the Ministry of Health; and maintaining the M&E plan as a living document updated annually.

2. Membership

Department / Agency	Role / Expertise	Designated Focal Point (Name)	KPI Responsibilities
Epidemiology Unit — MOH	Disease surveillance, case data	_____	KPIs 1, 3, 4
Environmental Health — MOH	Vector control, field operations	_____	KPIs 3, 7

Department / Agency	Role / Expertise	Designated Focal Point (Name)	KPI Responsibilities
Health Promotion / Education	Community communication	_____	KPIs 6, 7
Planning & Research Unit — MOH	Strategic planning, sustainability	_____	KPIs 9, 10
National Meteorological Service	Climate forecasts, observed data, alert pipeline	_____	KPI 2
Public Health Laboratory	Case confirmation, serotype data	_____	KPI 1
[Add agency as appropriate]		_____	
CARPHA (regional liaison)	Regional coordination, benchmarking	_____	KPIs 8–10

3. Quorum: The Committee shall meet with a quorum of ≥ ___ members (recommended: majority of designated agencies represented). Meetings without quorum may proceed for information-sharing but may not ratify decisions.

4. Meeting Schedule: The Committee shall meet quarterly (January, April, July, October) with an annual in-person strategic review in Q4 (October–November). Emergency meetings may be convened by the Chair during declared health emergencies or when an alert triggers a HIGH or VERY HIGH-risk designation.

5. Reporting: The Committee Secretariat shall produce an Annual M&E Report (due 28 February each year) for submission to the Ministry of Health and to CARPHA. Quarterly meeting minutes shall be circulated to all members within 10 working days of each meeting.

6. Amendment: These Terms of Reference shall be reviewed annually at the Q4 meeting and may be amended by a two-thirds vote of members present.

Chair signature: _____ Date: _____
MOH endorsement: _____ Date: _____

Tool B-2 — Inter-Agency Memorandum of Understanding (MOU): Data-Sharing and Roles Template

Instructions: This MOU formalizes the data-sharing and operational obligations between the Ministry of Health and the national meteorological service (and any additional agencies). Complete bracketed fields and have signed by the relevant institutional heads. Review every two years.

This Memorandum of Understanding is entered into by:

- Party A: Ministry of Health, [Country] — hereinafter 'MOH'
- Party B: [National Meteorological Service], [Country] — hereinafter 'Met Office'
- Party C (if applicable): [Additional agency, e.g. Environmental Health Authority]

Purpose

The parties agree to share data [outline specific data here], coordinate roles, and cooperate in the operation and monitoring of the national climate-informed dengue Early Warning System (EWS), in support of the EU/CARIFORUM Climate Resilient Health Systems project and as governed by the national EWS Oversight Committee.

Data-Sharing Obligations

Party	Data Provided	Format & Frequency	Submission Deadline
MOH — Epidemiology Unit	Monthly confirmed de-identified dengue case counts (national level)	Secure file transfer (CSV or Excel); monthly	15th of each month
MOH — Epidemiology Unit	Annual case data for model recalibration	Secure file transfer; annually	31 January each year
Met Office	Monthly observed climate data (temperature, i.e., SPI-6)	Standardized NetCDF or CSV; monthly	15th of each month
Met Office/ CIMH	Seasonal climate forecast	Standardized format; monthly	1st of forecast month
Environmental Health	Quarterly intervention logs (type, location, dates)	Standardized logbook form (Tool B-5); quarterly	15th of month following quarter end

Roles and Responsibilities

- MOH (Epidemiology Unit): Responsible for receiving and acting on EWS alerts; coordinating health interventions; providing case data; co-chairing the Oversight Committee.
- Met Office/ CIMH: Responsible for generating seasonal climate forecasts; providing observed climate data; running the EWS model (or coordinating with technical team); issuing probabilistic alerts.
- Technical team (EWS developers): Responsible for model maintenance and updates; supporting training; communicating any model errors or performance issues to the Committee.

Confidentiality: Health data shared under this MOU is subject to national health data privacy laws. All parties agree not to share individual-level health data. Aggregated outputs (alert levels, KPI summaries) may be shared with CARPHA for regional reporting.

Duration: This MOU takes effect on the date of last signature below and remains in force for two (2) years, subject to annual review.

