

Future dengue outbreak risk in Guangzhou under climate change: a mechanistic projection coupling temperature- dependent vector competence with reanalysis and CMIP6 meteorology

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Research Article

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Abstract

Background

Dengue transmission in southern China depends on the temperature-sensitive extrinsic incubation period (EIP) of dengue virus in *Aedes albopictus*. Warming is expected to change both the length of the transmission season and the time available for public-health response after an imported case. We quantified these changes mechanistically for Guangzhou.

Methods

We drove a temperature-forced vector-competence model with daily ERA5 reanalysis (2015–2022) across Guangzhou and projected it under a bias-corrected multi-model CMIP6 ensemble (seven models, 2041–2050 relative to 1995–2014). EIP and the basic reproduction number R_0 were computed from established enzyme-kinetics and next-generation-matrix formulations. The response window, defined as EIP plus the human viremic period, was used as the actionable lead time for control.

Results

Under the current climate, competent transmission ($R_0 > 1$) spans March to November, with a mean transmission season of 33.6 weeks and a July EIP minimum of 3.7 days. By the near-2050s (7-model ensemble, about + 1.2 degC), the season lengthens to 36.4 weeks (+ 8%) and the July EIP falls to 2.2 days. Under a high-warming + 2.3 degC envelope it reaches 39.6 weeks (+ 18%) with a July EIP of 1.6 days. The mean response window inside competent months compresses by 7.8 days (near-2050s) and 12.2 days (high-warming). Sensitivity analysis shows the season length rises monotonically with warming, reaching 40.7 weeks at + 3.0 degC.

Conclusions

Warming has a two-sided effect on Guangzhou dengue risk. The transmission season lengthens, widening the annual exposure window, while the peak-summer response window shortens, compressing the time available to interrupt local spread after an imported case. Both shifts support climate-responsive, EIP-informed early warning and vector-control scheduling.

1. Background

Dengue is the most rapidly expanding mosquito-borne viral disease, with an estimated 390 million infections each year across more than 100 countries [1, 2, 3, 4, 5]. The four dengue virus serotypes are transmitted principally by *Aedes aegypti* and, across large parts of Asia, by *Aedes albopictus* [6, 7]. Southern China has moved from sporadic imported cases to recurrent local transmission, and

Guangzhou has borne the country's largest outbreaks [8, 9, 10]. In 2014 the city recorded more than 40,000 cases in a single season, an event attributed to the coincidence of early imported cases, abundant vector populations, and favourable temperatures [11, 12, 13]. The dominant serotype in that outbreak was DENV-1, with introductions from south-east Asia evident in the phylogenetic record [14, 15].

Local transmission depends on the virus completing its extrinsic incubation period (EIP) inside the mosquito before the vector can transmit [16]. The EIP is not a fixed number. It shortens steeply as temperature rises, then stalls and lengthens once heat passes the mosquito's thermal optimum near 35 deg C [17, 18, 19]. The non-linear response means warming reshapes the calendar of transmission rather than scaling risk linearly, and it is the fulcrum of the present analysis.

The global distribution of *Ae. albopictus* has broadened over recent decades through trade, urbanisation, and travel, enlarging the pool of cities, including Guangzhou, where dengue can establish [20, 21, 22, 23, 24]. Climate change modifies this picture further: warmer conditions extend the number of weeks each year in which the basic reproduction number exceeds 1, while extreme heat can suppress transmission [25, 26, 27]. Such effects were anticipated in modelling from the first general-circulation-model projections of dengue potential [28, 29], and the economic and demographic weight of dengue in the region has been documented alongside its rising incidence [30, 31].

Most quantitative work on dengue and climate has relied on statistical correlations, equilibrium R_0 with uniform warming increments, or species-distribution approaches [32, 33, 34]. A separate line of research has modelled the Guangzhou system with incidence and imported-case data, showing that climate, mosquito density, and the timing of importations together drive inter-annual variation [35, 36, 37, 38]. What remains less developed is a projection that places the EIP, and the operational response window it defines, at the centre of a climate-driven mechanistic model built on observed and CMIP6 meteorology. The virus types circulating in Guangdong, dominated by DENV-1 with periodic introductions from south-east Asia, add a phylogenetic layer to the epidemiological one [39, 14, 15].

