Compound and cascading effects of climatic extremes on dengue outbreak risk in the Caribbean: an impact-based modelling framework with long-lag and short-lag interactions

Chloe Fletcher, Giovenale Moirano, Tilly Alcayna, Leslie Rollock, Cédric J Van Meerbeeck, Roché Mahon, Adrian Trotman, Laura-Lee Boodram, Tia Browne, Sabu Best, Daniela Lührsen, Avriel R Diaz, Willy Dunbar, Catherine A Lippi, Sadie J Ryan, Felipe J Colón-González, Anna M Stewart-Ibarra, Rachel Lowe

Summary

Background Small islands developing states in the Caribbean are exposed to increasingly frequent and intense extreme climatic events, which can exacerbate outbreaks of climate-sensitive infectious diseases. Few forecasting tools incorporate the compound and cascading effects of multiple delayed climatic indicators on disease outbreak risk. We aimed to create an impact-based modelling framework that employs interactions between climatic predictors to forecast the probability of a climate-sensitive infectious disease outbreak 3 months ahead, and to investigate the compound and cascading effects of temperature and long-lag and short-lag standardised precipitation index (SPI) on dengue outbreak risk in Barbados.

Methods We developed a modelling framework to predict the probability of a dengue outbreak in Barbados with a 3-month lead time. We assessed the relationships between dengue incidence and interacting long-lag and short-lag hydrometeorological predictors with confirmed cases from 1999 to 2022 and a Bayesian hierarchical framework accounting for seasonal and interannual variation. With this long–short-lag interaction model, we piloted a dengue early warning system in Barbados for the International Cricket Council Men's Twenty20 World Cup in June, 2024, as a real-world prospective example.

Findings We found that a three-way interaction between the 3-month averaged mean temperature anomaly lagged by 3 months, 6-month SPI (SPI-6) lagged by 5 months, and SPI-6 lagged by 1 month best predicted dengue outbreak risk in Barbados. Our findings showed that long-lag dry (lagged by 5 months), mid-lag hot (lagged by 3 months), and short-lag wet (lagged by 1 month) conditions led to the greatest dengue risk. During cross-validation from 2012 to 2022, the model exhibited a true positive rate (TPR) of 81% and a false positive rate (FPR) of 29%, outperforming a baseline model representing standard practice with a TPR of 68% and an FPR of 48%. For the Twenty20 World Cup, the model predicted a 95% outbreak probability due to epidemiological and climatic conditions, which was shared with the Barbados Ministry of Health and Wellness ahead of the tournament.

Interpretation Our impact-based modelling framework with long-lag and short-lag interactions explicitly accounted for the compound and cascading effects of drought, heat, and excessively wet conditions on dengue outbreak risk in Barbados. The model is being implemented in a national dengue early warning system with ongoing monitoring and evaluation to ensure its reliability and usefulness in operational contexts. Future work could explore the applicability of this methodology to modelling or predicting climate-sensitive infectious diseases in other endemic settings.

Funding Wellcome Trust, Horizon Europe, European Development Fund, and Royal Society.

Lancet Planet Health 2025

Published Online https://doi.org/10.1016/j.lanplh.2025.06.003

Barcelona Supercomputing Center (BSC), Barcelona, Spain (C Fletcher MSc, G Moirano PhD, T Alcayna MPH, D Lührsen MSc, Prof R Lowe PhD); **Department of Medicine & Life Sciences, Universitat Pompeu Fabra, Barcelona, Spain** (C Fletcher); **Centre on Climate Change & Planetary Health and Centre for Mathematical Modelling of Infectious Diseases, London School of Hygiene & Tropical Medicine, London, UK** (T Alcayna, F J Colón-González PhD, Prof R Lowe); **Red Cross Red Crescent Climate Centre, The Hague, Netherlands** (T Alcayna); **Health in Humanitarian Crises Centre, London School of Hygiene & Tropical Medicine, London, UK** (T Alcayna); **Ministry of Health & Wellness, St Michael, Barbados** (L Rollock DrPH); **Caribbean Institute for Meteorology and Hydrology, St James, Barbados** (C J Van Meerbeeck PhD, R Mahon PhD, A Trotman MPhil); **The Caribbean Public Health Agency, Port of Spain, Trinidad and Tobago** (L-L Boodram PhD); **Barbados Meteorological Services, Christ Church, Barbados** (T Browne MSc, S Best BSc); **International Research Institute for Climate & Society, Columbia University, Palisades, NY, USA** (A R Diaz MA); **Department of Earth & Environmental Sciences, Columbia University, New York, NY, USA** (A R Diaz); **The Global Council for Science and the Environment, Washington, DC, USA** (A R Diaz, W Dunbar PhD); **Department of Geography, University of Florida, Gainesville, FL, USA** (C A Lippi PhD, Prof S J Ryan PhD); **Emerging Pathogens Institute,**

Introduction

Caribbean small island developing states (SIDS) are highly vulnerable to the direct and indirect impacts of anthropogenic climate change on human health, in part due to frequent exposure to extreme climatic events.[1–5] Over the past 15 years, Caribbean SIDS have experienced explosive and concurrent outbreaks of arboviral diseases, such as dengue, chikungunya, and Zika virus infection.[6–8] In 2023, the region experienced its largest recorded dengue epidemic with over 97 000 cases, exceeding the previous peak in 2020 by nearly 20%.[9] Historically, Barbados reported the highest global age-standardised dengue incidence rate (DIR) per 100 000 population between 1990 and 2017.[10] In addition to case burdens, arboviruses also carry substantial economic impacts. In 2016, the estimated annual cost of dengue infection in the Latin American and Caribbean region was US$1·73 billion.[11] One study reported a 14-fold increase in the economic impact of *Aedes*-borne diseases between 1975 and 2020,[12] which has probably further increased due to explosive outbreaks in the past 5 years.

University of Florida, Gainesville, FL, USA (C A Lippi, Prof S J Ryan); Wellcome Trust, Data for Science and Health, London, UK (F J Colón-González); Inter-American Institute for Global Change Research, Panama City, Panama (A M Stewart-Ibarra PhD); Catalan Institution for Research & Advanced Studies (ICREA), Barcelona, Spain (Prof R Lowe)

Correspondence to: Chloe Fletcher, Barcelona Supercomputing Center (BSC), Barcelona 08034, Spain chloe.fletcher@bsc.es

or

Rachel Lowe, Barcelona Supercomputing Center (BSC), Barcelona 08034, Spain rachel.lowe@bsc.es

Research in context

Evidence before this study

We searched PubMed on Oct 28, 2024, with the terms "dengue", "risk", "drought", "climate" and "model", and subsequently included an additional term "interaction". No language or publication date restrictions were applied. Our search yielded three studies in Barbados, Brazil, and China, published between 2018 and 2023, all of which employed Bayesian models to examine the impact of drought on dengue risk. These studies confirmed the role of hydrometeorological extremes in driving dengue infections across multiple endemic settings. However, none employed an interaction model to investigate the compound or cascading effects of multiple predictors representing climatic extremes (such as droughts, heat, and excess rainfall) on dengue outbreaks in any location. Furthermore, these studies did not explicitly explore how disease risk drivers could be operationalised into a dengue prediction model within an early warning system.

Added value of this study

Our research outlines an impact-based modelling framework that integrates interacting long-lag and short-lag hydrometeorological predictors to forecast infectious disease outbreaks, capturing the compound effects of climatic conditions on disease risk. Focusing on dengue infection in Barbados, we show that the synergistic effect of long-lag drought, mid-lag heat, and short-lag excess rainfall leads to the greatest risk of dengue. Within our Bayesian prediction model, we leverage close-to-real-time dengue case data to dynamically redefine the disease season to better account for interannual variation. This interaction model will be implemented in a dengue early warning system, codeveloped with national and regional health and meteorological agencies. We piloted the early warning system in advance of a mass sporting event, the Twenty20 Cricket World Cup, in June, 2024. This study details a prediction framework that, with further validation, could support the development of other climate-informed disease early warning systems.

Implications of all the available evidence

This study highlights the potential value of incorporating interaction terms in prediction models to account for the compound and cascading effects of climate on disease risk, which could enhance model explainability and predictive performance. As the framework was applied to predict dengue outbreak risk in Barbados, its broader use for epidemic preparedness across other endemic settings or climate-sensitive infectious diseases requires further testing and validation. However, the model's integration into a national early warning system, including its use in advance of a major international event, shows a proof of concept that might be adaptable to other contexts. In Barbados, ongoing monitoring and evaluation of the early warning system, once operationalised, will be essential to assess the real-world effectiveness, reliability, and sustainability of the system in practice.