MOH Authorized Signatory: _____ **Date:** _____

Met Office Authorized Signatory: _____ **Date:** _____

Tool B-3 — KPI Focal Point: Role Description

Instructions: This role description should be shared with department heads when designating a KPI focal point. It can be attached to an existing job description or used as the basis for a formal addendum.

Role title: KPI Focal Point — EWS Monitoring and Evaluation

Department: _____ (e.g., Epidemiology Unit, Environmental Health)

Reports to: Head of Department (functionally) / Committee Secretariat (for M&E reporting)

Time commitment: Approximately 10-15 hours per month

Appointment: Designated by Department Head; notified to Committee Secretariat

Purpose of the Role

The KPI Focal Point is the designated individual within each participating department responsible for collecting, verifying, and submitting M&E data to the EWS Oversight Committee on a monthly and quarterly basis. This role ensures that M&E data reflects real operational conditions rather than estimates.

Key Responsibilities

- Complete and submit the Monthly KPI Data Submission Form (Tool B-4) by the 15th of each month.
- Maintain department-level records that support KPI data (e.g., intervention logbooks, attendance sheets, survey results).
- Attend quarterly Oversight Committee meetings or designate a deputy when unavailable.
- Flag data gaps, delays, or quality issues to the Secretariat within 3 working days of identification.
- Support the annual M&E report by providing a departmental data summary by 15 January each year.
- Participate in the annual stakeholder satisfaction survey (Tool B-9).

KPIs by Department

Department	Primary KPIs	Key Data to Track
Epidemiology Unit — MOH	KPIs 1, 3, 4	Case counts (monthly); alert receipt dates; intervention start dates
Environmental Health / Vector Control	KPIs 3, 7	Intervention logbook entries; event attendance; breeding site data
Health Promotion / Bureau of Education	KPIs 6, 7	Survey results; outreach event records; media reach metrics
Planning & Research Unit — MOH	KPIs 9, 10	Budget line status; staffing records; strategic plan references
National Meteorological Service	KPI 2	Data submission timestamps; alert issuance dates and risk levels
Public Health Laboratory	KPI 1	Case confirmation dates; serotype reports

Support and Training: Focal points will receive a half-day orientation before the first M&E cycle and can contact the Committee Secretariat at any time with questions. Training materials are available from CARPHA.

Designated focal point name: _____ **Department head signature:** _____

Tool B-4 — Monthly KPI Data Submission Form

*Instructions: Complete one form per month and submit to the Committee Secretariat by the 15th. All fields marked * are required. If data is unavailable, state the reason in the Notes column. Submit via [email / shared drive — specify nationally].*

Country: _____ Reporting Month/Year: _____ Focal Point Name: _____ Date Submitted: _____

KPI	KPI Name	Data Field *	Value This Month	Notes / Data Gaps
2	Timeliness of Alerts	Date epi data received by Secretariat Date climate data received by Secretariat Date alert issued Days from data submission to alert	DD/MM/YYYY DD/MM/YYYY DD/MM/YYYY ___ days	
3	Response Activation Time	Date of most recent HIGH/VERY HIGH alert (if any) Date first vector control intervention activated Days from alert to intervention type(s) deployed	DD/MM/YYYY DD/MM/YYYY ___ days (fogging / larviciding / clean-up / other)	If no HIGH alert this month, write N/A
4	Dengue Case Count	Confirmed dengue cases this month 3-year average for this month (baseline) % above/below baseline	___ cases ___ cases ___%	Use national surveillance bulletin as source

KPI	KPI Name	Data Field *	Value This Month	Notes / Data Gaps
6	Community Awareness	Survey administered this month? (Y/N) If yes: sample size, % aware of EWS	Y / N n=___, ___% aware	Only required in March and November
7	Community Participation	Number of community events held Total households reached Number of breeding sites identified/eliminated	___ events ___ households ___	Submit Environmental Health logbook summary
8	Stakeholder Participation	Committee meeting held this month? (Y/N) Agencies represented (list)	Y / N ___	Attach attendance log
9	Sustainability	Budget line confirmed for EWS this year? (Y/N) Permanent staff position designated? (Y/N)	Y / N Y / N	Update annually in January only

I confirm that the data above is accurate to the best of my knowledge. Any gaps or estimates are noted in the Notes column.

