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Extreme precipitation triggers a narrow, three-week emergency window for Aedes albopictus risk in Guangzhou, China: a scenario simulation for vector- control timing

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Research Article

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Abstract

Aedes albopictus is the main urban dengue vector in Guangzhou. Container habitats respond to rainfall in two opposing ways: heavy rain flushes eggs and immatures from full containers, yet rain after a dry spell fills new containers and triggers oviposition. Using ten years of daily precipitation (Open-Meteo, 2015 to 2024, Guangzhou) and a transparent tank model, we located the lagged window of highest *Ae. albopictus* emergence risk after extreme precipitation. Extreme events were a day above 100 mm or a 3-day total above 150 mm. The model tracked water stock, antecedent wetness, flushing on wet days, and replenishment after dry spells, with emergence lagged 14 days; weekly risk was averaged over the five weeks after each event. Eight extreme events were identified. The pooled mean risk peaked in week 3 (78.6), roughly 1.8-fold the neighbouring weeks 2 (42.8) and 4 (40.5); the week-3 peak held across all tested evaporation-decay (0.08–0.30), flushing-coefficient (0.20–0.50), and flush-threshold (60–100 mm) values. At the individual-event level, five of the eight events also peaked in week 3. The scenario yields a consistent three-week emergency window. Where surveillance is sparse, vector-control teams could prioritize the second to third week after extreme rainfall, pending calibration for operational use.

Introduction

Dengue imposes a heavy and uneven burden across the tropics and subtropics. Bhatt et al. (2013) estimated that 390 million infections occur each year, many more than are formally reported, while Shepard et al. (2016) put the annual economic cost above US$9 billion. Gubler (1998) reviewed the clinical and epidemiological scope of dengue and dengue haemorrhagic fever, and the disease keeps spreading as vectors expand their range (Brady et al. 2012; Kraemer et al. 2015; Mogi et al. 2017). In southern China the problem is intensifying. Guangdong Province recorded its largest outbreak in 2014, with more than 45 000 cases, and the 2024 season again pushed Guangzhou into emergency response (Sang et al. 2015; Sun et al. 2016; Cheng et al. 2021; Zhu et al. 2019).

Aedes albopictus is the dominant dengue vector in Guangzhou. Unlike *Ae. aegypti*, it is tied to peridomestic containers, discarded tyres, tree holes, and rooftop water stores (Yee 2008; Delatte et al. 2008; Kraemer et al. 2015; Kraemer et al. 2019). Urbanisation adds larval habitats and speeds the mosquito's development and survival (Li et al. 2014), and its abundance tracks rainfall, but the link is not simply positive. Intense rainfall can scour larvae and pupae from open containers, a flushing effect that lowers risk for a short period (Dieng et al. 2012; Benedum et al. 2018). Moderate rain after a dry interval can create new aquatic habitats and stimulate oviposition, raising risk two to four weeks later (Wong et al. 2011; Tran et al. 2013). Which effect dominates depends on antecedent wetness and on how the rain is distributed within an event.

Several studies have tied dengue or *Ae. albopictus* abundance to rainfall in Guangzhou and the wider Pearl River Delta. Lu et al. (2009) found that temperature, rainfall, and vapour pressure predicted local cases with a short lag. Cheng et al. (2021) showed that extreme weather drove the 2014 Guangdong outbreak, while Zhu et al. (2019) mapped spatial heterogeneity in transmission and Xu et al. (2017)

argued that climate variation, rather than any single variable, drives dengue dynamics at the regional scale. Wu et al. (2009) linked higher temperature and urbanisation to dengue patterns in subtropical Taiwan, and the same broad pattern appears elsewhere: Hales et al. (2002) built an early empirical climate-dengue model, Hopp and Foley (2001) described global climate links to *Ae. aegypti*, and Hii et al. (2009), Hu et al. (2012), Colón-González et al. (2011, 2018), and Vincenti-Gonzalez et al. (2018) tied dengue incidence to climate variability in Singapore, Queensland, Mexico, and Venezuela respectively. These studies sharpen the climate-dengue link but say little about the short window that matters most to a control programme after a single storm.

