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Urbanization, infrastructure, and mosquito thermal suitability shape the causal effects of extreme weather on dengue transmission

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GRAPHICAL ABSTRACT

PUBLIC SUMMARY

- Among extreme weather, heatwaves present the highest risk, followed by drought and wet events.
- Compound drought–heatwave events pose a lower dengue risk than individual events.
- Extreme weather increases dengue risk in rural areas compared with urban areas.
- Drought drives dengue in urban areas with better facilities and high mosquito thermal suitability.

Urbanization, infrastructure, and mosquito thermal suitability shape the causal effects of extreme weather on dengue transmission

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Dengue is a widespread arboviral disease and poses a persistent global health threat, particularly in Southeast Asia, a region characterized by frequent dengue and extreme weather. Urbanization, infrastructure, and mosquito thermal suitability are pivotal factors in shaping dengue dynamics. However, their roles in modulating the causal effects of extreme weather on dengue transmission remain unclear. Here, we compile monthly dengue data during 2000-2019 covering Singapore and 162 first–level administrative units in six Southeast Asian countries. A spatiotemporal Bayesian framework is developed to explicitly capture the interactions of extreme weather with urbanization and with infrastructure. We also apply convergent cross mapping (CCM) to identify causal associations between extreme weather and dengue, incorporating vector thermal suitability, urban development, and access to improved water and sanitation. Among extreme weather, heatwaves pose the highest relative risk (RR) [max RR 5.5, 95% CI: 3.27–9.25], followed by drought [max RR 5.21, 95% CI: 3.31–8.21], wet conditions [max RR 2.76, 95% CI: 1.79–4.26], and compound drought–heatwave events [max RR 2.55, 95% CI: 1.3–5.01]. Causal analysis indicates divergent pathways: in urban settings with improved infrastructure and high mosquito thermal suitability, drought and compound drought–heatwave events emerge as key drivers; in rural settings with poor infrastructure and low mosquito thermal suitability, their effects are not significant. This study reveals that extreme weather–driven dengue is modulated by social vulnerability and mosquito thermal suitability, and provides practical insights for integrating extreme weather into adaptation strategies for dengue control.

INTRODUCTION

Dengue fever is a globally prevalent mosquito-borne viral disease,[1] primarily transmitted by Aedes albopictus and Aedes aegypti mosquitoes.[2–5] Despite ongoing mosquito control measures, this disease continues to pose a significant health threat, with an estimated 100 to 400 million cases occurring annually, influencing nearly half of the global population.[4] The burden of dengue is severe in the Western Pacific, the Americas, and Southeast Asia, with Asia accounting for approximately 70% global disease burden.[6] In Southeast Asia, the risk of dengue has increased substantially, with cases rising by 46% between 2015 and 2019.[1] Thus, quantifying dengue risk is critical for targeted vector control and optimized interventions in Southeast Asia.

In Southeast Asia, where monsoon climates prevail,[7] dengue transmission exhibits a pronounced seasonal cycle,[8] with epidemic peaks generally occurring between July and September.[9] Notably**,** the household container index of *Aedes* infection shows a pronounced increase in the wet season relative to the dry season in Narathiwat, Thailand.[10] Such seasonal variability is highly affected by climate factors, which alter both the magnitude and spatial distribution of dengue by reshaping vector survival and virus dynamics.[11–13] In particular, temperature influences vector reproduction, lifespan, and the viral extrinsic incubation period, [11,14] whereas precipitation shapes breeding habitat dynamics.[15]

Although seasonal transmission patterns are largely driven by gradual climatic factors, abrupt changes in dengue risk may arise from short-term extreme events. Extreme drought, flooding, and heatwaves critically alter human–mosquito interactions and the ecological context of transmission in three major ways. First, breeding-site availability is reshaped, as drought intensifies reliance on household water storage and fosters larval habitats,[13] whereas floods may temporarily flush them out. Second, extreme weather alters mosquito biology and viral dynamics, as heatwaves stimulate the mosquito biting frequency, survival and viral replication,[16] though extreme temperatures can curtail adult survival.[11] Third, by directly damaging anti-mosquito infrastructure, floods or hurricanes can increase mosquito breeding and human–mosquito contact,[17,18] thereby heightening dengue risk.

Compound weather events, characterized here by the concurrent occurrence of drought/wet events and heatwaves, influence dengue transmission in complex ways.[19] Compound drought and heatwave conditions might reduce mosquito breeding habitats by shrinking natural water sources and dense vegetation, which restricts their capacity to regulate body temperature through shade-seeking and increases their overall vulnerability.[20] Concurrently, such conditions might drive population migration toward cooler, water-abundant areas,[21] potentially facilitating the spread of diverse dengue serotypes through international travel.[11] Wet–heatwave conditions often create highly favorable environments for vectors, as higher temperatures and humidity enhance mosquito activity.[16] However, these effects are not always reinforcing. Extreme heat can reduce adult mosquito survival,[11] and flooding can wash away larvae.[13] Taken together, the effects of compound extreme weather on dengue transmission remain insufficiently investigated.

Social vulnerability is a pivotal determinant of dengue epidemics. In this study, we conceptualize social vulnerability as arising from inadequate infrastructure and low levels of urbanization. Here, infrastructure is defined as access to improved/safe water and improved sanitation facilities, whereas urbanization refers to the proportion of the population residing in urban areas. These factors reshape dengue risk through altering human-mosquito interactions and healthcare access. First, inadequate infrastructure, including limited access to piped water, compels reliance on household water storage containers, thereby further amplifying breeding opportunities.[22] These artificial containers are especially important because female *Aedes aegypti* prefer to oviposit in water-holding containers located near humans, their primary blood source.[11,23] Second, poor urbanization may exacerbate dengue risk, with rural areas in some cases experiencing greater DENV risk than urban settings owing to land-use patterns, substandard housing, and restricted healthcare access.[24] Overall, the combination of poor urbanization and inadequate infrastructure constitutes social vulnerability, which not only elevates dengue risk but also interacts with extreme weather in ways that remain poorly understood.

Previous studies have primarily focused on the magnitude of hydrological events. However, the role of event timing, particularly compound events, on dengue epidemics remains inadequately explored across different countries. Moreover, little is known about how urbanization, infrastructure, and mosquito-related risks mediate the causal effects of extreme weather on dengue transmission. Traditional statistical models (e.g., regression analysis) deal with static conditions and are useful for identifying associations among variables under consistent experimental settings; nevertheless, they are inadequate for causal analysis, which is designed to capture dynamic conditions.[25] To overcome the above research gaps, we aimed to quantify the interaction effects of the timing of extreme weather events and social vulnerability on dengue transmission in Southeast Asia from 2000 to 2019, a region with significant exposure to both extreme weather and dengue. We also assessed the multiscale causal effects of extreme weather on dengue transmission, employing a method intended to capture dynamic causation.[26] This study introduces a modeling framework with two key enhancements. First, our analysis was derived from spatial-temporal models based on critical determinants (i.e., climate factors, wet, drought, heatwave, compound events, infrastructure, and urbanization) for dengue transmission. Second, we conducted causal analyses at two scales across seven Southeast Asian countries. The robustness of our findings is strengthened by explicitly accounting for the seasonal forcing of climate change. Overall, this study aimed to provide a scientific foundation for climate change adaptation measures aimed at establishing goals for dengue mitigation in Southeast Asia.

MATERIALS AND METHODS

Dengue data

Monthly total dengue cases from the whole of Singapore and 162 administrative level 1 (Admin-1) regions of six countries (i.e., Thailand, Vietnam, the Philippines, Cambodia, Malaysia, and Laos) from 2000 to 2019 (Table S1) are applied in this study.[11] The dengue data are primarily sourced from the official health ministry portals of Malaysia, the Ministry of Health in Singapore, and the Department of Health of the Philippines, as well as the OpenDengue database (https://opendengue.org/), statistical reports, and relevant literature (with detailed sources listed in Table S1). Among them, dengue case data for Vietnam (2012–2019), Laos (2014–2019), and Cambodia (2011–2019) at the national and weekly/monthly levels (Table S1). To ensure consistency across temporal scales, we aggregate weekly cases to the monthly scale (Supplementary Material). To ensure consistency across spatial scales, they are downscaled to the Admin-1 levels through interpolation (Supplementary Material).[11,27]

Interpolation bias is assessed for Laos, Vietnam, and Cambodia from 2001 to 2010 by country, year, and month, with most values between −0.1 and 0.1, indicating minimal systematic bias (Figure S3). To evaluate the assumption that monthly case fluctuations at the provincial level parallel national trends, we conduct a sensitivity analysis using 2000–2010 data from Vietnam, Cambodia, and Laos (Figure S4). Results show that, in most regions, the Admin-1 case dynamics exhibit moderate to strong correlations with national trends ($|r| \geq 0.5$; Figure S4). We also assess the variability of monthly dengue case proportions in each Admin-1 area relative to national totals, grouped by country and region over the same period in Laos, Vietnam, and Cambodia (Figure S5).