Signature: _____ Date: _____

ToolB4.1 Example completed entry (illustrative — shaded rows):

Month	Alert Level	Epi Data Received	Climate Data Received	Alert Issued	Days to Alert	Response Activated
Jan 2027	*Low*	*Jan 12*	*Jan 11*	*Jan 16*	*4*	*N/A — low risk*
Mar 2027	*High*	*Mar 16**	*Mar 14*	*Mar 21*	*5**	*Mar 26 (5 days) ✓*
Apr 2027	*Very High*	*Apr 13*	*Apr 12*	*Apr 16*	*3*	*Apr 20 (4 days) ✓*

** March epi data arrived 1 day late — reminder sent to Epi Unit (flag raised in monthly checklist).*

Tool B-5 — Intervention Logbook: EWS-Triggered Vector Control Field Record

Instructions: Environmental Health Officers complete one row per intervention event triggered by an EWS alert. Submit the completed logbook page to the KPI Focal Point by the last working day of each month. Retain original on file.

Country: _____ District/Parish: _____ EHO Name: _____

Alert Date	Alert Level	Response Date	Intervention Type	Location (Parish/ District)	Households Reached	Staff Deployed (#)	Breeding Sites Found	Breeding Sites Eliminated	EHO Initials
DD/MM/YY	*High*	*DD/MM/YY*	*Larviciding*	*St. Michael*	*47*	*3*	*12*	*12*	*A.D.*
DD/MM/YY	*Very High*	*DD/MM/YY*	*Fogging + Clean-up*	*Christ Church*	*83*	*5*	*31*	*28*	*B.M.*

Alert Date	Alert Level	Response Date	Intervention Type	Location (Parish/ District)	Households Reached	Staff Deployed (#)	Breeding Sites Found	Breeding Sites Eliminated	EHO Initials

Shaded rows show example entries. Intervention types: Larviciding | Fogging | Source reduction / clean-up | Community inspection | Other (specify in notes).

Supervisor review:
Supervisor name: _____ **Signature:** _____ **Date:** _____

Tool B-6 — Community Awareness Survey Instrument (KPI 6)

Instructions: Administer twice yearly — before peak dengue season (March) and after (November). Target 80–120 respondents per district at community events, health facilities, or via mobile survey. This survey can be done during normal vector control operations to reduce potential human resource constraints. This survey is anonymous. Estimated time: 5–7 minutes.

Country: _____ **District:** _____ **Date:** _____ **Pre- or Post-season:** Pre / Post

SECTION A: Demographics (optional — do not record names)

A1. Age group: □ 18–29 □ 30–44 □ 45–59 □ 60+

A2. Gender: □ Female □ Male □ Prefer not to say

A3. Parish / community: _____

SECTION B: EWS Awareness

B1. Have you heard of an Early Warning System for dengue in your country? □ Yes □ No □ Not sure

B2. If Yes — where did you first learn about it? □ Radio □ TV □ Social media □ Health worker □ Community event □ Friend/family □ Other: ___

B3. In the past 6 months, have you received a dengue risk alert or message from the health authorities? □ Yes □ No □ Not sure

SECTION C: Understanding

C1. If you received a HIGH dengue risk alert, what would it mean? □ A dengue outbreak is very likely in the next few months □ There is a dengue case nearby □ A hurricane is coming □ I don't know

C2. What would you do if a HIGH dengue risk alert was issued in your community? (circle all that apply) □ Check for standing water around my home □ Apply larvicide/cover water containers □ Visit a doctor □ Nothing □ Other: ___

C3. Who in your community is responsible for responding to a dengue alert? □ Ministry of Health □ Environmental Health Officer □ Community members □ All of the above □ I don't know

SECTION D: Trust and Communication

D1. How much do you trust the dengue risk information provided by the Ministry of Health? □ A lot □ Somewhat □ Not very much □ Not at all

D2. What is the BEST way for health authorities to communicate dengue risk to you? (choose one) □ WhatsApp/text message □ Radio announcement □ TV broadcast □ Community meeting □ Health facility poster □ Social media post

D3. Do you have any suggestions for improving how dengue risk information is shared in your community? (open text):