What remains underspecified is the operational timing. Given that an extreme rainfall event has just occurred, when in the following weeks should a programme with limited staff and insecticide concentrate its effort? Early-warning work has moved in this direction. Ooi et al. (2006) described 35 years of vector control in Singapore, Wai et al. (2012) compared wet- and dry-season vector abundance for targeted control in Asia, and Ramadona et al. (2016) combined surveillance with meteorological data to predict dengue outbreaks. Mechanistic models sharpen the question further. The CIMSiM framework of Focks and colleagues tracks container water volume, immature survival, and adult emergence from known container types (Focks et al. 1993a, 1993b, 1995, 1997, 2000), and Naish et al. (2014) reviewed quantitative climate-dengue models critically. Fully parameterised CIMSiM runs need detailed container surveys that routine control rarely has.

Our aim was to simulate the lagged emergence-risk trajectory after extreme precipitation events in Guangzhou, and to see whether a consistent post-event emergency window could be read from rainfall alone. We used an open, no-key data source and kept the model transparent so that every assumption can be inspected. The output is a testable prior for the risk peak, not a validated forecast.

Materials and Methods

Study area and precipitation data

Guangzhou (23.1291 °N, 113.2644 °E) sits in a humid subtropical zone with a summer monsoon and frequent convective rainfall from April to September. Daily precipitation for 1 January 2015 to 31 December 2024 came from the Open-Meteo archive API (https://open-meteo.com/). This product blends the ECMWF Integrated Forecasting System with national meteorological centre analyses and supplies freely accessible daily totals without registration. We chose it because it is reproducible, needs no institutional key, and covers the full study period. An auxiliary script switches the pipeline to ERA5 reanalysis (Hersbach et al. 2020) for users who hold a Copernicus Climate Data Store account. The precipitation file used in the main analysis is archived with the submission.

An extreme-precipitation event was either a single day with more than 100 mm, or any 3-day rolling total above 150 mm. These cut-points match the heavy-rain and torrential-rain standards of the China Meteorological Administration and align with definitions used in recent Guangdong dengue studies

(Cheng et al. 2021; Lu et al. 2022). Consecutive wet days were merged into one event; the event ended once two straight days recorded less than 10 mm. For each event we recorded start date, duration, total rainfall, and peak daily rainfall.

Mechanistic tank model

The model tracks small-container water stock, antecedent wetness, and two opposing rainfall effects: replenishment after dry spells and flushing during intense rain on already-wet containers. The equations are summarised here; the complete implementation is provided as supplementary code (jve_tank_model.py).

Daily water stock W_t in small containers was a single tank with evaporative decay: $W_t = (1 - d)\, W_{t-1} + P_t$, where d is the daily decay coefficient (baseline d = 0.15) and P_t is daily precipitation. Antecedent wetness S_t was the mean water stock over the preceding 7 days, normalised to the interval [0,1] by dividing by its maximum over the study period. Replenishment, the filling of dry containers and the oviposition that follows, rose with W_t and fell as antecedent wetness rose: $\text{replenish}_t = W_t\,(1 - S_t)$.

Flushing, the loss of immatures from containers already full or overflowing, switched on when daily rainfall passed 80 mm and grew stronger with antecedent wetness: $\text{flush}_t = -c \max(0, P_t - 80)\, S_t$, with c = 0.35. Net emergence potential on day t was then $E_t = \max(0, \text{replenish}_t + \text{flush}_t)$.

Eggs laid after replenishment must pass through larval and pupal stages before adults emerge. At Guangzhou summer temperatures *Ae. albopictus* completes egg-to-adult development in roughly 10-16 days (Rueda et al. 1990; Couret and Benedict 2014; Watts et al. 1987), and daily temperature fluctuation changes how fast dengue virus moves through the vector (Lambrechts et al. 2011; Carrington et al. 2013; Sharmin et al. 2015). We applied a fixed 14-day lag to E_t to obtain the adult emergence-risk index used in every analysis. The model outputs are unitless risk indices meant for relative comparison across weeks and events, not absolute mosquito counts.