The changing nature of climatic hazards is likely to aggravate the risk of climate-sensitive infectious diseases via multiple pathways.[3,13] Increasingly intense floods and tropical cyclones can damage or destroy crucial water and sanitation infrastructure, leading to the contamination of water and spread of water-borne diseases.[14] Protracted flooding can leave stagnant pools of water, which become mosquito breeding sites, increasing vector populations and the likelihood of disease transmission.[15] Concerning dengue, the ambient temperature, humidity, and availability of standing water influence the lifecycle, reproduction, survival, and biting rates of the mosquito vector, *Aedes aegypti*, alongside viral replication rates and host susceptibility, exposure, and behaviours.[15,16] Heatwaves and droughts can affect water storage behaviour, which can inadvertently create vector breeding sites close to homes, increasing the risk of exposure to infected vectors.[17,18] Furthermore, the interaction of successive extreme climatic events can create cascading pathways that cause economic instability, deepen inequality, and alter environmental conditions not only in the immediate aftermath of a shock but cumulatively over time, resulting in increased vulnerability to outbreaks. As we improve our understanding of the impacts of extreme climatic events on disease, developing early warning systems that can help predict outbreak occurrence becomes possible, allowing the public health sector to take early actions to reduce adverse health outcomes.

Impact-based forecasting provides actionable information that helps decision makers prepare for, mitigate, prevent, or respond to a disaster, with a focus on early action to enhance resilience and protect communities, infrastructure, and resources.[19] A global study on the economic burden of *Aedes*-borne diseases found that costs of damages and losses were 10-times higher than investments in disease management, highlighting substantial human and economic benefits of anticipatory approaches.[12] Timely forecasts can guide emergency efforts in preparation or response to hazards from tropical cyclones, such as Hurricane Beryl, which caused devastation across the Caribbean in 2024.[20] These approaches can also be embedded into climate-informed dengue early warning systems by using hydrometeorological drivers of disease incidence to predict when, and sometimes where, disease outbreaks are likely to occur.[21] These tools enable public health authorities to mobilise resources effectively, prepare and train relevant personnel, carry out vector control activities, and communicate risks to the public in advance.

We aimed to cocreate an impact-based modelling framework that employs interactions between climatic predictors to forecast the probability of a climate-sensitive infectious disease outbreak 3 months in advance. To achieve this aim, we explicitly investigated the compound and cascading effects of temperature and long-lag and short-lag standardised precipitation index (SPI) on dengue outbreak risk in Barbados. Among other Caribbean SIDS, Barbados has been actively developing climate-informed disease prediction models and early warning systems, which seek to support public health decision making to prevent or mitigate the risk of future climate-sensitive infectious disease epidemics.[21–24]

Methods

In this study, we developed an impact-based modelling framework to forecast dengue outbreak risk in Barbados 3 months ahead using interactions between predictors representing hydrometeorological extremes. To enhance the consistency, quality, and reproducibility of the predictive framework, we followed the EPIFORGE 2020 guidelines for epidemic forecasting research.[25]

Study area and dengue data

Barbados is a Caribbean SIDS with a population of over 281 000 people across 11 parishes (appendix p 9).[26] We obtained monthly confirmed dengue cases reported at the national level, spanning from January, 1999, to December, 2022, from the Epidemiology Unit in the Barbados Ministry of Health and Wellness. Cases were confirmed either by IgM and IgG ELISA, dengue virus-specific real time RT-PCR assays, or the dengue virus non-structural protein 1 antigen test. Annual population estimates were obtained from World Bank Open Data to calculate the dengue DIR per 100 000 people.[27]

Meteorological data

Monthly meteorological indicators were provided by the Caribbean Institute for Meteorology and Hydrology (CIMH) from January, 1981, to December, 2022, for two weather stations, the Grantley Adams International Airport (GAIA) and CIMH station (appendix p 9). For each meteorological variable, we calculated the mean across both weather stations. We collated monthly and 3-monthly averaged mean, minimum, and maximum temperatures, and 1-month, 3-month, 6-month, and 12-month SPI values per month. SPI represents the total precipitation in units of standard deviation from the historical average over a given period, assuming a γ-fitted distribution, and characterises excess dryness (negative SPI) or excess rainfall (positive SPI) at different timescales. Temperature anomalies were calculated by subtracting the mean of each variable from June, 1981, to May, 2022.

Model formulation

During model fitting, a dengue year was defined from June to May. We specified a Bayesian hierarchical model with monthly dengue case counts from June, 1999, to May, 2022, as the response variable. Dengue cases were assumed to follow a negative binomial distribution to account for potential overdispersion. Annual population data were used as a model offset to account for changing population size. Temporal random effects were included to capture seasonal and interannual variation in dengue incidence not explained by the climate covariates. We formulated three-way interaction models with temperature anomalies (lagged by 0–6 months), long-lag SPI (lagged by 4–6 months), and short-lag SPI (lagged by 1–3 months) to quantify both the individual and compound effects of climate predictors on dengue risk (appendix pp 1–2, 11). An additional fixed-effect term that captures the log-transformed DIR lagged by 4 months was also included. All interaction models were compared with a baseline model that included only the seasonal random effect, representing standard surveillance in Barbados, and a mixed-effects model with lagged DIR and no climate covariates.

Model selection criteria

Exploratory analysis and goodness-of-fit metrics, such as the deviance information criterion (DIC), Watanabe–Akaike information criterion (WAIC), mean absolute error (MAE) and R^2_{LR} likelihood ratio for mixed-effects models, were used for model selection. First, we compared the goodness of fit across groups with different combinations of interacting long-lag and short-lag SPI variables to identify which timescales performed best overall. For the best-performing SPI combination, we selected up to ten candidate models for cross-validation on the basis of three criteria: maximised goodness-of-fit metrics compared with the baseline and DIR models; decreased random effects (ie, tending towards zero); and greater fixed effect sizes, ideally with 95% credible intervals (CrIs) that did not contain zero.

See Online for appendix

For World Bank Open Data see https://data.worldbank.org

Cross-validation scheme

We evaluated the predictive performance of each candidate model with a rolling-origin cross-validation approach and a 3-month lead time, simulating real-world prediction (appendix p 12). For each forecast target month, we excluded all subsequent data from the time series along with case counts between and including the forecast issue and target months to account for lead time. We simulated out-of-sample predictions on the last 10 years of data, from June, 2012, to May, 2022, with all available data from June, 1999, until the forecast issue. In our cross-validation scheme, we redefined the dengue year for each simulated prediction to ensure that the forecast target month represented the final month of the season. This approach meant that the yearly random effect was consistently informed by 8 months of case counts.

The outbreak threshold was set as the month-specific population-adjusted 75th percentile of cases, calculated with the historical DIR up to the forecast issue, multiplied by the annual population per 100 000 for the forecast target year. By drawing 1000 samples from the posterior distribution, we calculated the probability of exceeding this outbreak threshold and compared this value with observed