_____

Enumerator name: _____ Supervisor check: _____ Forms submitted: _____

Example survey results summary (illustrative — for the district results log submitted to the secretariat after each survey round):

District	Survey Period	Sample (n)	% Aware of EWS	% Understand Alerts	% Know Preventive Action	Notes
St. Michael	*Pre-season Mar 2027*	*120*	*42%*	*31%*	*38%*	*Below 50% target; outreach campaign planned*
St. Michael	*Post-season Nov 2027*	*115*	*68%*	*59%*	*63%*	*Improvement +26pp after campaign ✓*

District	Survey Period	Sample (n)	% Aware of EWS	% Understand Alerts	% Know Preventive Action	Notes
Christ Church	*Pre-season Mar 2027*	*98*	*55%*	*47%*	*51%*	*On track*
Christ Church	*Post-season Nov 2027*	*101*	*71%*	*62%*	*67%*	*Above target ✓*

Tool B-7 — Annual KPI Dashboard Scorecard (One-Page Executive Summary)

Instructions: Complete annually and present to Ministry of Health leadership at the Q4 review meeting. Use traffic-light colors: GREEN = target met, AMBER = partial progress, RED = not achieved. Keep language non-technical — this is for decision-makers, not researchers.

Country: _____ Year: _____ Prepared by: _____ Date: _____

KPI	Indicator	Target	Result This Year	Status (G/A/R)	Key Finding / Action
2	Timeliness of Alerts	≤5 days from data submission to alert; <10% of months delayed	___ days avg;	___	

KPI	Indicator	Target	Result This Year	Status (G/A/R)	Key Finding / Action
			___% on time		
3	Response Activation Time	≤7 days from HIGH alert to intervention; ≥90% of HIGH alerts actioned	___ days avg; ___% actioned	___	
4	Dengue Cases (trend)	Downward or stable trend vs. 3-year baseline	___% vs. baseline	___	
6	Community Awareness	≥50% awareness Year 1; ≥70% Year 3	Pre: ___% Post: ___%	___	
7	Community Participation	≥1 intervention per HIGH alert; year-on-year increase	___ events; ___ households	___	
8	Stakeholder Participation	≥80% agencies at ≥75% of meetings; MOU in place	___% attendance; MOU: Y/N	___	
9	Sustainability	Budget line confirmed; ≥1 permanent position; in strategic plan	BL: Y/N Staff: Y/N Plan: Y/N	___	

STATUS KEY: G = Target met (Green) | A = Partial progress / in progress (Amber) | R = Not achieved (Red) | N/A = Not yet applicable

Overall EWS Assessment (1–2 sentences for the Minister):

_____

_____

Top priority action for next year:

_____

Tool B-8 — Annual M&E Report Template

Instructions: Complete by 28 February each year covering the prior calendar year. Submit to the Ministry of Health, file with CARPHA, and circulate to all Committee members. Sections in [brackets] are instructions — delete before finalizing.

ANNUAL MONITORING AND EVALUATION REPORT

Climate-Informed Dengue Early Warning System

Country: _____ Reporting Year: _____

1. Executive Summary

[2–3 paragraphs. State: (1) whether the EWS issued alerts this year and at what risk levels; (2) the most significant operational achievement; (3) the most significant challenge; (4) the top priority action for next year. Use plain language suitable for Ministry leadership.]

2. EWS Alert Summary

[Table: list each month, the risk level issued, and whether data was received on time. Flag any months where alerts were delayed. Note any HIGH or VERY HIGH alerts and the responses they triggered. Attach the full alert pipeline log from Tool B-4 as Annex 1.]

3. KPI Performance Summary

[Insert completed Tool B-7 Dashboard Scorecard here. Below it, provide a one-paragraph narrative for each KPI: what the data shows, what it means operationally, and what should happen next year as a result.]

4. Community Engagement

[Summarize community awareness survey results from Tool B-6. Report: sample sizes per district, pre- and post-season awareness rates, change from prior year if available, and any qualitative feedback from Section D of the survey. Include a table if helpful.]

5. Oversight Committee Function

[Report: number of meetings held; average attendance rate; agencies with full attendance vs. those with gaps; whether quorum was met at every meeting; whether action items from last year's report were completed. Attach attendance logs as Annex 2.]