Climate factors and extreme weather events

Climate factors include monthly minimum, mean, and maximum temperature, precipitation in the whole of Singapore, and 162 Admin-1 regions of six nations between 2000 and 2019 (Table S5 and Figure S1). Extreme weather events here are assessed by timing, expressed as monthly total days of drought, wet, heatwave, and compound (drought–heatwave, wet–heatwave) weather. First, extreme wet and drought events are defined using the daily Standardized Precipitation Evapotranspiration Index (SPEI).[28] Normal and mild conditions are excluded, while moderate, severe, and extreme categories are included (i.e., absolute SPEI ≥ 1), to capture the spectrum of hydrological extremes frequently observed in Southeast Asia.[28,29] We then calculate the monthly totals of drought days (SPEI ≤ −1) and wet days (SPEI ≥ 1) to characterize extreme drought and wet conditions in this study. Second, extreme heatwave thresholds are defined using the 90th percentile.[30] A heatwave day is defined as any day on which the daily mean temperature reaches or exceeds the 90th percentile of the area-specific daily mean temperature distribution for the given year. The total number of heatwave days is then calculated for each month. Finally, we quantify the total days of simultaneous drought/wet and heatwave for each month, namely compound drought-heatwave or wet-heatwave events.[31] Furthermore, the original climate factors and SPEI are provided as raster data with varying spatial resolutions. To preserve the higher resolution of the original datasets, we do not resample them to a coarser grid. Instead, to ensure accurate spatial alignment with administrative boundaries, we aggregate the raster data (e.g., by calculating regional averages) within each area.

Mosquito data

We use mosquito occurrence records (i.e., published points with longitude and latitude) reported in the previous research.[32] Namely, mosquito occurrence point records from 1980 to 2011 are extracted to obtain the distributions of *Aedes aegypti* and *Aedes albopictus*.[20,32] For each species, in cases of duplicate records with the same location and year, only a single record is retained. In the subsequent analysis, we focus on latitudinal temperature variation while minimizing potential confounding from elevation.[20] Therefore, only records between 0 and 2,500 meters above sea level are included in the analysis.[20]

Social factors

Social factors, including urbanization,[13] infrastructure,[15] total population, and human migration,[11] are shaping the dynamics of dengue. High-density urban areas that experience intermittent water supply in times of water scarcity are more vulnerable to dengue outbreaks following droughts.[13] Improved sanitation systems may reduce dengue risk by limiting water storage containers, whereas poorly maintained septic tanks and drains create favorable conditions for mosquito breeding.[15] High population density provides new habitat for *Aedes aegypti*, which preferentially breeds in artificial water-holding containers near humans.[11] International human migration may increase the availability of susceptible human hosts and facilitate the spread of diverse dengue serotypes.[11] Drawing on theoretical foundations from previous research, we collect key data on the annual-resolution total population, human migration, urban population proportion, and household access to improved water and sanitation facilities in Singapore, together with comparable data from 162 Admin-1 regions in six countries between 2000 and 2019 (Tables S2-S5 and Figure S2). The source of social factors includes the local statistical bureau and literature sharing (Tables S2-S4). Among these, urbanization and infrastructure data are collected at the Admin-1 level and for Singapore. With at least two observations for each urbanization and infrastructure indicator, we estimated a constant annual trend between the first and last available years to linearly interpolate missing values, constraining the results to the range [0, 100]. For each area, we generate a yearly series for 2000–2019. Total population and net human migration data are available as raster datasets, for which we preserved their original spatial resolution (Table S5). We then aggregate the data by administrative units and the whole of Singapore, using the sum for human migration and population. Furthermore, urban population, access to improved water, access to improved toilets, and net human migration are standardized (mean-centered and scaled to unit variance) for subsequent Bayesian modeling.

Study design overview

There are three key steps in this study (Figure 1). First, data inputs are conducted to include dengue cases, climate factors, extreme weather events, urbanization, and infrastructure (i.e., access to improved toilets and water). Second, we identify the risk windows of climate factors and extreme weather on dengue transmissions. Here, risk windows refer to the climatic thresholds and lag periods corresponding to the maximum dengue risk, thus reflecting peak transmission potential. Notably, the risk window varies depending on the factor considered. Specifically, the risk windows of extreme weather on dengue risk, along with their interactions with urbanization and infrastructure levels, are further examined using a Bayesian model integrated with a Distributed Lag Non-Linear Model (DLNM). Third, we estimate mosquito thermal suitability through a thermal suitability indicator, and then conduct causal analysis at two levels: across clusters and within each area. Overall, this analysis follows two complementary paths: identifying risk windows and quantifying causal effects across two spatial scales.

Identification of risk windows

Nonlinear and lagged effects of extreme weather. Bayesian models are primarily implemented using the integrated nested Laplace approximations (INLA).[33,34] As a deterministic algorithm, INLA avoids issues of sample convergence, thereby enabling more efficient inference.[35] A Bayesian model integrated DLNM is employed to quantify the nonlinear and delayed effects of extreme weather and climate factors on dengue transmission. We incorporate DLNMs of climate factors and weather events, and set delays ranging

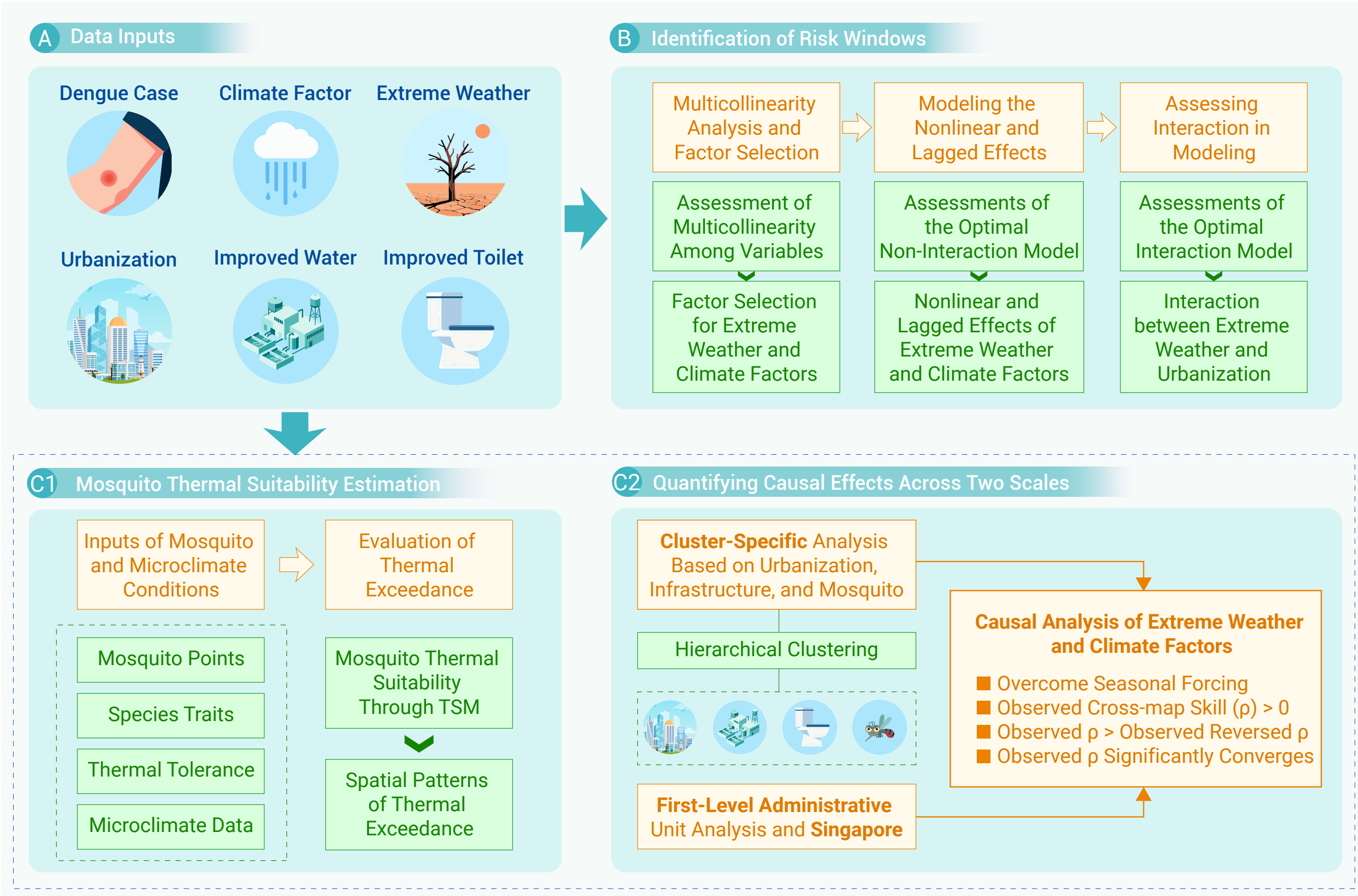

Figure 1. Flowchart of the study.