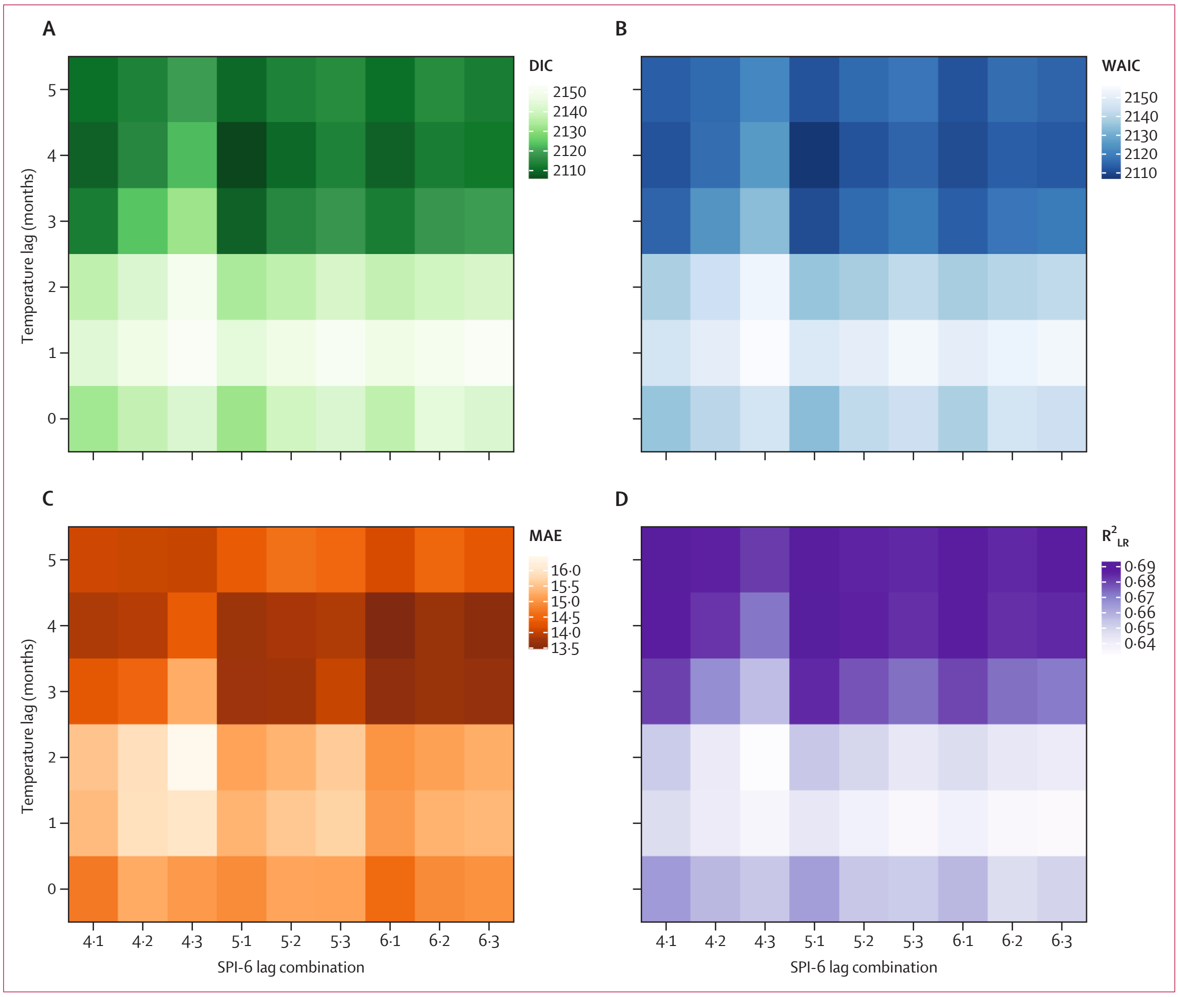

Figure 1: **Goodness-of-fit metrics for models that include a three-way interaction between 3-month average mean temperature anomaly, long-lag SPI-6, and short-lag SPI-6 at different lag times**

(A) DIC, where lower values indicate better model balance between goodness of fit and complexity. (B) WAIC, where lower values indicate better out-of-sample predictive performance. (C) MAE, where lower values represent smaller errors compared with observed case data. (D) R^2_{LR} likelihood ratio for mixed-effect models, where higher values represent a larger proportion of variation in the dengue incidence rate explained by the model compared to an intercept-only model. For each metric, darker colours represent improved goodness of fit. The SPI-6 lag combination is marked as (long lag)·(short lag). For example, 5·1 indicates the combination of SPI-6 lagged by 5 months and SPI-6 lagged by 1 month. DIC=deviance information criterion. MAE=mean absolute error. SPI-6=6-month standardised precipitation index. WAIC=Watanabe–Akaike information criterion.

dengue cases. The receiver operating characteristic (ROC) curve identified the optimal trigger threshold (ie, minimum outbreak probability to trigger an alert) by maximising the true positive rate (TPR; sensitivity) and minimising the false positive rate (FPR; 1 – specificity). We evaluated each model's predictive performance with the continuous rank probability score, area under the ROC curve (AUC), TPR, and FPR.

Combined contribution of climatic variables

To assess the compound effect of climatic variables on dengue outbreak risk, we evaluated the combined contribution of different temperature, long-lag SPI, and short-lag SPI values on the response, $\log(\rho_t)$, where ρ_t is the DIR, for the selected model—denoted as $\log(RR_{CC})$—ie, the logarithm of the relative risk of dengue attributable to climate covariates. We tested $\log(RR_{CC})$ under two different temperature scenarios, cool (ie, the 10th temperature percentile from 1981 to 2022) and warm (ie, the 90th percentile), across all combinations of long-lag and short-lag SPI values from –2·5 (excessively dry) to 2·5 (excessively wet) in 0·25 increments. For each climate scenario, we generated 1000 estimates of $\log(RR_{CC})$ by sampling the posterior distributions of climatic coefficients in the model. We report the mean $\log(RR_{CC})$ and associated 95% CrIs to assess the credibility of the effect.

Early warning system framework

We codeveloped a climate-informed early warning system framework with the Ministry of Health and Wellness (MHW),

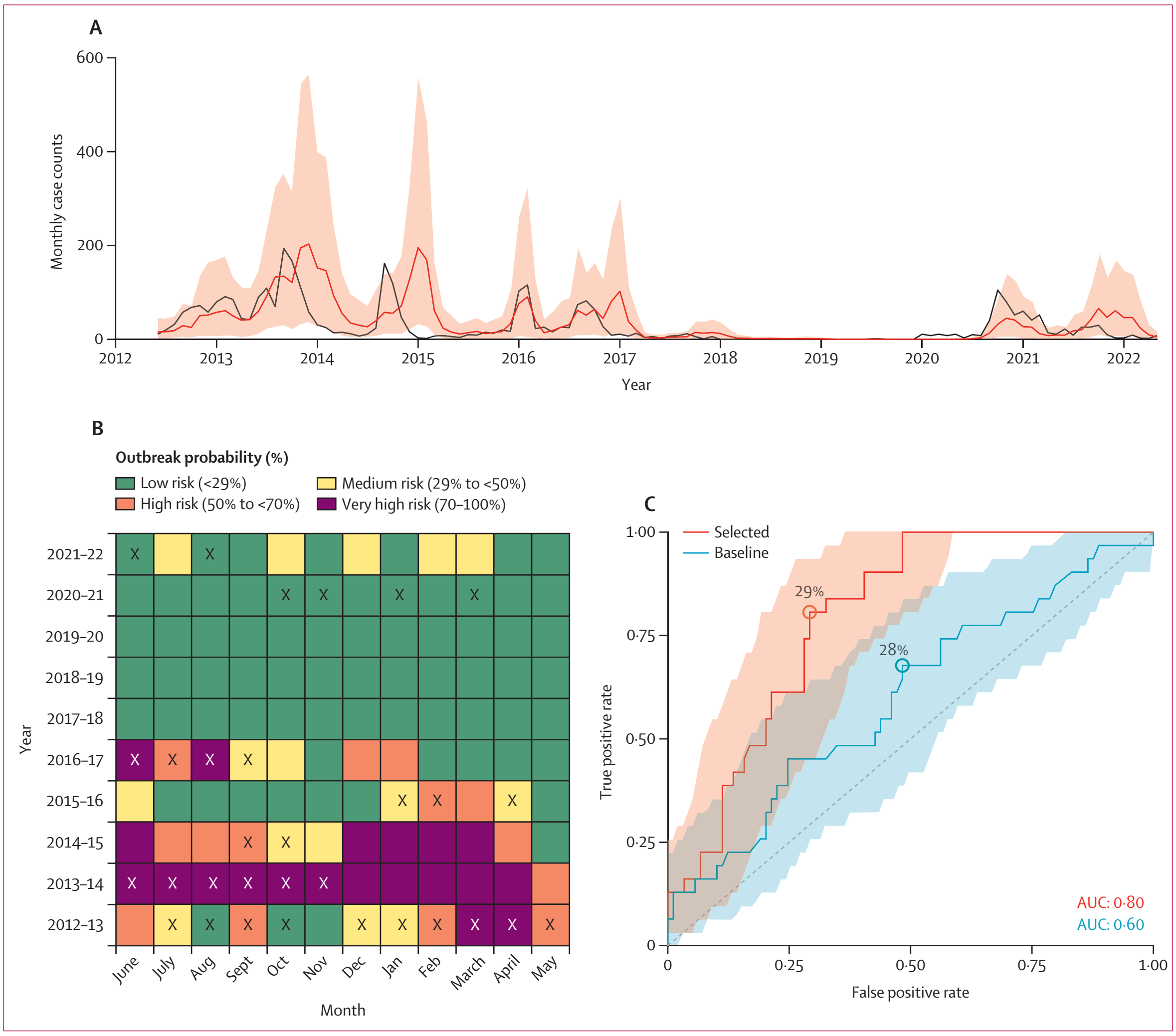

Figure 2: **Evaluation of the selected model after performing rolling-origin cross-validation from June, 1999, to May, 2022**
(A) Monthly predicted dengue cases for the selected interaction model (the solid orange line indicates the mean and the orange shading indicates the 95% CrI) compared with observed dengue cases (solid black line). (B) Probability of an outbreak (%) each month categorised as low (green), medium (yellow), high (orange), and very-high (red) risk levels compared with observed outbreaks (indicated by a cross). (C) ROC curve for both the selected interaction (orange) and baseline (blue) models, which are displayed with 95% CIs (shading). The ROC curve can statistically establish the best probability trigger (indicated by a circle) by maximising the true positive rate (ie, specificity) and minimising the false positive rate (ie, 1 – sensitivity). The AUC measures the prediction accuracy, where 1 represents a perfect system such that the true positive rate=1 and the false positive rate=0. AUC=area under the ROC curve. CrI=credible interval. ROC=receiver operating characteristic.