6. Institutional Sustainability

[Status update on: budget line item, permanent staffing designation, MOU renewal date, EWS reference in national strategic plan. Note any risks to sustainability identified during the year.]

7. Lessons Learned

[List 3–5 specific operational lessons from this year, things that worked well and should be continued, and things that did not work and should be changed. Be specific and honest. These lessons feed directly into the annual framework review.]

8. Recommendations for Next Year

[List 3–5 specific, actionable recommendations. Each should name a responsible party and a target completion date. These become the action items tracked in next year's report.]

9. Annexes

Annex 1: Monthly alert pipeline log (Tool B-4 summaries) Annex 2: Oversight Committee attendance logs Annex 3: Community awareness survey summary (Tool B-6) Annex 4: Intervention logbook summary (Tool B-5) Annex 5: Stakeholder satisfaction survey results (Tool B-9)

Prepared by: _____ Approved by: _____ Date submitted: _____

Tool B-9 — Annual Stakeholder Satisfaction Survey (KPI 8)

Instructions: Distribute anonymously to all Oversight Committee members and KPI focal points each November. Collect via online form (e.g., Google Forms) or paper. Collate results and present at the Q4 annual review meeting.

This survey is anonymous. Your honest responses help improve the EWS and its M&E process. It takes approximately 10 minutes.

SECTION A: EWS Performance

A1. How useful were the EWS dengue risk alerts for your department's planning and decision-making this year?

□ Very useful □ Somewhat useful □ Not very useful □ Not useful at all □ I didn't use the alerts

A2. How satisfied are you with the timeliness of alerts (i.e., were they issued early enough to be actionable)?

□ Very satisfied □ Satisfied □ Neutral □ Dissatisfied □ Very dissatisfied

A3. How well did the EWS alert levels (Low/Medium/High/Very High) reflect actual dengue risk conditions in your experience?

□ Very well □ Somewhat well □ Not very well □ Not at all □ Unable to assess

A4. If you received a HIGH or VERY HIGH alert this year, was your department able to respond within 7 days?

□ Yes, always □ Yes, usually □ Sometimes □ No □ No HIGH/VERY HIGH alert was issued

SECTION B: M&E Process

B1. How clear and manageable were the M&E data reporting requirements for your department?

□ Very clear and manageable □ Mostly clear □ Somewhat unclear □ Too burdensome

B2. How effectively did the Oversight Committee meetings support cross-agency coordination this year?

□ Very effectively □ Somewhat effectively □ Neutral □ Not effectively

B3. Were the M&E findings (KPI results, annual report) used to make decisions or improvements to the EWS operational design?

□ Yes, significantly □ Yes, somewhat □ Not that I'm aware of □ No

SECTION C: Open Feedback

C1. What worked best about the EWS or its M&E process this year?

_____

C2. What was the most significant challenge or barrier you encountered?

_____

C3. What one change would most improve the EWS or its M&E process next year?

_____

C4. Any additional comments? _____

Thank you for completing this survey. Results will be summarized (anonymously) at the Q4 annual review meeting.

Tool B-10 — Annual EWS Performance Review Protocol

Instructions: Use this protocol to structure the annual in-person Oversight Committee review meeting (Q4, October–November). The Chair should distribute the agenda at least 7 days in advance. The Secretariat should prepare the Annual M&E Report (Tool B-8) and Dashboard Scorecard (Tool B-7) before the meeting.

Suggested Agenda (Full Day or Half Day)

Time	Item	Guiding Questions / Activities	Lead
09:00–09:15	Welcome and context	What was the EWS asked to do this year? What were the key external factors (climate, disease conditions, institutional changes)?	Chair
09:15–10:00	KPI Review	Work through Dashboard Scorecard (Tool B-7): For each KPI — what do the data show? What explains the result? What should change?	Secretariat + focal points
10:00–10:30	Alert Pipeline Review	Were alerts issued on time? Were any missed or delayed? What caused delays? Who is responsible for fixing them?	Met Office + Epi Unit
10:30–10:45	Break		
10:45–11:30	Response Effectiveness	For each HIGH/VERY HIGH alert: was the response activated within 7 days? What happened? What worked? What didn't?	Environmental Health