Post-event risk and sensitivity analysis

For each extreme event, the mean emergence-risk index was computed for weeks 1-5 after the event start date. The peak week was the week with the highest mean index. We also recorded the peak week for each individual event to check whether the pooled pattern held event by event.

Container evaporation is uncertain and changes with shade, material, and temperature, so we tested five decay values: d = 0.08, 0.12, 0.15, 0.20, and 0.30. These span plausible 1- to 2-week evaporation windows for small urban containers. A shift in the peak week would mean the operational window depends on an unknown parameter; a fixed peak would mean it is stable in this scenario.

Results

Eight extreme-precipitation events occurred in Guangzhou between 2015 and 2024 (Table 1). Totals ranged from 169.4 mm (8 October 2021) to 523.6 mm (18 April 2024), and durations from 2 to 16 days. Four events included a single day above 100 mm; the remaining four met only the 3-day rolling threshold of 150 mm. The largest event, in April 2024, fell at the start of that year's Guangdong dengue season.

Table 1. Extreme-precipitation events in Guangzhou, 2015-2024.

Event	Start date	Duration (days)	Total rainfall (mm)	Peak daily rainfall (mm)
1	2016-01-27	6	175.5	89.2
2	2018-06-05	4	288.4	157.7
3	2020-05-25	16	452.7	69.4
4	2021-10-08	2	169.4	106.1
5	2022-05-10	6	210.8	65.5
6	2023-09-06	5	268.5	180.5
7	2024-04-03	5	290.1	97.2
8	2024-04-18	13	523.6	114.6

In the baseline model (d = 0.15) the mean emergence-risk index across all events was 38.9 in week 1, 42.8 in week 2, 78.6 in week 3, 40.5 in week 4, and 43.6 in week 5. Week 3 was the clear peak, with a mean index roughly 1.8-fold that of weeks 2 and 4 (Figure 1).

The week-3 peak was not an artefact of averaging: the pooled mean peaked in week 3 under every parameter setting tested. At the event level, five of eight events peaked in week 3; the remaining three peaked in weeks 1-2, concentrated among the two extended 2024 rainfall events whose windows overlapped in time. Figure 2 shows the event-level pattern.

Sensitivity to the decay coefficient was low. The peak week stayed at week 3 for d = 0.08, 0.12, 0.15, 0.20, and 0.30. The peak height dropped as decay rose, because faster evaporation leaves less standing water between events, but the timing did not move. The same held when the flushing coefficient c was varied (0.20, 0.35, 0.50) and when the flush threshold was varied (60, 80, 100 mm); the peak height changed by less than 1% across these values. The three-week window is therefore stable to uncertainty about container evaporation, flushing strength, and flush threshold in this precipitation-only scenario.

Discussion

The simulation points to a three-week emergency window after extreme rainfall in Guangzhou. Week 3 carried roughly 1.8-fold the modelled emergence risk of the neighbouring weeks, and the result held

across a wide range of evaporation rates. The timing fits *Ae. albopictus* biology: eggs deposited during or soon after a rain pulse need about two weeks to become host-seeking adults at local summer temperatures (Rueda et al. 1990; Lambrechts et al. 2011). Week 3 is the interval when adults from that cohort would first be numerous.

The dual-pathway design is what gives this shape. Had we kept only the flushing effect, risk would have fallen straight after heavy rain and the window would have slipped later. Had we kept only replenishment, risk would have risen in the first week and the window would have come earlier. Letting the balance between flushing and replenishment depend on antecedent wetness produces the intermediate peak seen here. This agrees with field work in Singapore and Malaysia, where heavy rain on already-wet containers can suppress immature counts while rain after dry periods raises them (Dieng et al. 2012; Benedum et al. 2018). It also sits within the broader climate-dengue modelling literature that treats rainfall as one term in a larger transmission system (Naish et al. 2014; Liu-Helmersson et al. 2016; Stoddard et al. 2014).