Barbados Meteorological Services (BMS), CIMH, and Caribbean Public Health Agency (CARPHA) to provide monthly probabilistic forecasts of dengue outbreak risk 3 months ahead. The forecast lead time was selected to be optimal for carrying out preparedness actions while maintaining seasonal climate forecast skill. For prediction, the model integrates recent dengue cases, observed and forecasted meteorological variables based on lagged associations, and annual population estimates. The dengue year was redefined such that the forecast target month represented the final month of the season. Outbreak probabilities were categorised into risk levels (low, medium, high, and very high) reflecting the model's confidence in predicting an outbreak due to epidemiological and climatic conditions. The trigger threshold derived from the ROC curve informed the low–medium risk boundary. The remaining risk categories were calibrated to ensure consistent probability ranges (appendix pp 3–4). We applied this early warning system framework to predict the dengue outbreak risk in Barbados in June, 2024, during the International Cricket Council Men's Twenty20 (T20) World Cup 2024 with a 3-month lead time.

Role of the funding source

The funders of this study had no role in the study design, data collection, data analysis, data interpretation, or writing of the report.

Results

From June, 1999, to May, 2022, there were 7681 confirmed dengue cases in Barbados, with a mean monthly DIR of

	Equation	CRPS	AUC (95% CI)	Probability trigger threshold	True positive rate	False positive rate
Models with only random effects						
Seasonal effect (baseline)	$\alpha + \delta_{m(t)}$	11·500	0·60 (0·48–0·72)	0·28	0·68	0·48
Seasonal effect + interannual effect	$\alpha + \delta_{m(t)} + \gamma_{a(t)}$	10·588	0·69 (0·59–0·78)	0·31	0·77	0·43
Models with only covariates						
DIR	$\alpha + \eta\log(\rho_{t-4} + 1)$	9·925	0·60 (0·48–0·71)	0·37	0·55	0·37
Temperature + long SPI-6 + short SPI-6	$\alpha + \beta_T X_T + \beta_L X_L + \beta_S X_S$	13·090	0·64 (0·52–0·77)	0·35	0·58	0·29
Temperature * long SPI-6 * short SPI-6	$\alpha + \beta_T X_T + \beta_L X_L + \beta_S X_S + \beta_{T,L} X_T X_L + \beta_{T,S} X_T X_S + \beta_{L,S} X_L X_S + \beta_{T,L,S} X_T X_L X_S$	13·523	0·65 (0·53–0·78)	0·33	0·65	0·38
Models with mixed effects (excluding DIR)						
Seasonal effect + interannual effect + temperature + long SPI-6 + short SPI-6	$\alpha + \delta_{m(t)} + \gamma_{a(t)} + \beta_T X_T + \beta_L X_L + \beta_S X_S$	9·441	0·74 (0·65–0·83)	0·19	0·81	0·40
Seasonal effect + interannual effect + temperature * long SPI-6 * short SPI-6	$\alpha + \delta_{m(t)} + \gamma_{a(t)} + \beta_T X_T + \beta_L X_L + \beta_S X_S + \beta_{T,L} X_T X_L + \beta_{T,S} X_T X_S + \beta_{L,S} X_L X_S + \beta_{T,L,S} X_T X_L X_S$	7·960	0·76 (0·68–0·85)	0·24	0·81	0·36
Models with mixed effects (including DIR)						
Seasonal effect + interannual effect + DIR	$\alpha + \delta_{m(t)} + \gamma_{a(t)} + \eta\log(\rho_{t-4} + 1)$	10·416	0·70 (0·61–0·80)	0·41	0·65	0·29
Seasonal effect + interannual effect + temperature + long SPI-6 + short SPI-6 + DIR	$\alpha + \delta_{m(t)} + \gamma_{a(t)} + \beta_T X_T + \beta_L X_L + \beta_S X_S + \eta\log(\rho_{t-4} + 1)$	7·994	0·75 (0·67–0·84)	0·25	0·77	0·37
Seasonal effect + interannual effect + temperature * long SPI-6 * short SPI-6 + DIR	$\alpha + \delta_{m(t)} + \gamma_{a(t)} + \beta_T X_T + \beta_L X_L + \beta_S X_S + \beta_{T,L} X_T X_L + \beta_{T,S} X_T X_S + \beta_{L,S} X_L X_S + \beta_{T,L,S} X_T X_L X_S + \eta\log(\rho_{t-4} + 1)$	7·348	0·80 (0·72–0·88)	0·29	0·81	0·29

Temperature is the 3-month average mean temperature anomaly lagged by 3 months, long SPI-6 is the 6-month SPI lagged by 5 months, short SPI-6 is the 6-month SPI lagged by 1 month, and the DIR is the logarithm of the DIR plus 1, lagged by 4 months. Asterisks indicate interactions, whereas plus symbols indicate additive effects. α=intercept. AUC=area under the ROC curve. β_T=temperature coefficient. β_L=long-lag SPI coefficient. β_S=short-lag SPI coefficient. $\beta_{T,L}$=temperature-long SPI coefficient. $\beta_{T,S}$=temperature-short SPI coefficient. $\beta_{L,S}$=long-short SPI coefficient. $\beta_{T,L,S}$=temperature-long SPI-short SPI coefficient. CRPS=continuous rank probability score. $\delta_{m(t)}$=monthly random effect. DIR=dengue incidence rate. $\gamma_{a(t)}$=yearly random effect. η=lagged DIR coefficient. ρ_{t-4}=DIR-lagged 4 months covariate. ROC=receiver operating characteristic. SPI=standardised precipitation index. X_T=temperature covariate. X_L=long-lag SPI covariate. X_S=short-lag SPI covariate.

Table: **Cross-validation outputs for models of increasing complexity**

10·2 cases per 100 000 people. During model selection, models with the 3-month averaged mean temperature anomaly, long-lag SPI-6, and short-lag SPI-6 best satisfied all selection criteria. Figure 1 shows the DIC, WAIC, MAE, and R^2_{LR} likelihood ratio for the 54 models that employ a three-way interaction between these variables at different delays. These results indicate an improved goodness of fit with temperature lagged by 3 months or more, SPI-6 lagged by 5–6 months, and SPI-6 lagged by 1–2 months. From all goodness-of-fit criteria, we found that the best model employed a three-way interaction between the 3-month average mean temperature anomaly lagged by 3 months, long-lag SPI-6 lagged by 5 months, and short-lag SPI-6 lagged by 1 month. A comparison of the goodness-of-fit metrics for the best interaction model with models of reduced complexity is provided in the appendix (p 21). The selected interaction model accounted for 69% of the variation in the DIR, exceeding the baseline model, which accounted for only 17%. The selected model showed improved goodness of fit compared with all other model formulations (appendix p 21).