from 0 to 9 months to comprehensively capture the lag effect. The overall average values of variables in the study area are used as reference points for relative risk (RR = 1). The formulas are presented as follows:[13,36]

$$y_{rt} \mid \mu_{rt}, \kappa \sim \text{NegBin}(\mu_{rt}, \kappa) \tag{1}$$

$$\log(\mu_{rt}) = \log(p_{ry(t)}) + \log(\rho_{rt}) \tag{2}$$

$$\begin{gathered}\log(\rho_{rt}) = \alpha + \beta_{c(c)m(t)} + \varphi_{ry(t)} + \upsilon_{ry(t)} + \\ \text{Net Human Migration}_{ry(t)} + \text{dlnm} \\ (\text{climate factors}_{rm(t)}, \text{lag}) + \text{dlnm}(\text{weather events}_{rm(t)}, \text{lag})\end{gathered} \tag{3}$$

We hypothesize that dengue cases follow a negative binomial distribution to account for their possible over-dispersion.[13] In formula (1), the term y_{rt} represents the monthly dengue cases across 162 Admin-1 regions in six Southeast Asian countries and the whole of Singapore from January 2000 to December 2019. μ_{rt} refers to the corresponding average value of the distribution, and κ represents the scale parameter.[13]

In formula (2) and (3), $p_{ry(t)}$ represents the annual population per 100,000 from 2000 to 2019, and $\log(\rho_{rt})$ consists of intercept (α), monthly random effects at the country level ($\beta_{c(c)m(t)}$), spatially annual unstructured ($\varphi_{ry(t)}$) and structured ($\upsilon_{ry(t)}$) random effects for Admin-1 regions and Singapore[22], scaled human migration, and DLNMs for climate factors and weather events. Temporal random effects are modeled using a first-order random walk (RW1) to account for geographic variability in the seasonality of dengue.[15] Spatial random effects are modeled using the Besag-York-Mollié 2 (BYM2) model, which comprises unstructured and structured components.[35] The unstructured component captures unknown and unmeasured factors, such as mosquito control interventions, herd immunity, and healthcare facilities.[13] The structured component accounts for spatial dependence, with the effect in a given region informed by those of its neighboring areas.[35] Spatial autocorrelations of dengue data (using January 2000, June 2011, and December 2019) are also significantly identified (Table S6). Priors for the random effects are estimated using the Penalized Complexity (PC) method, with detailed parameter specifications provided in the Supplementary Material.[13,36]

Interactions of extreme weather with urbanization and with infrastructure. We investigate the interactions of extreme weather with urbanization and with infrastructure on dengue transmission. The formula with interaction is as follows:[13]

$$\begin{gathered}\log(\rho_{rt}) = \alpha + \beta_{c(c)m(t)} + \varphi_{ry(t)} + \upsilon_{ry(t)} + \\ \text{Net Human Migration}_{ry(t)} + \text{dlnm}(\text{climate factors}_{rm(t)}, \text{lag}) + \\ \text{dlnm}(\text{weather events}_{rm(t)}, \text{lag}) + \text{dlnm}(\text{weather events}_{rm(t)}, \text{lag}) \times \\ \text{urban or infrastructure factor}_{l,ry(t)} + \text{urban or infrastructure factor}_{ry(t)}\end{gathered} \tag{4}$$

Based on the overall interaction model (e.g., one that incorporates overall urbanization), we classify each urban/infrastructure factor into three levels: high, medium, and low.[13] For example, to distinguish levels of urbanization, the urban population variable is centered at the 25th, 50th, and 75th percentiles, representing rural (low), semi-urban (medium), and urban (high) areas, respectively.[13] The standardized variable is then rescaled by subtracting these percentile values to obtain three centered measures corresponding to the above levels of urbanization. This process has generated three submodels, aimed at analyzing the interaction between varying levels of specific urban or infrastructure factors and weather events on dengue transmission. We provide detailed model specifications, including prior choices and sensitivity analysis (Supplementary Material), and perform the computations primarily using the R-INLA package (version 24.05.10).[33,34]

Multicollinearity analysis and factor selection. The baseline model includes an intercept, spatial and temporal random effects, scaled human migration, and DLNMs of temperature and precipitation. These factors are included in the baseline model, as most have been implicated in dengue transmission in previous studies.[11,13,15] To better represent the thermal constraints on dengue transmission, both maximum and minimum temperatures are initially considered. Sensitivity analysis indicates that using minimum temperature results in better model performance (Table S7). Accordingly, the maximum temperature is excluded to avoid multicollinearity. Multicollinearity among the variables (with minimum temperature as the temperature variable) is evaluated using the Variance Inflation Factor (VIF) in Table S8, whereby values exceeding 10 are considered indicative of severe multicollinearity warranting adjustment.[37]

We apply the deviance information criterion (DIC) to identify the optimal model through a three-step procedure. First, each candidate variable is added individually to the baseline model, and its impact on reducing the DIC is used to evaluate relative importance (Table S9). Variables that do not reduce the DIC or lead to minimal improvement are excluded. Second, the remaining variables are ordered in descending order of relative importance and sequentially added to the current best model, retaining only those that further reduce the DIC. The model with the lowest DIC is then selected as the optimal non-interaction model (Table S10). Third, building on this model (formula (3)), we introduce interactions between each urban/infrastructure factor and weather event, as well as the factor itself (formula (4)), and identify the model with the lowest DIC as the optimal interaction model (Table S10). For sensitivity analysis, we further validate that the negative binomial specification slightly outperformed the Poisson model (Table S11).

Estimates of mosquito thermal suitability

For Aedes-borne virus, the most critical constraint on disease transmission is the shortened mosquito lifespan under high-temperature conditions.[20] Thus, we use thermal safety margin (TSM), which reflects the mosquito's capacity to tolerate climatic warming (i.e., thermal suitability), as a proxy for mosquito thermal suitability. A lower TSM indicates a greater likelihood that mosquitoes are approaching or exceeding their thermal tolerance limit. In this study, TSM denotes adult critical thermal maximum (CT_{max}) temperature under the unvarying-temperature laboratory estimates, minus the peak hourly body temperature in the coolest accessible microhabitat (i.e., full shade).[20] Hourly body temperature is estimated based on hourly microclimatic data and mosquito biological traits, including body size, diel activity patterns, and thermal tolerance limits.[20] For numerous locations with TSM values, we employ a spatial interpolation approach to construct a static negative TSM spatial surface (Figure S14), representing thermal exceedance. We compute the average thermal exceedance for each area, along with the annual mean levels of urbanization (2000–2019) and access to improved water and sanitation facilities (2000–2019). These indicators are incorporated into a hierarchical clustering framework. We calculate the Euclidean distance matrix to quantify dissimilarity and apply the Ward.D2 method to form clusters, which are subsequently used for causal analyses (Supplementary Material).

Quantifications of causal effects across scales

Certain climatic and extreme weather factors might exert causal effects on dengue transmission with relatively small magnitudes and thus may not be fully captured by the Bayesian framework. To address this limitation, we apply CCM to evaluate their individual causal contributions to dengue epidemics. We conduct causal analyses at two levels: across area clusters and within individual regions. Effects are estimated for clusters stratified by mosquito thermal suitability, urbanization, and infrastructure, as well as for each Admin-1 unit and for Singapore in its entirety.

Dengue transmission is sensitive to climate change,[38] and the shared seasonality of dengue data and climate variables may lead cross-mapping analyses to detect apparent interactions, even when no direct causal relationship exists. To enhance robustness and address the above issue, where shared seasonal patterns influence predictions of cross-mapping, we compare predictions from actual climate factors and weather events with those using null expectations.[2] To build null expectations, we use cross-mapping with surrogate data, keeping the seasonal patterns of the actual time-series while including random anomalies;[2] these surrogate data are generated using the rEDM packages (version 1.15.4).[39,40] In this process, we utilize both the Ebisuzaki (EBI) null model and the seasonal (SEA) null model.[2] The EBI null model maintains periodicity (except for seasonality) of real data but randomizes the time-series phase in the Fourier transform, and the SEA null model preserves seasonal signals, whereas, including randomized inter-annual variations, the two approaches can yield divergent causal inferences (Figures S6-S7 & S16).[2] To ensure robustness, we restrict our interpretation to associations consistently supported by both models.

Causal effects are inferred only when all of the following conditions were satisfied: (i) cross-map predictions for the observed data significantly exceed those for null surrogates (t-test, FDR-adjusted $p \le 0.05$);[2] (ii) the observed cross-mapping skill (ρ) is positive and greater than the reversed ρ at the maximum library size (L); and (iii) ρ converges with increasing library size (Figures 1 & S8; Supplementary Material). Convergence is evaluated using Kendall's τ test, with convergence defined as $\tau > 0$ and statistically significant ($p \le 0.05$).[41] We conduct CCM in 161 Admin-1 regions and Singapore, where all monthly extreme weather events have exhibited non-unique values over the past 20 years. Furthermore, the CCM calculations are primarily performed using the R package rEDM (version 1.15.4).[40]

RESULTS

Descriptive analysis

The spatial distribution of average monthly dengue cases from 2000 to 2019 for Singapore as a whole and each Admin-1 of the 6 countries is presented in Figure 2A. Areas with a high risk of dengue fever are primarily concentrated in the Philippines, southern Vietnam, and western Malaysia, while regions with fewer cases are predominantly found in northern Vietnam (Figure 2A). Figure 2B illustrates the levels of both wet and drought events. The color scheme represents different intensity levels: pink indicates a high level of wet and a low level of drought events, while blue signifies opposite situations. Dark purple denotes areas experiencing both drought and wet events at high levels. Overall, Malaysia, Vietnam, and Singapore exhibited high dengue incidence from 2000 to 2019 (Figure 2C). During the same period, the Philippines and Malaysia frequently experienced heatwaves (Figure 2D). Singapore in 2007 and Cambodia in 2016 experienced prolonged wet events (Figure 2E). Additionally, Singapore experienced prolonged drought events in 2019 (Figure 2F).