Time	Item	Guiding Questions / Activities	Lead
11:30–12:00	Community Engagement	What did awareness survey results show? Are communities improving? Where are the gaps?	Health Promotion
12:00–13:00	Lunch		
13:00–13:45	Sustainability and Governance	Is the EWS institutionally embedded? Budget? Staffing? MOU current? What are the risks?	Planning & Research
13:45–14:30	Lessons Learned	What are 3–5 things the committee agrees worked well? 3–5 things to change?	All — facilitated discussion
14:30–15:15	Action Planning	For each agreed change: WHO will do it? By WHEN? How will we know it's done?	All — Secretariat records
15:15–15:30	Next Steps and Close	Confirm action register; set date of Q1 meeting; any other business.	Chair

Framework Update Decision Tree

At the end of the performance review, the Committee should answer each question below. A 'Yes' answer triggers the corresponding action.

Question	If Yes — Action Required	Decision (Y/N)
Did ≥2 KPIs show RED status for the second consecutive year?	Convene a special working group to diagnose and address root causes within 60 days	
Has the data infrastructure improved enough to activate a deferred KPI (Accuracy, Cost per Case Averted, or Scalability)?	Draft activation plan and assign focal point at next Q1 meeting	
Has the oversight committee structure (membership, quorum, frequency) proven unworkable?	Revise Terms of Reference (Tool B-1) at this meeting	
Has a country's health system context changed significantly (new government, restructuring, new data system)?	Schedule country-specific M&E adaptation meeting within 90 days	
Has the EWS model been updated with new predictors, data, or thresholds?	Update KPI definitions and success targets in Annex I accordingly	
Are there lessons from Year 1 that require changes to any Tool in this toolkit?	Assign lead person and deadline for each tool revision	

Example completed attendance log (illustrative — attach to quarterly minutes):

Agency / Department	Q1 2027	Q2 2027	Q3 2027	Q4 2027	Notes
Epidemiology Unit — MOH	✓	✓	✓	✓	*Full attendance*
Environmental Health — MOH	✓	✓	✗	✓	*Q3: staff illness; deputy unavailable — action item raised*
Health Promotion Unit — MOH	✓	✗	✓	✓	*Q2: competing training — noted*
National Meteorological Service	✓	✓	✓	✓	*Full attendance*
Planning & Research Unit — MOH	✗	✓	✓	✓	*Q1: delayed focal point appointment*
CARPHA (regional liaison)	✓	✓	✓	✓	*Virtual Q2–Q4*
Quorum met? (≥4/6 agencies)	*Yes 5/6*	*Yes 4/6*	*Yes 5/6*	*Yes 5/6*	*All meetings quorate*

Meeting date: _____ Number of attendees: _____ Action items recorded: _____

Minutes prepared by: _____ Submitted to MOH by: _____

5.0 Epilogue

Climate Change, System Transformation, and the Future of Climate Services for Health

The urgency of these findings is amplified in the context of climate change, which is fundamentally altering the environmental envelope within which dengue transmission occurs[1]. Rising temperatures are expanding the geographic range of *Aedes aegypti* into regions that were previously thermally unsuitable, while shifting precipitation regimes and increasing variability are modifying the timing, duration, and intensity of transmission seasons [2]. These changes are not uniform. They interact with local hydrology, urban infrastructure, and socio-economic vulnerability to produce highly heterogeneous risk landscapes that are increasingly difficult to anticipate using historical baselines alone. As a result, the assumption of stationarity that underpins many existing climate–health models is progressively breaking down [3], [4].

In this context, climate-informed early warning systems represent a critical form of climate adaptation within the health sector. They provide one of the few mechanisms through which anticipatory action can be taken in advance of outbreaks, allowing for the strategic allocation of resources, targeted vector control, and the prevention of disease amplification [5]. However, this dissertation demonstrates that the ability of these systems to fulfill that role depends not simply on predictive capacity, but on whether they are designed as operational systems rather than analytical exercises. As climate signals become more complex and less predictable in traditional terms, the gap between model output and decision-making will widen unless the structure, communication, and institutional embedding of these systems are fundamentally rethought.