Figure 2 illustrates the predictive performance of the selected model after performing rolling-origin cross-validation. Figure 2A represents the time series of both observed and predicted dengue cases from June, 2012, to May, 2022. Figure 2B displays the outbreak probabilities categorised by risk level, compared with observed outbreaks. Ideally, outbreak probabilities associated with medium, high, or very-high risk correspond with observed outbreaks. The optimal trigger threshold was calculated as 29% from the ROC curve (figure 2C). The two ROC curves represent the predictive performances of the baseline and selected models at all trigger thresholds. The selected model showed an AUC of 0·80 (95% CI 0·72–0·88), a TPR of 81%, and an FPR of 29%, which outperformed the baseline model, which had an AUC of 0·60 (95% CI 0·48–0·72), a TPR of 68%, and an FPR of 48% (table; figures 2; 3). Additionally, the interaction model outperformed the additive model with an AUC of 0·75 (95% CI 0·67–0·84), a TPR of 77%, and an FPR of 37% (table; figure 3), indicating that the selected model could better discriminate an outbreak from no outbreak compared with the baseline and additive models. Furthermore, we confirmed that the climate variable effect sizes were stable across the 10-year validation period (appendix p 14).

For the selected model, we explored how the $\log(RR_{CC})$, ie the compound contribution of climate on the DIR, varied under different climatic conditions (figure 4). Figure 4A presents the forecast schematic under two distinct scenarios that contribute to higher and lower dengue outbreak risk. Our results indicate that long-lag dry (lagged by 5 months), mid-lag hot (lagged by 3 months) and short-lag wet (lagged by 1 month) conditions lead to the highest dengue outbreak risk, whereas cool and extended dry conditions lead to the lowest risk. This was shown through two temperature scenarios with historical 3-month average mean temperature values, cool (ie, 25·7°C; 10th percentile; figure 4B) and warm (ie, 27·7°C; 90th percentile; figure 4C), for different combinations of long-lag and short-lag SPI-6 values.

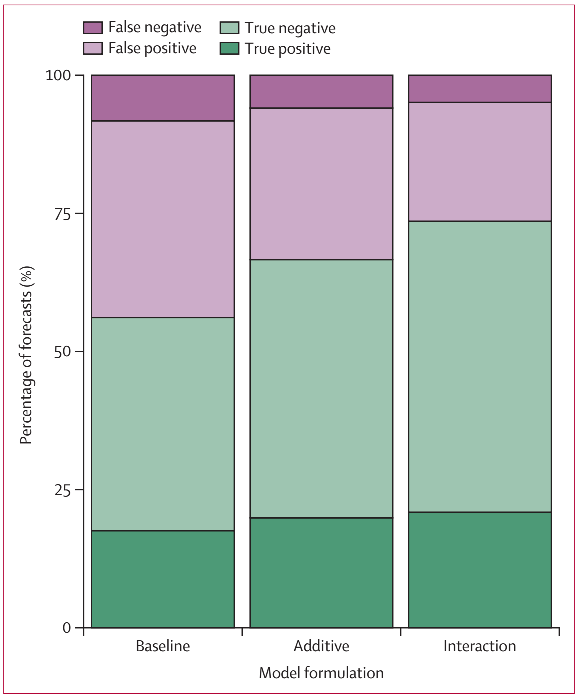

Figure 3: **Cross-validation performance comparison of baseline, additive, and interaction model formulations**

The interaction model represents the selected model and the additive model represents the selected model without interaction terms. The stacked bars show the proportions of true positives (ie, an outbreak occurred and an outbreak was predicted), true negatives (ie, no outbreak occurred and no outbreak was predicted), false positives (ie, no outbreak occurred but an outbreak was predicted), and false negatives (ie, an outbreak occurred but no outbreak was predicted).

We applied the interaction model framework to predict the dengue outbreak risk in June, 2024, during the T20 Cricket World Cup in Barbados with a 3-month lead time (figure 5). Due to epidemiological and climatic conditions, the model predicted a 95% outbreak probability corresponding with very-high risk (figure 5A). Figure 5B represents the probability density function of the posterior predictive distribution of dengue cases, with a mean prediction of 108 cases (95% CrI 8–332 cases) and an outbreak threshold of 13 cases. This forecast was used to inform further public health actions to mitigate or prevent a potential outbreak during the mass sporting event, including further checks and retreatments of known mosquito breeding sites around the cricket grounds and surrounding communities (appendix pp 6–7).

Discussion

In this study, we present an impact-based modelling framework that employs interacting long-lag and short-lag meteorological variables to forecast the risk of a climate-sensitive infectious disease outbreak 3 months in advance. This long–short-lag interaction approach captures the synergistic effects of compound and cascading climatic conditions on disease incidence, such as the combined effect of two variables (eg, long-term dry and short-term wet conditions) and three variables (eg, long-term dry, mid-term hot, and short-term wet conditions), providing a more nuanced interpretation of the climatic drivers of dengue outbreaks in Barbados. We found that the optimal forecasting model applied a three-way interaction between the 3-month average mean temperature anomaly lagged by 3 months, SPI-6 lagged by 5 months, and SPI-6 lagged by 1 month.

Previous research employing a distributed lag non-linear model (DLNM) has highlighted the delayed impact of hydrometeorological extremes on dengue risk in Barbados,[22] with reported outbreak risk increasing 4–5 months after drought events and 0–2 months after excess rainfall events. These results are consistent with the findings presented in this study, which show that temperature, drought, and excess rainfall are positively associated with increased dengue incidence. We opted to use temperature anomalies to ensure all meteorological predictors were on a similar scale with both positive and negative values, aiding the interpretability of compound effects and better accounting for extreme heat or cold events that exceed historically observed limits. The 3-month average mean temperature values in this study (26·9°C [range 24·7–28·3]) are often within the optimal temperature range for arboviral transmission (ie, 26–29°C).[16] However, as Barbados has experienced notable increases in extreme temperature and precipitation events over the past few decades,[28] further changes could impact future dengue dynamics.

Interactions between climatic and socioeconomic factors have been shown to influence dengue outbreaks across endemic settings. In southern Taiwan, outbreaks were affected by short-term or cumulative rainfall combined with older housing infrastructure.[29] In Brazil, the relationship between dengue incidence and long-lag and short-lag drought severity varied when interacted with urbanisation.[30] In southern Viet Nam, dengue risk was shown to be affected by interacting hydrometeorological variables and water supply coverage.[31] In this study, we show the importance of interacting interdependent climatic drivers in modelling dengue risk in Barbados. Our findings indicate that the compound effects of long-lag dry, mid-lag hot, and short-lag wet conditions lead to the highest dengue outbreak risk. This interplay of climatic variables can influence dengue transmission by creating optimal conditions for mosquito breeding and virus spread at different timescales. Droughts can exacerbate water scarcity, leading to increased water storage in containers close to homes. These containers, if not covered or regularly treated with larvicide, can become breeding sites for *A aegypti* mosquitoes.[17,18] As water availability increases, the urgency for active management of stored water might decrease, potentially leading to neglected containers that perpetuate vector reproduction. Warmer temperatures might further accelerate vector development and activity, alter human behaviour, and shorten viral incubation.[16,18] Collectively, these sequential climatic events could synergistically