The risk windows of extreme weather on dengue risk

In this study, risk windows are defined as the climatic or extreme weather thresholds and lag periods associated with the highest dengue risk, reflecting peak transmission potential. We first present the process of model selection, then quantify the nonlinear and lagged impacts of individual extreme weather events, and finally examine their interactions with urbanization and infrastructure separately.

Model selection. The optimal model is selected using the minimum DIC, through a two-step process involving the non-interaction model and the interaction model. For the optimal non-interaction model, spatial and temporal random effects, scaled net human migration, and DLNMs of minimum temperature, precipitation, drought, heatwaves, wet, and compound drought–heatwave events are included (Figure 3 and Tables S9-S10). For the optimal interaction model, interactions between extreme weather and overall urbanization are incorporated, and the model shows good predictive performance across most data (Figures S9-S11 and Table S10). Based on this model, urbanization is categorized into three levels, and the interaction effects with extreme weather are presented in Figure 4.

Nonlinear and lagged effects of individual factors. Overall, the RR estimates reveal that dengue risk is driven by climate factors and extreme weather events (Figure 3). The RR is highest at a minimum temperature of 25°C, with a lag of 3.5 months (max RR 10.04, 95% CI: 6.63-15.2), as shown in Figure 3A. In Figure 3B, the highest risk occurs with a total precipitation of 460 mm, with a lag of 1.5 months (max RR 5.85, 95% CI: 3.97–8.61). In Figure 3C, the highest risk occurs with monthly drought events of 13.5 days with a lag of 5.25 months (max RR 5.21, 95% CI: 3.31–8.21). In Figure 3D, the highest risk occurs with monthly drought-heatwave events of 10.5 days with a lag of 4.25 months (max RR 2.55, 95% CI: 1.3–5.01). As presented in Figure 3E, the maximum risk occurs with monthly wet events of 12 days without lags

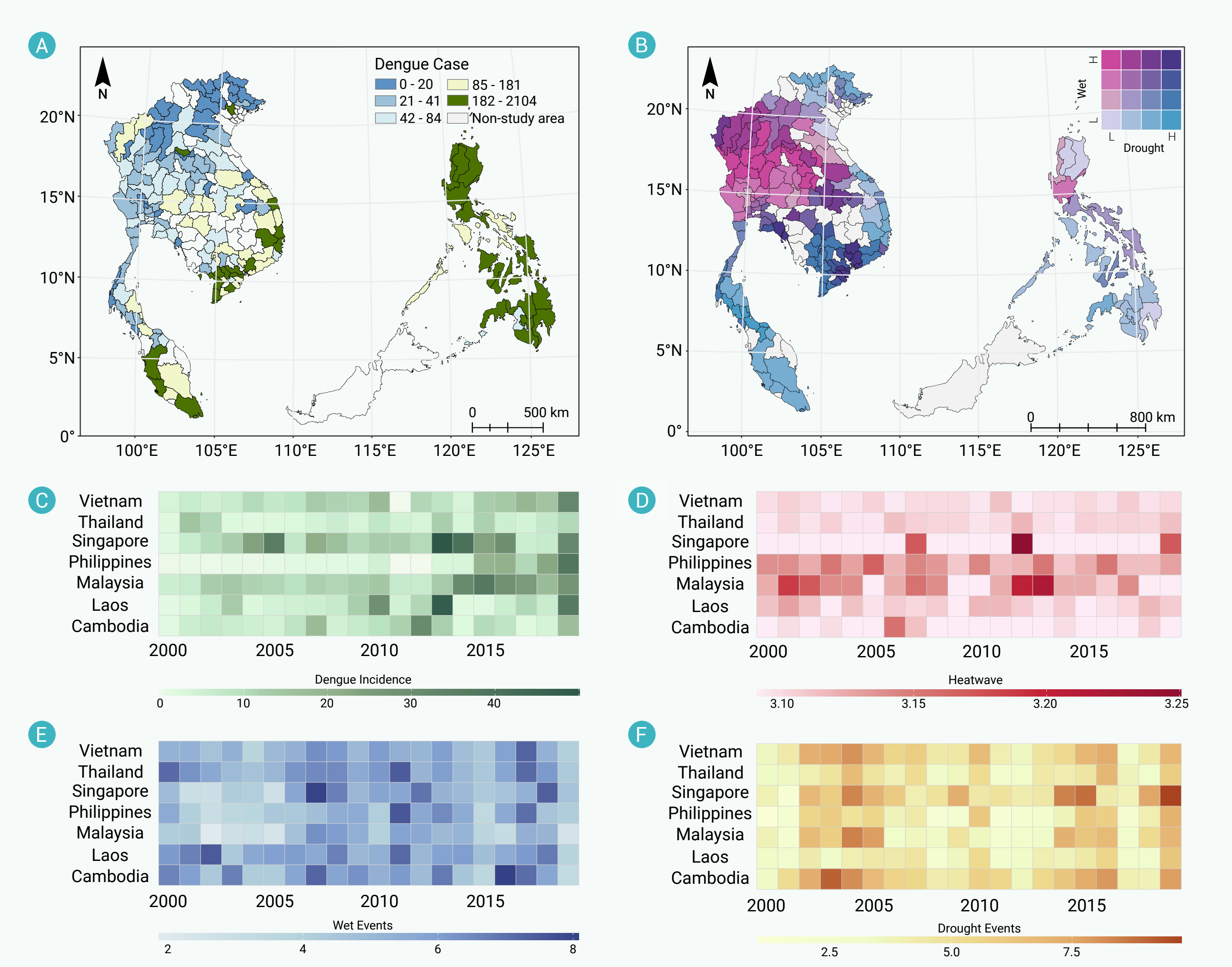

Figure 2. Temporal and spatial variations of dengue and extreme weather events from 2000 to 2019 (A) Average spatial distribution of dengue cases; white areas indicate non-study areas. (B) Average levels of wet and drought days; grey areas indicate non-study areas. (C–F) Temporal variations in annual averages by country: (C) dengue incidence (cases per 100,000 population), (D) heatwave events, (E) wet events, and (F) drought events.

(max RR 2.76, 95% CI: 1.79–4.26). Finally, Figure 3F indicates that heatwave events of 12 days yield the highest risk with a lag of 3.75 months (max RR 5.5, 95% CI: 3.27–9.25).

Interactions effects with urbanization/infrastructure levels. Beyond the non-linear and delayed effects of extreme weather, we also assess its interactions with urbanization and with infrastructure.

In general, areas with low urbanization levels face a higher risk of dengue fever in response to extreme weather events. With regard to wet events, the highest RR is consistently associated with 12 wet days per month across all urbanization levels, though with different lag periods (Figures 4A–C). Peak risks occur at a 2.5-month lag in low-urbanization areas (RR = 5.28, 95% CI: 3.87–7.2), a 3-month lag in medium-urbanization areas (RR = 4.70, 95% CI: 3.4–6.51), and a 3.75-month lag in high-urbanization areas (RR = 3.77, 95% CI: 2.72–5.22). For drought, the highest RR is associated with drought at a 5.25-month lag across all urbanization levels, though with varying total event days per month (Figures 4D–F). Peak risks occur with 12.5 drought days per month in low-urbanization areas (RR = 15.65, 95% CI: 10.43–23.48), 12.5 days in medium-urbanization areas (RR = 10.6, 95% CI: 7.05–15.93), and 12 days in high-urbanization areas (RR = 5.16, 95% CI: 3.5–7.62). For heatwaves, the highest RR is associated with heatwaves, with 11.5 days per month and a 3.75-month lag in low-urbanization areas (RR = 14.76, 95% CI: 8.93–24.41; Figure 4G) and in medium-urbanization areas (RR = 9.91, 95% CI: 5.98–16.42; Figure 4H). In high-urbanization areas, the peak occurs with 11 heatwave days per month and a 4-month lag (RR = 4.59, 95% CI: 2.81–7.51; Figure 4I).

In the case of compound drought-heatwave events, in low-urbanization areas, the peak risk is linked to 10 drought–heatwave days per month with a 4.5-month lag (RR = 2.51, 95% CI: 1.29–4.9; Figure 4J). In medium-urbanization areas, 9.5 days per month with the same lag yield the maximum risk (RR = 2.03, 95% CI: 1.05–3.94; Figure 4K). In contrast, in high-urbanization areas, the peak emerges with 10 days per month but at a 9-month lag (RR = 1.46, 95% CI: 0.61–3.50; Figure 4L). For the independent effects of overall urbanization, we find that it promotes dengue transmission, and human migration also contributes positively to dengue transmission (Table S12).