A practical reading is that vector-control programmes could treat the second to third week after an extreme event as the priority period for emergency adulticiding and targeted larviciding. That is not a reason to stop routine source reduction; it tells a programme where to put limited surge capacity once a weather trigger has fired. In Guangzhou, where the 2014 and 2024 outbreaks followed unusually wet springs (Sang et al. 2015; Cheng et al. 2021), a simple rainfall-triggered protocol might have allowed earlier ultra-low-volume spraying or focused container treatment. Comparable ideas have been tried elsewhere: Ooi et al. (2006) described sustained Singapore control, and Ramadona et al. (2016) combined meteorological data with surveillance for outbreak prediction.

Several caveats must be stated plainly. First, the model is a scenario simulation, not a validated forecast. It was not calibrated against larval surveys, pupal counts, BG-Sentinel trap catches, or dengue cases, and the risk index carries no direct entomological unit. Second, temperature was held constant through the lag term even though it strongly shapes *Ae. albopictus* development and dengue virus incubation (Watts et al. 1987; Couret and Benedict 2014; Carrington et al. 2013). Spring and autumn events therefore receive the same biological response in the model, although real development would be slower in cooler months. Third, human density, movement, immunity, and virus introduction are absent, so the paper does not claim to predict dengue incidence; Johansson et al. (2009, 2019) discuss how hard such forecasts remain. Fourth, container heterogeneity is collapsed into one tank, while real cities mix tyre piles, flowerpots, construction sites, and underground sumps with very different hydrologies.

The precipitation thresholds are transparent but can be adjusted. A single-day cut of 100 mm or a 3-day cut of 150 mm could be tuned to a local warning protocol. We checked that the qualitative result did not hinge on small threshold changes: lowering the 3-day cut to 120 mm added minor events but left week 3 as the dominant peak. The stability of the peak week to the evaporation parameter matters more than the exact threshold.

Future work should link this precipitation-driven prior to entomological surveillance. If larval or adult abundance in Guangzhou peaks 2–4 weeks after extreme rain, the three-week window gains empirical support and could be built into an early-warning system. If the observed peak differs, the model would need temperature-dependent development, container-type stratification, and spatial detail. Either result would move the operational use of weather triggers in *Ae. albopictus* control forward.

Using ten years of open-access daily precipitation data and a transparent tank model, we found that simulated *Ae. albopictus* emergence risk in Guangzhou peaked three weeks after each of eight extreme rainfall events. The peak held under uncertainty in container evaporation. The model is deliberately simple and still needs empirical calibration, but the consistency of the three-week window suggests that vector-control programmes in subtropical Chinese cities could treat the second to third week after extreme rainfall as a high-priority emergency interval.

Declarations

Funding: This research received no external funding.

Competing interests: The author declares no conflicts of interest.

Ethics approval: Not applicable. The study used publicly available meteorological data only.

Data availability: Daily precipitation data were obtained from the Open-Meteo archive API (https://open-meteo.com/). All analysis code (jve_tank_model.py), the event list, model output (CSV), and figure source files are publicly available at https://github.com/GustaveKateb0709/extreme-precipitation-aedes-window (archived on Zenodo; DOI to be assigned).

AI use: During the preparation of this work the author used Kimi K3 (Moonshot AI) for code development and language editing. The author reviewed and edited all AI-generated content and takes full responsibility for the integrity and accuracy of the publication.

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Author contributions: Tian-Yu Wang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review and editing, Visualization.