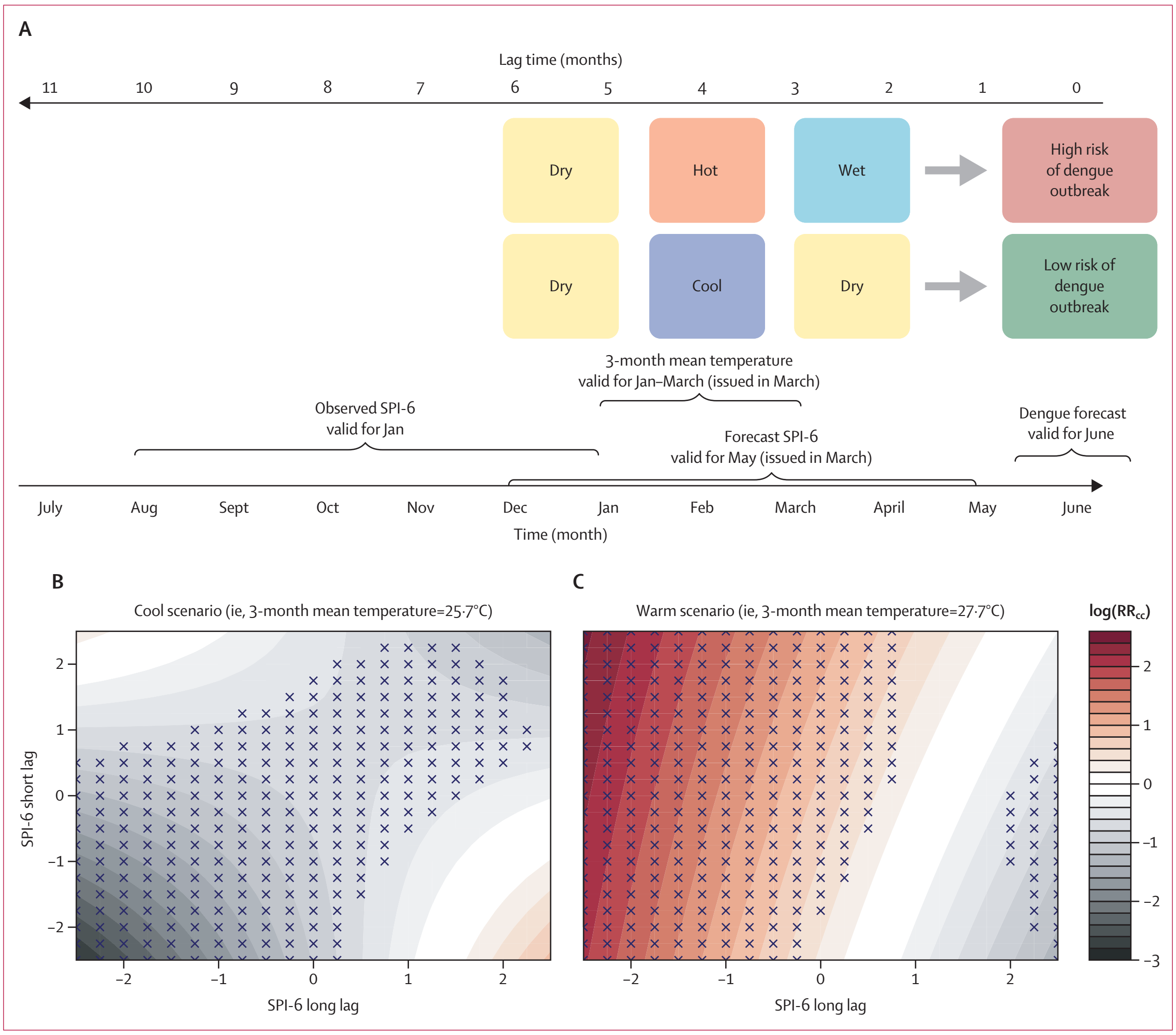

Figure 4: **Compound contribution of climate on dengue incidence rate (ie, log[RR_{CC}]) under different climatic conditions**
(A) Forecast scheme for the compound effect of temperature, long-lag SPI-6, and short-lag SPI-6 on dengue outbreak risk in Barbados. The scheme shows the data required to issue a forecast in March for a dengue risk in June along with the climatic conditions that lead to the highest and lowest dengue risk. (B) and (C) Mean log (RR_{CC}), where crosses indicate estimates with 95% CrIs of the log(RR_{CC}) not including zero. We tested different long-lag and short-lag SPI-6 combinations with a cool 3-month average mean temperature (25·7°C [ie, the 10th percentile]; B) and a warm 3-month average mean temperature (27·7°C [ie, the 90th percentile]; C). CrI=credible interval. RR_{CC}=the relative risk of dengue attributable to climate covariates. SPI-6=6-month standardised precipitation index.

elevate the risk of dengue outbreaks by optimising conditions for the virus, vectors, and hosts.

During cross-validation, we evaluated the predictive performance of multiple model formulations. Interaction models consistently outperformed baseline and additive models, indicating that the inclusion of interaction terms can enhance predictive skill without needing additional data inputs. Performance was also consistently improved with the inclusion of lagged DIR and random effects that account for unknown seasonal and interannual variation. These unmeasured drivers might reflect vector control interventions, disasters (eg, hurricanes), population susceptibility and immunity, dominant serotype switching, or disease importation.[32–34] In a prediction framework, modelling interannual variation presents challenges, often requiring real-time case data, case estimations, or prior assumptions regarding the year ahead.[22,35] In a dengue forecasting model for Viet Nam, cases were estimated by a generalised linear mixed-effects model and propagated through log-linear and yearly effect terms at multiple lead times.[36] In contrast, the DLNM for Barbados treated the year as unknown during out-of-sample predictions, meaning the yearly random effect had a mean value of zero.[22] In this study, close-to-real-time case data were used to forecast dengue risk 3 months ahead. We redefined the dengue season for each prediction month, ensuring that the yearly effect was consistently informed by 8 months of case counts, and log-transformed the 4-month lagged DIR. This approach enabled us to leverage available case data to strengthen predictive performance while maintaining operational feasibility.

Since 2017, a transdisciplinary team of international researchers and national and regional health and meteorological bodies have been coproducing the climate-informed dengue early warning system in Barbados.[23,24] This work included a modelling framework employing a DLNM.[22] Although DLNMs are powerful for understanding the non-linear and lagged effects of individual predictors, when used operationally, these models necessitate that climate service providers generate multilead climate forecasts on a routine basis, which might not align with operational practices. This requirement can represent a barrier in resource-limited settings where the generation of or access to timely high-quality data and computational resources can be challenging.[22,37] Additionally, DLNMs can lead to unpredictable outcomes when input variables exceed the historical range used to define non-linear associations, as the model must extrapolate coefficients in unfamiliar territory. Unlike linear models, which assume stationarity (ie, that statistical relationships remain constant over time), DLNMs are more sensitive to boundary conditions, increasing the potential for uncertain results. Furthermore, relationships between disease incidence and climate covariates in a DLNM can be challenging to interpret and communicate to non-technical audiences. In contrast, interaction models offer a straightforward and flexible approach, accounting for any input value without the need for complex lag structures. This relative simplicity reduces computational demands while enhancing the interpretability of climate–disease relationships, which are key for translating findings into practice.

Our interaction model is being implemented within the national dengue early warning system in Barbados, jointly maintained by MHW, BMS, CIMH, and CARPHA. The applicability of this framework could be tested to predict climate-sensitive infectious diseases in other endemic settings with similarly consistent, long-term, and high-quality epidemiological and meteorological records, including other Caribbean SIDS. However, early warning systems need to be cocreated alongside decision makers with explicit mandates for the provision of local health care and cross-sectoral collaborators, including meteorologists, researchers, government agents, and communities.[38] These actors are crucial for interpreting results and identifying key barriers to early warning system implementation, operationalisation, and sustainability, which affect long-term use.[24] Early warning systems can support epidemic preparedness and response planning to prevent or mitigate outbreaks. One example is the growing practice of anticipatory action by governments and humanitarian agencies. Anticipatory action combines the use of observations and forecasts with in-depth risk analysis to predict where and when a disaster might occur in order to intervene in advance and reduce negative impacts.[39] For example, the Red Cross Red Crescent Movement formalises early warnings from forecasts into early action protocols to ensure emergency funding is released and appropriate early actions are taken during the lead time afforded by early warnings.[40]

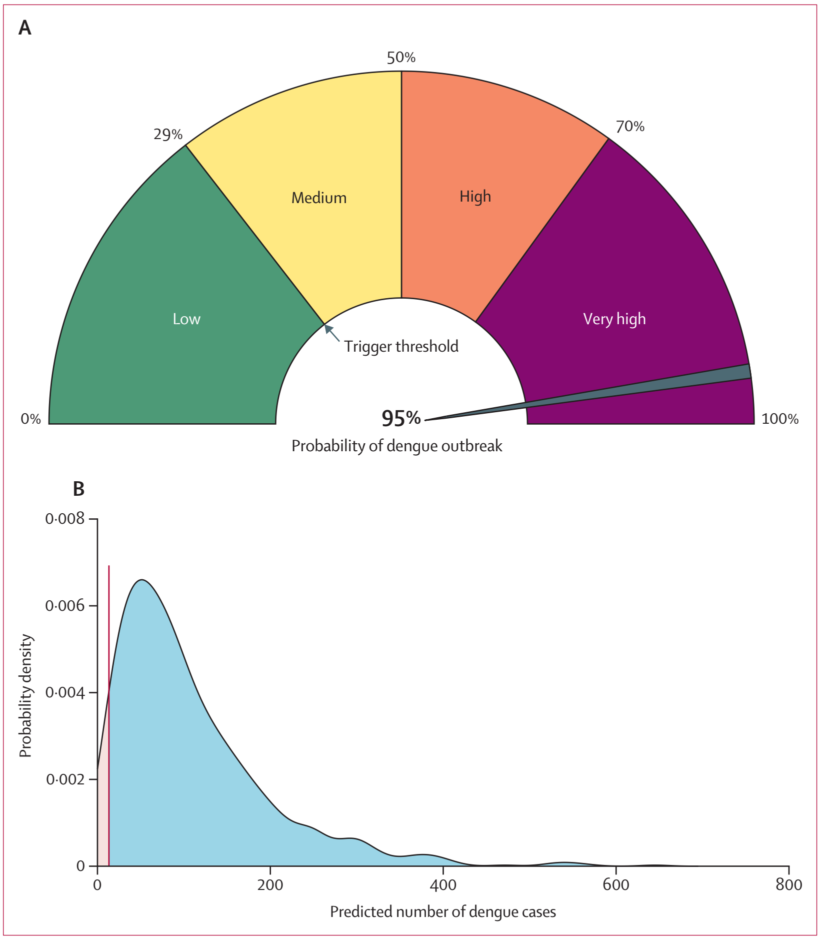

Figure 5: **Dengue risk forecast issued for Twenty20 World Cup in Barbados in June, 2024, 3 months ahead**
(A) The outbreak probability and associated outbreak risk level with the trigger threshold annotated (arrow and text). (B) The probability density function of the model-predicted dengue cases with the outbreak threshold annotated (red line).