To validate the robustness of the interaction effects, we compared the RR of extreme weather between low and high urbanization levels. The interactions are statistically significant for all types of extreme weather ($P < 0.0001$, overall probability = 1; Table S13). The risk associated with extreme weather is consistently higher under low urbanization than under high urbanization.

We also assess the interactions of extreme weather separately with levels of access to improved toilets and to improved water, with the full results shown in Figures S12-S13. Notably, under poor toilet conditions, the highest risk is observed with 12 wet days per month without lag (RR = 2.08, 95% CI: 1.35–3.21), 12.5 drought days per month with a 5-month lag (RR = 4.22, 95% CI: 2.81–6.32), and 11.5 heatwave days per month with a 3.5-month lag (RR

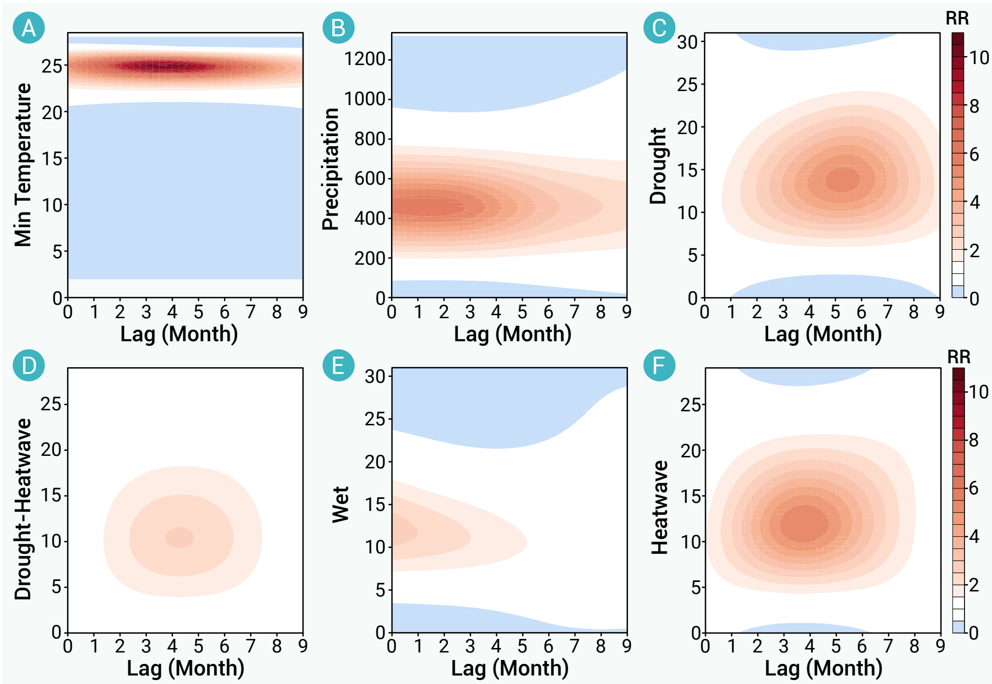

Figure 3. Associations between key climate factors and extreme weather events and dengue risk (A) Minimum temperature, (B) precipitation, (C) number of drought days per month, (D) number of compound drought-heatwave days per month, (E) number of wet days per month, and (F) number of heatwave days per month. Results are based on the best-performing model without interaction terms. RR indicates relative risk.

= 4.10, 95% CI: 2.47–6.81; Figure S12). Under poor water conditions, the peak risk occurs with 11.5 wet days per month at a 2.75-month lag (RR = 1.91, 95% CI: 1.41–2.57), 12.5 drought days per month at a 5.25-month lag (RR = 2.62, 95% CI: 1.74–3.95), and 11 heatwave days per month at a 3.75-month lag (RR = 2.71, 95% CI: 1.65–4.44; Figure S13).

Causal effects of extreme weather across scales

We conduct causal analyses at two levels: across clusters of areas and within individual areas. Specifically, we estimate causal effects for clusters defined by mosquito thermal suitability, urbanization, and infrastructure, as well as for each Admin-1 region and for Singapore as a whole.

Mediation by mosquito Thermal Suitability and urbanization, infrastructure disparities. Based on thermal exceedance of mosquitoes, urbanization levels, and infrastructure disparities, the study delineates three distinct clusters (Figures 5A-B & S14-S15). Cluster 1 is characterized by limited access to basic infrastructure, including improved water sources and sanitation facilities, low levels of urbanization, and low mosquito thermal suitability (i.e., low TSM), predominantly covering the majority of the Admin-1 regions in Laos. Cluster 2 comprises areas with well-developed infrastructure, moderate levels of urbanization, and low mosquito thermal suitability, primarily encompassing most administrative regions in Thailand. Cluster 3 includes regions with well-developed infrastructure, high levels of urbanization, and high mosquito thermal suitability, such as Singapore and most Admin-1 regions in the Philippines. To ensure robustness, we considered results to be consistently supported only when cross-map predictions using the actual data exceeded those using both the SEA and EBI null surrogates. Both models consistently identified precipitation and wet events as the primary causal drivers of dengue transmission across all clusters (Figures 5C-D). Furthermore, drought, drought–heatwave, and wet–heatwave events emerged as significant causal drivers primarily in urban areas with well-developed infrastructure and favorable mosquito thermal suitability (i.e., cluster 3), as indicated consistently by both models (Figure 5).

Causal effects of extreme weather at a finer spatial scale. We further evaluate the causal effects of temperature, precipitation, and extreme weather events across the different regions (Figures 6-7). At the maximum L, squares, triangles, and asterisks denote the observed ρ values of environmental drivers. Squares indicate non-causal drivers; inverted triangles indicate causality detected by the SEA null model; right triangles indicate causality detected by the EBI null model; and asterisks indicate causality supported by both models (Figures 6-7). In Thailand, wet events are identified as causal drivers in 32 Admin-1 regions, followed by precipitation (27), drought (21), maximum temperature (23), minimum temperature (23), and mean temperature (19). In Vietnam, drought and drought–heatwave are the primary drivers, affecting 21 Admin-1 regions, followed by maximum temperature (18), wet events (17), precipitation (15), and wet–heatwave events (15). In the Philippines, wet events are the causal driver in 10 Admin-1 regions, followed by drought (9), drought–heatwave (7), and wet–heatwave events (7). In Malaysia and Cambodia, heatwaves are the dominant driver, influencing the greatest number of Admin-1 regions for each nation. Mean temperature is also a key driver affecting the greatest number of Admin-1 regions in Malaysia. In Laos, precipitation is the primary driver, affecting 5 Admin-1 regions, followed by wet events (4), wet-heatwave events (4), and drought-heatwave events (4). In Singapore, only precipitation emerges as a causal driver under both null models.

DISCUSSION

Main advancements

Accounting for the interactions between extreme weather and social vulnerability is essential for guiding climate adaptation strategies aimed at reducing dengue risk in underdeveloped areas. This study provides key evidence on how dengue transmission is caused by extreme weather events, with its effects shaped by both social vulnerability and mosquito thermal suitability. The main advancements are demonstrated across four aspects.

First, dengue risk is generally elevated in areas with poor water infrastructure and in rural regions characterized by low urbanization, as extreme weather events amplify community susceptibility, vector exposure, and their interactions (Figures 4 & S13). Inadequate water systems heighten susceptibility by forcing reliance on unsafe sources, while droughts and unreliable supplies drive household water storage, creating breeding habitats that intensify mosquito exposure.[13,17] Extreme floods damage fragile infrastructure, contaminate water supplies, and displace populations,[42] simultaneously increasing susceptibility and vector exposure. In rural areas, outdoor labor such as farming and grazing elevates exposure through more frequent human–mosquito contact.[43] Weak public health and medical systems further increase risk by limited vector control and delaying case detection and treatment.[44] Proximity to vegetation and primate hosts facilitates the periodic reintroduction of arboviruses, thereby reinforcing the convergence of human vulnerability and environmental risk.[24] These combined vulnerabilities are also magnified during heatwaves, which accelerate mosquito development and expand their geographical range.[16]

Second, the lag and nonlinear effects of climate factors and extreme weather on dengue transmission differ significantly. For climate factors, the analysis reveals that the maximum RR occurs at a minimum temperature of 25 °C, with a lag of 3.5 months (RR = 10.04, 95% CI: 6.63–15.2) in Figure 3A. Consistent with our findings, one study reported that RR peaked at a maximum T_{min} of 25.5 °C with a lag of 2–4 months,[13] while another indicates a non-linear, one-month lagged effect of monthly mean temperature on dengue transmission, with RR peaking at around 27 °C.[15] The observed time lag associated with temperature reflects its indirect influence on dengue transmission via mosquito population dynamics and viral replication. This influence begins with egg hatching, advances through larval–pupal develop-