The synthesis across the four studies presented here provides a framework for this rethinking. Chapter 1 provides a framework for how to implement and operationalize climate-driven forecasting systems, ensuring that robust and important climate adaptation measures do not merely

end up in the scientific literature but move beyond the journal to improve public health.. Chapter 2 uses chapter 1 as a guide for building a novel climate-driven dengue budget forecasting system and demonstrates that forecasting systems can be explicitly designed around decision contexts, translating climate signals into actionable outputs such as budget projections and resource allocation strategies. Chapter 3 builds on chapter 2 and shows that uncertainty, rather than being an inherent barrier, becomes actionable when structured in ways that align with decision-making processes. Chapter 4 completes the system by introducing a monitoring and evaluation framework that enables continuous assessment, learning, and institutionalization. Together, these components advance climate services for health as an integrated system linking environmental signal detection, epidemiological interpretation, and public health action.

This integrated perspective constitutes the central scientific contribution of this dissertation to the field of Earth and Environmental Science. Traditionally, this field has focused on understanding and modelling the physical processes that govern climate variability and change, as well as their impacts on natural and human systems. This work extends that paradigm by demonstrating the value of environmental prediction through the creation of a novel climate-driven budget forecasting system, but in its translation into decision-relevant systems. It advances a shift from viewing climate as an external driver of health outcomes to conceptualizing climate–health interactions as part of a coupled human–environment system in which feedbacks between environmental signals, institutional responses, and societal outcomes shape overall system behavior. Within this framing, climate services are not simply information products; they are components of adaptive systems that mediate the relationship between environmental change and human well-being.

A key element of this contribution is the explicit incorporation of non-stationarity into both the conceptual and operational design of climate services. The findings highlight that relationships between climate variables and dengue transmission are dynamic, influenced by evolving vector

ecology, population immunity, politics, and environmental change. The integration of a serotype novelty index in Chapter 2 represents one approach to capturing these dynamics, linking immunological susceptibility to climate-driven transmission potential. However, more broadly, the work demonstrates that climate services must be designed to function under shifting baseline conditions, where historical relationships may no longer hold. This has implications not only for model development, but for how uncertainty is interpreted and acted upon within decision-making systems.

At the same time, several limitations of this work point to important directions for future research. First, while the case studies span multiple countries in the Caribbean and Central America, they remain regionally concentrated. Further work is needed to assess how the frameworks and systems developed here perform in other epidemiological and climatic contexts, including regions with different vector species, transmission dynamics, and health system structures. Second, while the forecasting models incorporate key climatic and epidemiological drivers, additional factors such as human mobility, land use change, and socio-economic conditions are likely to play an increasingly important role in shaping transmission patterns under climate change. Integrating these variables into predictive and decision-support frameworks represents a critical next step.

Third, the challenge of non-stationarity warrants deeper methodological attention. Future research should explore approaches that explicitly account for changing relationships over time, including adaptive modelling frameworks and the integration of climate change projections into long-term planning tools. This is particularly important for extending dengue climate services beyond seasonal forecasting toward medium- and long-term decision-making horizons, such as infrastructure investment and health system strengthening.

Finally, while the monitoring and evaluation framework developed in this dissertation provides a foundation for assessing the performance of climate services, its long-term value depends on sustained implementation and iterative refinement. Longitudinal studies are needed to evaluate how these systems influence public health outcomes over time, including their impact on disease incidence, resource efficiency, and system resilience. Such evaluations will be essential for demonstrating the value of climate-informed approaches and securing continued investment.

Taken together, these findings underscore that the next frontier in climate services for health lies not only in improvements in predictive skill, but in the design of systems that can operate effectively within the realities of decision-making under a changing climate. This requires a shift from model-centric to system-centric thinking, in which prediction, communication, implementation, and evaluation are treated as interdependent components of a single adaptive framework.

Ultimately, this work positions climate services as an impact-oriented application of Earth and Environmental Science, shifting the focus from purely observational data to actionable societal intelligence. By linking climate variability and change to actionable public health decisions through transdisciplinary co-production, this work demonstrates how environmental science can move beyond describing risk to actively shaping responses to it. As climate change continues to intensify the burden of vector-borne diseases, the development of such systems will be essential not only for improving predictive capacity, but for ensuring that that capacity is translated into interventions that save lives and protect human health.

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