Despite these advancements, this research has several limitations. The temperature and SPI values used in this study were averaged from two weather stations, CIMH and GAIA, which were chosen for their long, high-quality records, which allow for more accurate SPI calculations, and proximity to populated areas. However, these data might not fully capture the climatic conditions across the entire island. Furthermore, seasonal climate forecasts increase in uncertainty with lead time due to systematic biases, poor predictability of interannual climate variability, and imperfect initial conditions. These factors will subsequently affect dengue risk predictions, although the direct assessment of these impacts is beyond the scope of this study. To minimise uncertainty, we make use of multiple ensemble members and persistence components in the short-lag SPI and temperature forecasts.

Dengue infection data only included laboratory-confirmed symptomatic cases from individuals who sought medical care. Thus, infected individuals who were asymptomatic or had mild symptoms, constituting most dengue infections,[41] were not captured. For the early warning system, time constraints in accessing real-time dengue cases might result in incomplete counts due to delays in receiving data from testing laboratories. Despite this limitation, our prediction model showed a consistent detection of true outbreaks in the absence of close-to-real-time cases and could be adapted accordingly if such data became unavailable. Other relevant data, such as serology, vector control activities, interventions, and entomological indices, could enhance model accuracy, although high-quality records are challenging to obtain. Growing evidence suggests that entomological data might not reliably predict dengue outbreaks, with multiple studies finding little evidence of direct associations between vector indices and dengue cases.[42–46] In Barbados, the MHW highlight that vector surveillance efforts often increase during suspected dengue outbreaks to evaluate the effectiveness of interventions. Reactive surveillance can compromise the quality and consistency of entomological data, thereby distorting causal relationships with reported cases.[47] The inclusion of data on water supply shortages could provide a more direct representation of water storage practices, rather than relying solely on assumptions linked to drought; however, to our knowledge, these data were not readily available. Instead, we opted to use random effects to account for unknown temporal variation in dengue incidence. This approach, we argue, would factor in inevitable interruptions in dengue diagnostic and testing capacity during the COVID-19 pandemic. In Barbados, most cases of COVID-19 occurred between July, 2021, and October, 2022. We developed an approach to account for the yearly random effect with close-to-real-time case data. This approach might result in an underestimation of cases during the high season and an overestimation of cases during the low season, although the seasonal random effect should compensate for such variation. Outputs and parameters for the early warning system will need to be monitored and evaluated periodically to ensure the prediction model remains operationally relevant and reliable over time.

For **GitLab** see https://earth.bsc.es/gitlab/ghr/lsl-interaction-barbados-2025

Overall, this study highlights the compound and cascading effects of climatic extremes on dengue outbreak risk in Barbados with interacting long-lag and short-lag predictors, and outlines an impact-based forecast model for integration into a national dengue early warning system. Additionally, we detailed an approach that redefines the dengue season and leverages close-to-real-time case data to potentially improve the predictive performance of Bayesian mixed-effects models. In future work, we aim to systematically monitor and evaluate the effectiveness of the early warning system to understand its real-world performance, including the reliability and timeliness of alerts, response to alerts, quantifiable reductions in case numbers and outbreaks, and financial costs. This monitoring is crucial to ensure the early warning system provides tangible benefits to the wellbeing of the communities it is intended to serve. Further testing of the long–short-lag interaction model could also be carried out in other settings with endemic climate-sensitive infectious diseases to evaluate its robustness across different epidemiological and climatic contexts.

Contributors

CF and RL conceptualised the study. LR, CJVM, AT, TB, SB, CF, DL, CAL, and RL were responsible for data curation. CF and RL did the formal analysis. L-LB, AMS-I, and RL were responsible for funding acquisition. CF, ARD, WD, RM, and SJR did the investigation. CF, RL, and GM were responsible for the methodology. ARD was responsible for project administration. LR, AT, L-LB, AMS-I, and RL provided the resources. CF, DL, FJC-G, RL, and GM were responsible for the software. RL, SJR, and AMS-I were responsible for supervision. CF, DL, RL, GM, CAL, and SJR were responsible for data visualisation. CF, TA, and RL wrote the draft manuscript. All authors edited, reviewed, and approved the final manuscript. CF, GM and RL validated the data. All authors had full access to the data. All authors had final responsibility to submit for publication.

Declaration of interests

We declare no competing interests.

Data sharing

The data and code used to produce the analysis are available on GitLab and archived in a permanent Zenodo repository.[48]

Acknowledgments

We acknowledge support from the Wellcome Trust under grant number 226069/Z/22/Z (IDExtremes) and the EU's Horizon Europe research and innovation programme (E4Warning; grant agreement 101086640) and financing under the European Development Fund with Central Registration & Identification Scheme number FED/2019/41949 (Strengthening Climate Resilient Health Systems in the Caribbean). RL was supported by a Royal Society Dorothy Hodgkin Fellowship.

References

1 Trotman A, Mahon R, Guillemot J, Lowe R, Stewart-Ibarra A. Strengthening climate services for the health sector in the Caribbean. *WMO Bull* 2018; **67:** 14–19.

2 Caribbean Public Health Agency. State of public health in the Caribbean report 2017–2018. Climate and health: averting and responding to an unfolding health crisis. Caribbean Public Health Agency. 2018. https://carpha.org/Portals/0/Documents/CARPHA_SoPH_2017_2018_Preface_Acknowledgements_Glossary.pdf (accessed Oct 17, 2024).

3 Climate Studies Group Mona, The University of the West Indies. The state of the Caribbean climate. Caribbean Development Bank. 2020. https://www.caribank.org/sites/default/files/publication-resources/The%20State%20of%20the%20Caribbean%20Climate%20Report.pdf (accessed Oct 17, 2024).

4 Van Meerbeeck C. Climate trends and projections for the OECS region. OECS Climate Change Adaptation Strategy & Action Plan. Organisation of Eastern Caribbean States. 2020. https://rcc.cimh.edu.bb/files/2021/08/OECS-Climate-Report.pdf (accessed Oct 17, 2024).

5 Mycoo M, Wairiu M, Campbell D, et al. Small islands. In: Pörtner H-O, Roberts DC, Tignor M, et al., eds. Climate change 2022: impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, 2022: 2043–121.

6 Caribbean Public Health Agency. State of public health in the Caribbean region 2014–2016. Building resilience to immediate and increasing threats: vector-borne diseases and childhood obesity. Caribbean Public Health Agency. 2017. https://carpha.org/Portals/0/Documents/State-of-Public-Health-in-the-Caribbean-2014-2016.pdf (accessed Oct 17, 2024).

7 Dommar CJ, López L, Paul R, Rodó X. The 2013 chikungunya outbreak in the Caribbean was structured by the network of cultural relationships among islands. *R Soc Open Sci* 2023; **10:** 230909.

8 Zhang Q, Sun K, Chinazzi M, et al. Spread of Zika virus in the Americas. *Proc Natl Acad Sci USA* 2017; **114:** E4334–43.

9 Pan American Health Organization, WHO. PLISA health information platform for the Americas. Dengue and severe dengue. Pan American Health Organization. 2024. https://www3.paho.org/data/index.php/en/mnu-topics/indicadores-dengue-en/dengue-regional-en/261-dengue-reg-ano-en.html (accessed Oct 1, 2024).

10 Zeng Z, Zhan J, Chen L, Chen H, Cheng S. Global, regional, and national dengue burden from 1990 to 2017: a systematic analysis based on the Global Burden of Disease study 2017. *EClinicalMedicine* 2021; **32:** 100712.