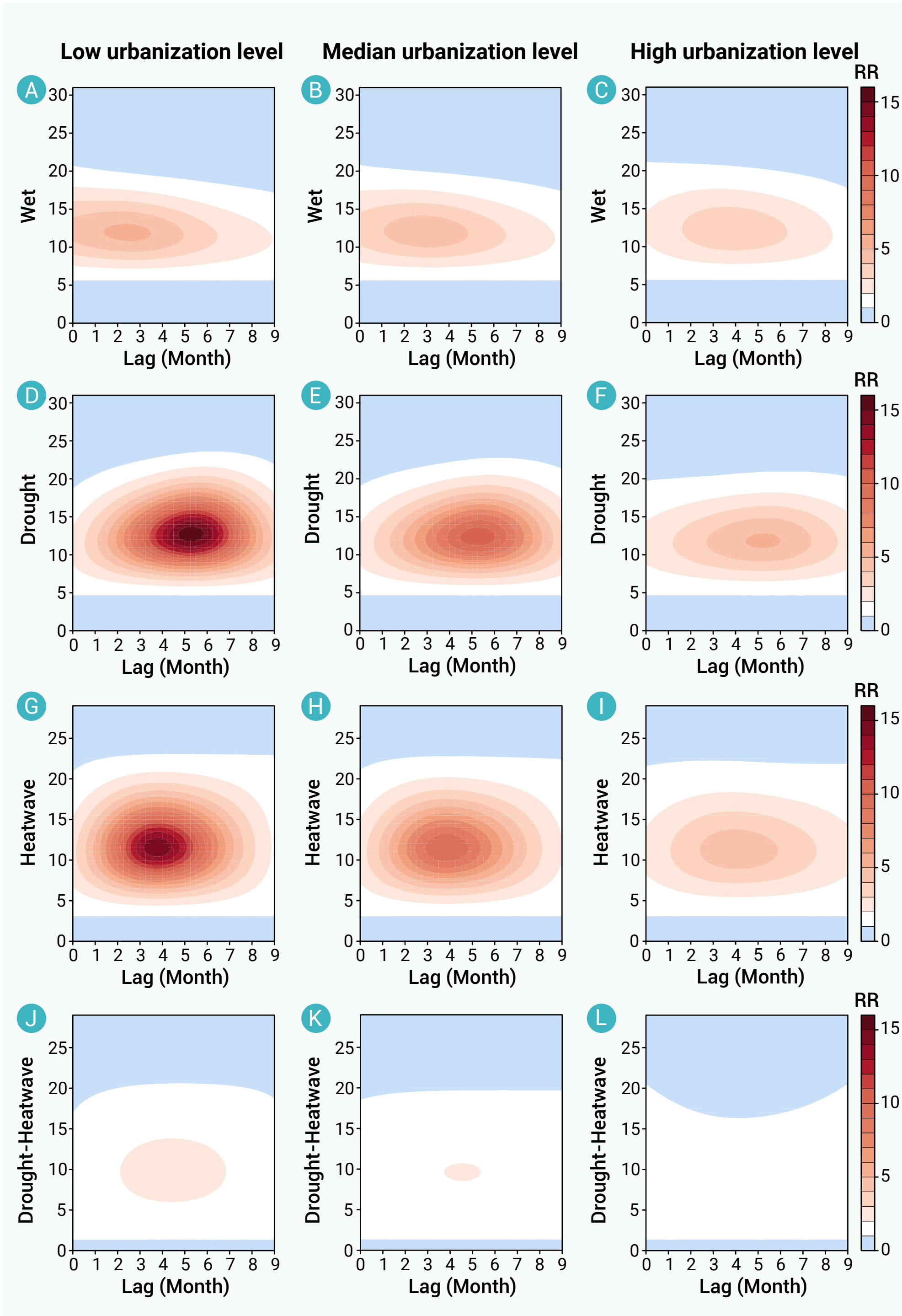

Figure 4. Interactive effects of extreme weather events and urbanization levels on dengue risk
(A-C) Illustrate the effects of wet events under low, medium, and high urbanization levels, respectively. (D-F) Present the corresponding effects of drought events, while (G-I) display the effects of heatwave across the same urbanization gradient. Finally, (J-L) depict the impacts of compound drought–heatwave events under varying levels of urbanization. RR denotes relative risk.

ment to the adult stage, and proceeds with viral replication in the mosquito, incubation in the human host, and subsequent transmission cycles.[45] The cumulative effects of these sequential stages ultimately contribute to a time lag in dengue cases. [45] The observed non-linear effects may be attributed to extremely low or high temperatures negatively affecting larval development.[14] Survival reaches its maximum at approximately 27 °C across all developmental stages, with lower temperatures being particularly unfavorable.[5] Feeding activity is also affected by temperature, being suppressed or ceased at <15 °C and can be restricted at >36 °C.[5]

For extreme weather events, the highest RR is observed with 12 wet days per month without lag (RR = 2.76, 95% CI: 1.79–4.26; Figure 3E), and with 13.5 drought days per month at a 5.25-month lag (RR = 5.21, 95% CI: 3.31–8.21; Figure 3C). These results highlight distinct peak risks and lagged effects on transmission, with droughts typically showing longer delays and higher maximum RRs than wet events. A prior study in Brazil similarly reported that when RR reaches peak, drought effects persist for a longer delay than wet events, but with comparable magnitude.[13] Specifically, drought is positively associated with dengue risk after 3–5 months (max RR = 1.43, 95% CI: 1.22–1.67, with a 4-month lag), whereas extreme wet conditions increase risk within 3 months (max RR = 1.56, 95% CI: 1.41–1.73, with a 1-month lag).[13] Compared with the study in Brazil, which found comparable magnitudes of maximum RR for drought and wet events, our observation of stronger drought effects likely reflects regional climatic differences. The long lag observed could be explained by the ability of *Aedes aegypti* eggs to survive for up to 120 days under drought conditions.[46] In addition, when people become aware of an ongoing drought, they gradually increase water storage practices to secure household supply.[13] This progressive increase in stored water creates additional habitats, which could further contribute to the prolonged lag effect.[13]

Third, compound drought-heatwave conditions pose a lower maximum RR of dengue compared with individual heatwave and drought. The maximum RR for compound drought–heatwave events is lower than that observed for drought and heatwave events alone (Figure 3). This could be explained by the lower frequency of compound drought–heatwave events compared with individual events. Such compound events also simultaneously reduce vegetative shelters [47] and standing water, thereby impairing mosquito behavioral thermoregulation by limiting access to shaded microhabitats and decreasing the suitability of breeding habitats.[20] Furthermore, acute heatwaves can increase adaptation costs.[48] Although the relatively low frequency of these compound events, their potential impacts on dengue transmission should not be underestimated.

Fourth, causal analysis indicates that both drought and compound drought–heatwave events substantially influence dengue transmission in urban settings with improved infrastructure and high mosquito thermal suitability (cluster 3 in Figures 5C-D). In contrast, such causal effects are not observed in rural areas with poor infrastructure and low mosquito thermal suitability (cluster 1 in Figures 5C-D), where households routinely rely on water storage containers because of intermittent or limited water supply.[49] Rural populations rely more on self-supplied (non-public) water than urban populations; thus, unexpected drought conditions may not markedly alter household storage practices in rural areas, exerting only a limited additional effect on mosquito breeding. By contrast, in well-infrastructure urban areas (cluster 3 in Figure 5), where routine water storage is uncommon, and