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Figures

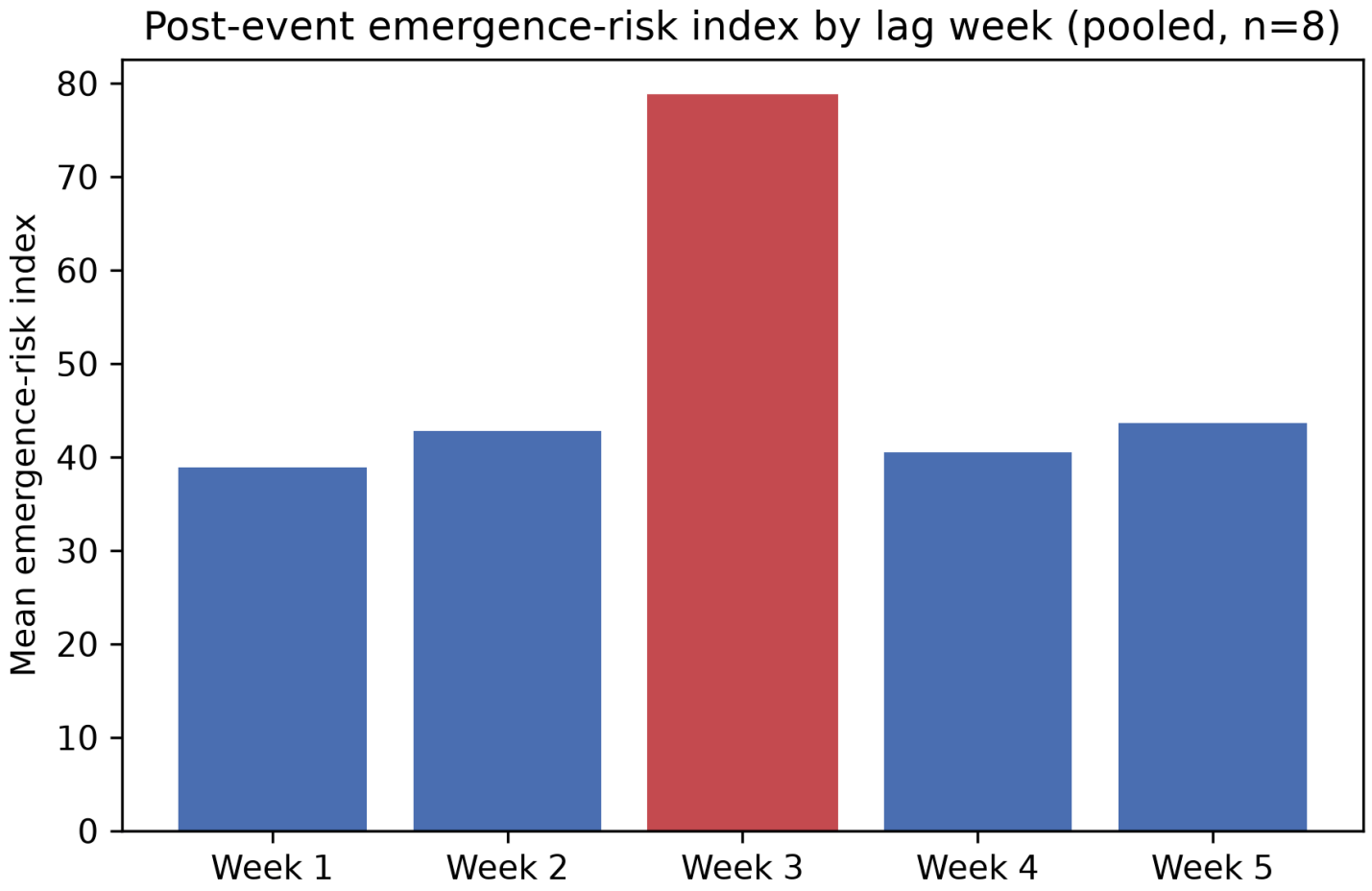


Figure 1

Mean modelled emergence-risk index in the five weeks after extreme-precipitation events in Guangzhou, 2015-2024. The dashed line marks the week-3 peak.