11 Shepard DS, Undurraga EA, Halasa YA, Stanaway JD. The global economic burden of dengue: a systematic analysis. *Lancet Infect Dis* 2016; **16:** 935–41.

12 Roiz D, Pontifes PA, Jourdain F, et al. The rising global economic costs of invasive *Aedes* mosquitoes and *Aedes*-borne diseases. *Sci Total Environ* 2024; **933:** 173054.

13 Mora C, McKenzie T, Gaw IM, et al. Over half of known human pathogenic diseases can be aggravated by climate change. *Nat Clim Chang* 2022; **12:** 869–75.

14 Alcayna T, Fletcher I, Gibb R, et al. Climate-sensitive disease outbreaks in the aftermath of extreme climatic events: a scoping review. *One Earth* 2022; **5:** 336–50.

15 Semenza JC, Rocklöv J, Ebi KL. Climate change and cascading risks from infectious disease. *Infect Dis Ther* 2022; **11:** 1371–90.

16 Mordecai EA, Cohen JM, Evans MV, et al. Detecting the impact of temperature on transmission of Zika, dengue, and chikungunya using mechanistic models. *PLoS Negl Trop Dis* 2017; **11:** e0005568.

17 Pontes RJS, Freeman J, Oliveira-Lima JW, Hodgson JC, Spielman A. Vector densities that potentiate dengue outbreaks in a Brazilian city. *Am J Trop Med Hyg* 2000; **62:** 378–83.

18 Stewart Ibarra AMS, Ryan SJ, Beltrán E, Mejía R, Silva M, Muñoz A. Dengue vector dynamics (*Aedes aegypti*) influenced by climate and social factors in Ecuador: implications for targeted control. *PLoS One* 2013; **8:** e78263.

19 Merz B, Kuhlicke C, Kunz M, et al. Impact forecasting to support emergency management of natural hazards. *Rev Geophys* 2020; **58:** e2020RG000704.

20 Hertelendy AJ, Fugate C, Ciottone GR. Hospital preparedness for one of the worst predicted hurricane seasons on record—why this time is different. *Lancet Reg Health Am* 2024; **37:** 100842.

21 Lowe R, Ryan SJ, Mahon R, et al. Building resilience to mosquito-borne diseases in the Caribbean. *PLoS Biol* 2020; **18:** e3000791.

22 Lowe R, Gasparrini A, Van Meerbeeck CJ, et al. Nonlinear and delayed impacts of climate on dengue risk in Barbados: a modelling study. *PLoS Med* 2018; **15:** e1002613.

23 Stewart-Ibarra AM, Rollock L, Best S, et al. Co-learning during the co-creation of a dengue early warning system for the health sector in Barbados. *BMJ Glob Health* 2022; **7** (suppl 7)**:** e007842.

24 Díaz AR, Rollock L, Boodram LLG, et al. A demand-driven climate services for health implementation framework: a case study for climate-sensitive diseases in Caribbean small island developing states. *PLOS Clim* 2024; **3:** e0000282.

25 Pollett S, Johansson MA, Reich NG, et al. Recommended reporting items for epidemic forecasting and prediction research: the EPIFORGE 2020 guidelines. *PLoS Med* 2021; **18:** e1003793.

26 Barbados Statistical Service. 2021 population and housing census report. Barbados Statistical Service. 2023. https://stats.gov.bb/wp-content/uploads/2024/02/2021-Population-and-Housing-Census.pdf (accessed Sept 16, 2024).

27 World Bank. World Bank Open Data: population, total—Barbados. World Bank Open Data. 2024. https://data.worldbank.org/indicator/SP.POP.TOTL?locations=BB (accessed March 1, 2024).

28 Mohan S, Clarke RM, Chadee XT. Variations in extreme temperature and precipitation for a Caribbean island: Barbados (1969–2017). *Theor Appl Climatol* 2020; **140:** 1277–90.

29 Chen THK, Chen VYJ, Wen TH. Revisiting the role of rainfall variability and its interactive effects with the built environment in urban dengue outbreaks. *Appl Geogr* 2018; **101:** 14–22.

30 Lowe R, Lee SA, O'Reilly KM, et al. Combined effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: a spatiotemporal modelling study. *Lancet Planet Health* 2021; **5:** e209–19.

31 Gibb R, Colón-González FJ, Lan PT, et al. Interactions between climate change, urban infrastructure and mobility are driving dengue emergence in Vietnam. *Nat Commun* 2023; **14:** 8179.

32 Bowman LR, Donegan S, McCall PJ. Is dengue vector control deficient in effectiveness or evidence?: systematic review and meta-analysis. *PLoS Negl Trop Dis* 2016; **10:** e0004551.

33 Katzelnick LC, Fonville JM, Gromowski GD, et al. Dengue viruses cluster antigenically but not as discrete serotypes. *Science* 2015; **349:** 1338–43.

34 Abdul-Ghani R, Mahdy MAK, Al-Eryani SMA, et al. Impact of population displacement and forced movements on the transmission and outbreaks of *Aedes*-borne viral diseases: dengue as a model. *Acta Trop* 2019; **197:** 105066.

35 Bastos LS, Economou T, Gomes MFC, et al. A modelling approach for correcting reporting delays in disease surveillance data. *Stat Med* 2019; **38:** 4363–77.

36 Colón-González FJ, Soares Bastos L, Hofmann B, et al. Probabilistic seasonal dengue forecasting in Vietnam: a modelling study using superensembles. *PLoS Med* 2021; **18:** e1003542.

37 Stewart-Ibarra AM, Romero M, Hinds AQJ, et al. Co-developing climate services for public health: stakeholder needs and perceptions for the prevention and control of *Aedes*-transmitted diseases in the Caribbean. *PLoS Negl Trop Dis* 2019; **13:** e0007772.

38 Hess J, Boodram LG, Paz S, Stewart Ibarra AM, Wasserheit JN, Lowe R. Strengthening the global response to climate change and infectious disease threats. *BMJ* 2020; **371:** m3081.

39 Coughlan de Perez E, van den Hurk B, van Aalst MK, Jongman B, Klose T, Suarez P. Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. *Nat Hazards Earth Syst Sci* 2015; **15:** 895–904.

40 Red Cross Red Crescent. Red Cross Red Crescent forecast-based financing practitioners manual. Red Cross Red Crescent. 2021. https://manual.forecast-based-financing.org/en/chapter/fbf-manual-introduction/ (accessed Oct 14, 2024).

41 Asish PR, Dasgupta S, Rachel G, Bagepally BS, Girish Kumar CP. Global prevalence of asymptomatic dengue infections—a systematic review and meta-analysis. *Int J Infect Dis* 2023; **134:** 292–98.

42 Bowman LR, Runge-Ranzinger S, McCall PJ. Assessing the relationship between vector indices and dengue transmission: a systematic review of the evidence. *PLoS Negl Trop Dis* 2014; **8:** e2848.

43 Cromwell EA, Stoddard ST, Barker CM, et al. The relationship between entomological indicators of *Aedes aegypti* abundance and dengue virus infection. *PLoS Negl Trop Dis* 2017; **11:** e0005429.

44 Morales-Pérez A, Nava-Aguilera E, Hernández-Alvarez C, et al. Utility of entomological indices for predicting transmission of dengue virus: secondary analysis of data from the Camino Verde trial in Mexico and Nicaragua. *PLoS Negl Trop Dis* 2020; **14:** e0008768.

45 Garjito TA, Hidajat MC, Kinansi RR, et al. *Stegomyia* indices and risk of dengue transmission: a lack of correlation. *Front Public Health* 2020; **8:** 328.

46 Schultes OL, Morais MHF, Cunha MDCM, Sobral A, Caiaffa WT. Spatial analysis of dengue incidence and *Aedes aegypti* ovitrap surveillance in Belo Horizonte, Brazil. *Trop Med Int Health* 2021; **26:** 237–55.

47 Azil AH, Li M, Williams CR. Dengue vector surveillance programs: a review of methodological diversity in some endemic and epidemic countries. *Asia Pac J Public Health* 2011; **23:** 827–42.

48 Fletcher C, Moirano G, Alcayna T, et al. Data and R code to accompany "Compound and cascading effects of climatic extremes on dengue outbreak risk in the Caribbean: an impact-based modelling framework with long-lag and short-lag interactions" (version v1.0.0). *Zenodo* 2025. https://doi.org/10.5281/zenodo.15731719.