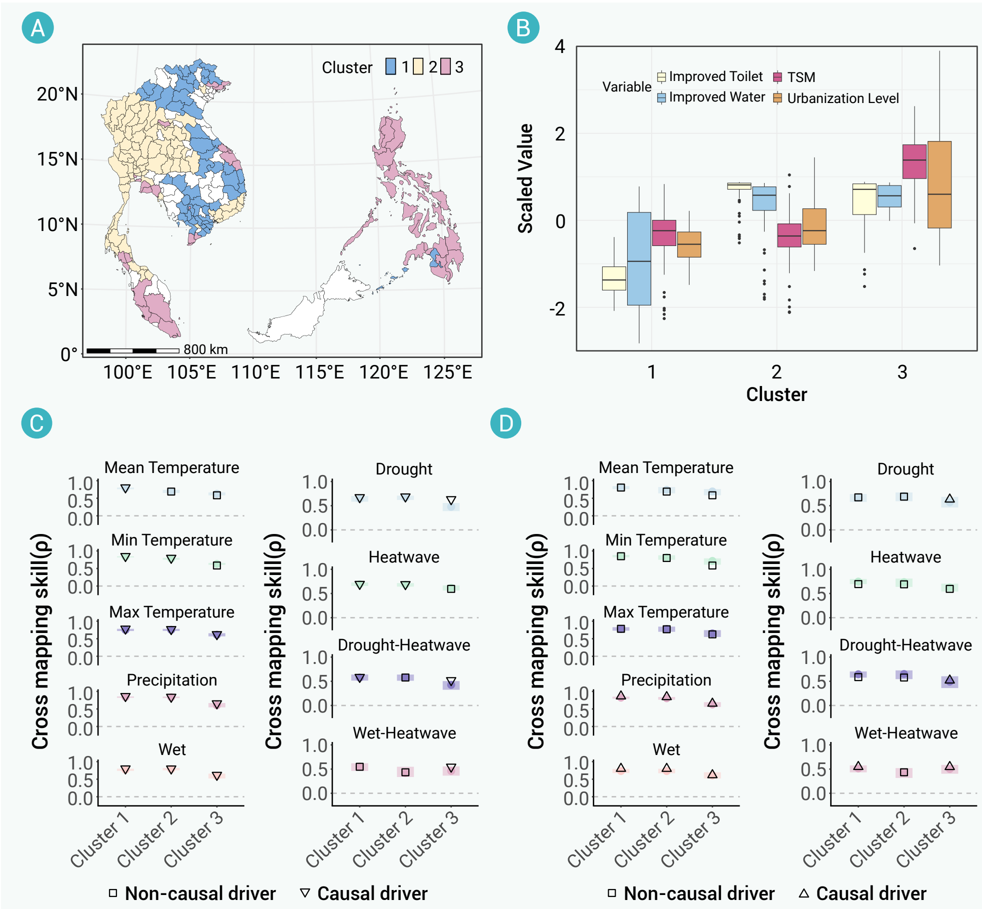

Figure 5. Causal effects of extreme weather and climate factors on dengue transmission across area clusters characterized by mosquito thermal suitability, urbanization, and infrastructure
(A) Spatial distribution of the identified clusters. (B) Distributions of urbanization level, access to improved water and toilets, and mosquito thermal suitability across each cluster. (C) Causal effects of extreme weather and climate factors using the SEA null model. (D) Causal effects of extreme weather and climate factors using the EBI null model. At the maximum L, colored horizontal bars with endpoints represent the distribution of ρ from randomized surrogate datasets under the null model, with the endpoints indicating the 2.5th and 97.5th percentiles and the colored circles marking the mean ρ. Triangles and squares indicate the observed ρ at the maximum L.

mosquito thermal suitability is favorable, drought-induced increases in water storage might exert a greater marginal impact on mosquito proliferation and dengue transmission compared with rural contexts (cluster 1 in Figure 5). Furthermore, the concurrence of heatwaves and droughts amplifies water demand, with the urban heat island effect intensifying local warming and thereby further reinforcing these behaviors.

Practical implications

Our findings provide policy-relevant insights to guide strategies for addressing droughts, wet events, and heatwaves. They highlight the need for coordinated action across sectors, with meteorological agencies ensuring timely monitoring, health authorities implementing rapid interventions, and communities contributing actively to improve dengue response capacity.

Drought has a pronounced causal effect on dengue transmission in urban areas with robust infrastructure and high TSM (Figure 5). To mitigate this threat, interventions should operate across several dimensions. Infrastructure-targeted measures should strengthen urban water supply resilience through unconventional resources such as artificial recharge, wastewater treatment, and cloud seeding.[50] Repairing damaged pipelines is equally critical to prevent leakages that create small-scale water accumulations.[51] Management measures should include graded drought warnings via social media, community education, and enforcement mechanisms, with each level tied to preventive actions, including setting appropriate water restrictions.[52] Where storage is unavoidable, containers must be tightly sealed and cleaned regularly to eliminate mosquito eggs.[53] Temporal measures are required during the 5–6 months following droughts (Figure 3C), a high-risk window requiring intensified case surveillance, stringent clinical management, and vector control, including indoor residual spraying and biological methods (e.g., Wolbachia).[54]

Extreme wet events have a significant causal effect on dengue transmission regardless of local infrastructure, mosquito thermal suitability, or urban–rural context (Figure 5). Infrastructure measures should include routine monitoring of the integrity of current facilities, as well as further development to prevent structural damage during floods.[55] This includes constructing wastewater drainage systems, rehabilitating wastelands, converting abandoned dumpsites into vegetable plots, and upgrading solid waste disposal facilities.[51] Management measures should encompass community engagement, with emphasis on the removal of potential breeding sites, particularly containers likely to retain stagnant water.[53] Temporally, dengue risk peaks when wet events occur for 12 days per month without lag (Figure 3E). This highlights the need for an interagency coordination and data-sharing system.[16] Meteorological agencies should enhance daily monitoring of wetting events, while health authorities must promptly intensify vector-control interventions, alongside active community mobilization, once the threshold of 12 wet days per month is reached.

Mitigating dengue risk from heatwaves likewise requires measures across multiple aspects. Infrastructure measures should include the installation of mosquito-control and cooling facilities in public spaces, the promotion of reflective materials,[16] and the enhancement of building ventilation to mitigate the risk. Building designs in Southeast Asia require sustainability that accounts for future climate change, while conserving energy and reducing carbon emissions through advanced air-conditioning and electrical systems.[56] For management measures, during heatwaves, people tend to gather indoors;[16] therefore, it should aim to prevent overcrowding by facilitating timely evacuation, thereby reducing the risk of amplifying dengue virus transmission chains. For temporal measures, the highest RR is observed with monthly heatwave events of 12 days at a lag of 3.75 months (max RR 5.5, 95% CI: 3.27–9.25) in Figure 3F. Thus, a multi-departmental system for time warnings of heatwaves and joint responsibility is required, and the early warning system should be structured with multiple levels of alerts to mitigate dengue risk.[56] Furthermore, short-term heat exposure forces mosquitoes (i.e., thermal acclimation for one generation) to increase resistance of the fusing agent virus (CFAV), but this heightened resistance is accompanied by substantial fitness costs.[48] In contrast, prolonged heat exposure (i.e., thermal evolution across ten generations) promotes adaptations that increase mosquito tolerance to CFAV while maintaining, and potentially improving, overall mosquito fitness.[48] Accordingly, CFAV-based interventions should incorporate the local heatwaves into their design.

Artificial intelligence (AI) offers innovative tools for dengue prediction and control,[57,58] including detecting early outbreak signals from large-scale internet data.[57] AI-based image recognition and intelligent systems advance mosquito surveillance and habitat detection, enabling more efficient vector control.[58] In addition, AI can support early clinical diagnosis, vaccine design, and optimize integrated control strategies by simulating interventions (e.g., contact tracing).[57] Real-time analysis of community engagement (e.g., water container cleaning) through mobile platforms further improves dengue prevention.[58] Nevertheless, AI applications face certain challenges. The multi-