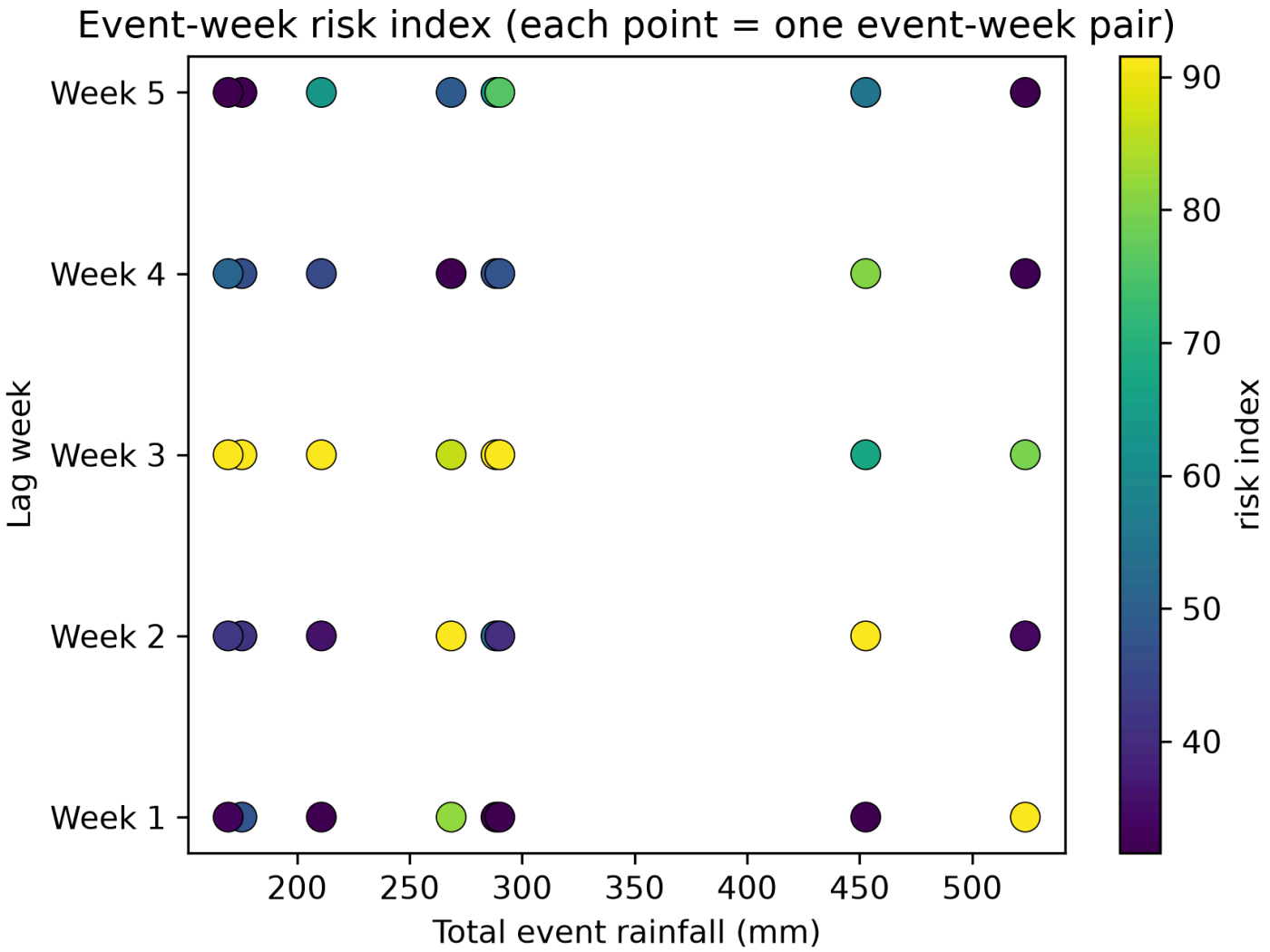


Figure 2

Event-level relation between total event rainfall, lag week, and modelled emergence-risk index. Each sphere is one event-week pair; colour shows the risk index. High-risk points cluster in the week-3 band.