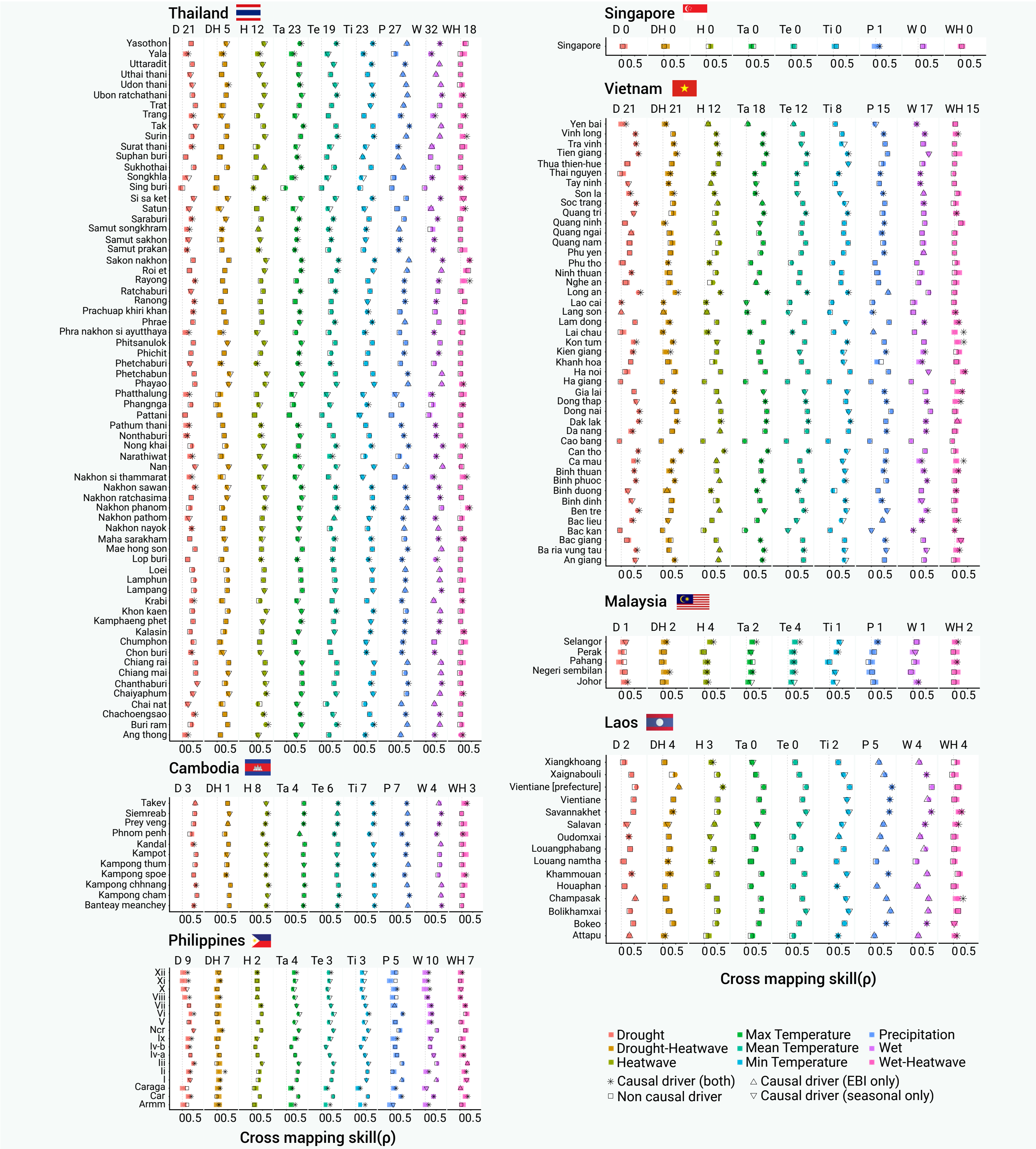

Figure 6. Detection of causal drivers of climate factors and extreme weather events on dengue transmission for the whole of Singapore and each Admin-1 across six nations using the SEA null model D denotes drought events; DH, compound drought–heatwave events; H, heatwaves; Ta, maximum temperature; Te, mean temperature; Ti, minimum temperature; P, precipitation; W, wet events; and WH, compound wet–heatwave events. At the maximum L, squares denote non-causal drivers; inverted and right triangles denote causality detected by the SEA and EBI null models, respectively; and asterisks denote causality supported by both. At the maximum L, colored horizontal bars with endpoints represent the distribution of ρ from randomized surrogate datasets under the SEA null model, with the endpoints indicating the 2.5th and 97.5th percentiles and the colored circles marking the ρ. The number above represents the number of Admin-1s or the country (i.e., Singapore) with causal environment drivers supported by both null models.

dimensional and non-standardized nature of internet data can introduce biases into predictive models, and the limited interpretability of some AI models, with opaque internal logic, hampers their translation into policy.[57] The collection of behavioral and health data could raise privacy concerns, emphasizing the need for comprehensive security protocols, data governance, and ethical principles.[57]

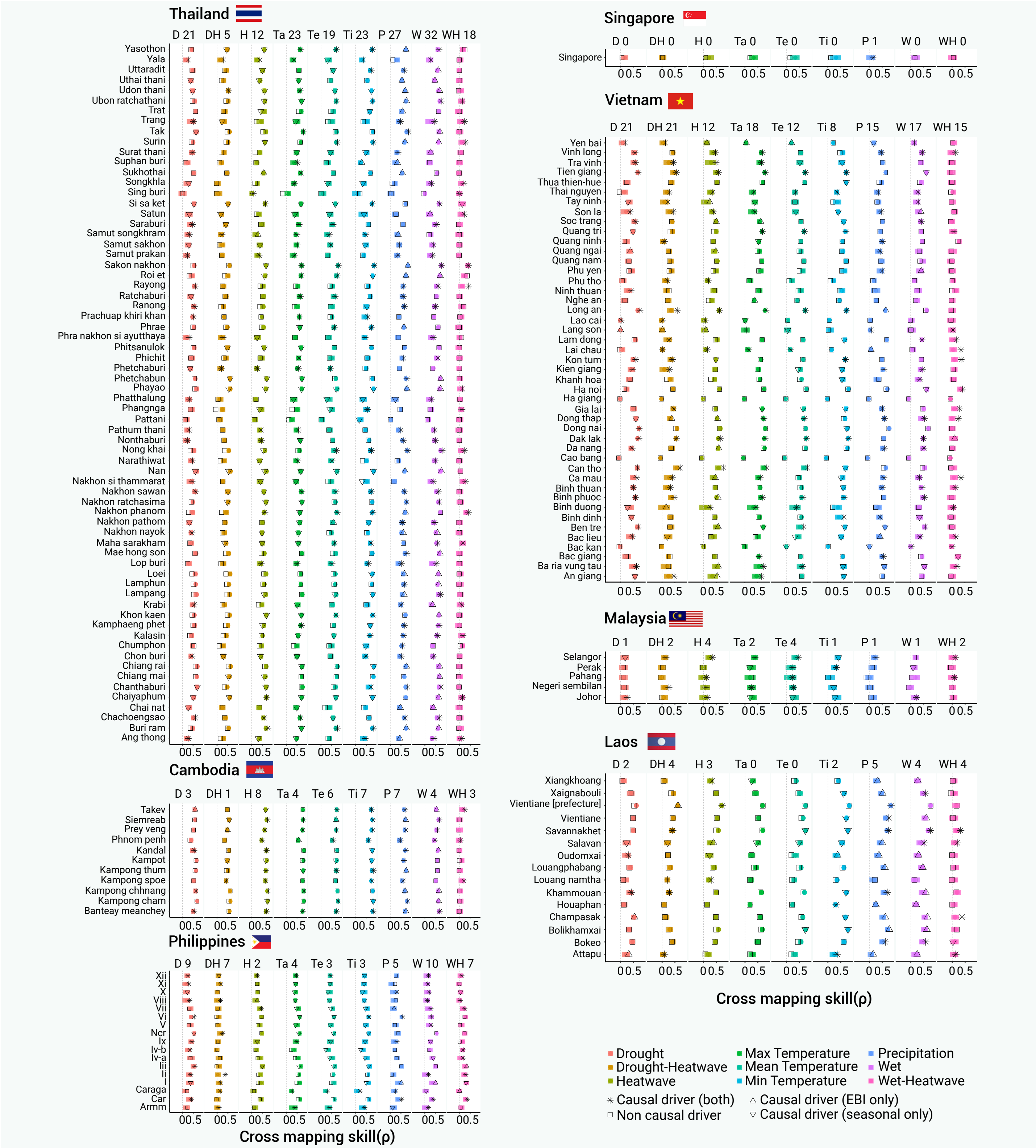

Figure 7. Detection of causal drivers of climate factors and extreme weather events on dengue transmission for the whole of Singapore and each Admin-1 across six nations using the EBI null model D denotes drought events; DH, compound drought–heatwave events; H, heatwaves; Ta, maximum temperature; Te, mean temperature; Ti, minimum temperature; P, precipitation; W, wet events; and WH, compound wet–heatwave events. At the maximum L, squares denote non-causal drivers; inverted and right triangles denote causality detected by the SEA and EBI null models, respectively; and asterisks denote causality supported by both. At the maximum L, colored horizontal bars with endpoints represent the distribution of ρ from randomized surrogate datasets under the EBI null model, with the endpoints indicating the 2.5th and 97.5th percentiles and the colored circles marking the ρ. The number above represents the number of Admin-1s or the country (i.e., Singapore) with causal environment drivers supported by both null models.

Limitations

This study has several acknowledged limitations. First, dengue case monitoring capabilities vary across countries, and surveillance capacity in underdeveloped regions may be inadequate, with some daily case records missing (Table S1). Despite using fine-temporal (i.e., weekly or monthly) case data and conducting multi-faceted sensitivity analyses, the interpolation approach inevitably introduces certain uncertainty. Second, while individual factors such as age structure, occupation, and sex are pivotal in modeling, the available cohort data do not permit their inclusion across the entire study period and geographical scope. Social and behavioral factors (e.g., health-seeking behavior, community knowledge and awareness, and economic constraints on vector control) warrant further investigation. Notably, because social factor data have an annual resolution, they do not align with the monthly resolution of dengue data. Although these social factors vary minimally across months, this temporal mismatch might result in non-differential misclassification, potentially attenuating effect modification and biasing estimates toward the null. Third, our estimate of mosquito thermal suitability is primarily based on thermal suitability (i.e., TSM), as informed by species traits and hourly microclimatic data, while this estimate could not fully reflect other ecological dimensions (e.g., land use). Additionally, the absence of adequate and complete time-series data on monthly mosquito data hinders opportunities for detailed assessment of mosquito thermal suitability associated with extreme weather events.

CONCLUSION

Overall, this study identifies risk windows of extreme weather for dengue transmission, including wet, drought, heatwave, and compound events, which further intensify dengue risk in poorly urbanized areas. The causal effects of specific extreme weather on dengue transmission are shaped by urbanization, infrastructure, and mosquito thermal suitability. Drought and compound drought-heatwave events play a causal role in urban settings with better infrastructure and favorable mosquito thermal suitability. These findings provide new evidence supporting the integration of extreme weather considerations into climate change adaptation strategies for dengue prevention and control.

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AUTHOR CONTRIBUTIONS

Danyang Wang: Methodology (Lead), visualization (Lead), writing - original draft (Lead). Xiaoxu Wu: Conceptualization (Lead), writing - review & editing (Lead). Jin Chen: Funding acquisition (Lead). Lu Zhao: Methodology (Supporting). All authors contributed to and approved the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

Not Applicable.

DATA AND CODE AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/j.xinn-med.2026.100188.