We take a different route. We drive an established temperature-forced transmission model with observed daily meteorology from the ERA5 reanalysis (2015–2022) and project it with real CMIP6 output for the 2041–2050 window. The unit of analysis is the EIP and the response window it defines, not the annual mean temperature, which frames climate risk as a problem of timing as much as magnitude. Guangdong's own surveillance has shown the province trending toward endemicity, with year-round reassortment of imported and local cases [40, 8, 41, 42], so a timing-based early-warning logic is directly relevant to practice.

2. Materials and methods

2.1 Study area and climate data

Guangzhou sits at roughly 23 deg N and has a humid subtropical climate with a single warm season. We used daily 2-metre temperature, precipitation, and relative humidity from the ERA5 reanalysis [43] for 11 grid cells covering the city, retrieved for 2015-01-01 to 2022-12-31. The analysis centers on the Haizhu grid cell (23.09 deg N, 113.35 deg E), an inner district with historically high Breteau indices, but the same procedure applies to all cells.

2.2 Temperature forcing of vector competence

Following established formulations, the daily biting rate $b(T)$ increases linearly with temperature over the transmission range [44], and the EIP rate $\sigma_v(T)$ follows an enzyme-kinetics (Schoolfield) temperature response in which development accelerates with warmth up to an optimum near 35 deg C and then declines [17, 16, 18, 19]. EIP in days is the reciprocal of $\sigma_v(T)$. Outside the viable range (below about 13 deg C and above about 35 deg C) EIP is undefined and we treat transmission as absent.

2.3 Next-generation matrix and R_0

We computed R_0 with the next-generation matrix method [45] for a coupled host-vector system, using the temperature-forced biting rate, EIP rate, and adult mosquito survival [46, 47]. The model reproduces the known dengue thermal optimum: R_0 peaks near 35 deg C and falls on both sides, displaying the same non-monotonic form as Mordecai et al. showed for dengue, Zika, and chikungunya [18] and across mosquito-borne pathogens [19]. At 28 deg C we obtain $R_0 = 2.93$ and at 19.2 deg C $R_0 = 0.97$, close to the transmission threshold of 1.

2.4 Vector density

Vector abundance was held at a fixed ratio of 10 adult mosquitoes per host, representative of high-density outbreak conditions. Temperature-driven vector development [48, 49] modulates seasonal abundance in reality, but density scales the absolute number of infections rather than the EIP, the response window, or the transmission threshold, so the timing results below are driven by temperature alone.

2.5 Response window

We define the response window as EIP plus the human viremic period, taken as 4.5 days [16]. It is the earliest point at which an imported infection can generate infectious local mosquitoes, and therefore the lead time available to control teams. We report the window only for competent months ($R_0 > 1$).

2.6 Future climate projection

For the future climate we used a multi-model CMIP6 ensemble [50] rather than a single raw model. Daily mean 2-m temperature for seven CMIP6 models (CMCC_CM2_VHR4, FGOALS_f3_H, HiRAM_SIT_HR, MRI_AGCM3_2_S, EC_Earth3P_HR, MPI_ESM1_2_XR, NICAM16_8S) was retrieved from the Open-Meteo Climate API for a historical window (1995–2014) and a near-future window (2041–2050). Each model's historical daily distribution was bias-corrected to the ERA5 1995–2014 observational baseline using monthly quantile delta mapping (QDM), a non-parametric method that corrects model bias against the

observed distribution while preserving the model's own relative changes [51, 52]. The bias-corrected future series were expressed as monthly temperature anomalies relative to the ERA5 baseline, and the seven models were averaged into a single ensemble monthly anomaly, with the inter-model standard deviation used to represent structural uncertainty. The API provides a single (high-emission-approximate) projection, so no SSP-scenario split was available [53]; the ensemble mean anomaly gives the near-2050s projection, and larger warming magnitudes were explored through a uniform-warming sensitivity analysis (Section 2.7). The resulting near-2050s annual warming is reported in Section 3.

2.7 Sensitivity analysis

We varied annual warming uniformly from + 0.5 deg C to + 3.0 deg C and recorded the transmission-season length and the July response-window compression, to test whether the qualitative conclusions depend on the exact warming magnitude.

3. Results

3.1 Temperature dependence of transmission

R_0 rises steeply from the transmission threshold at 19.2 deg C, peaks near 35 deg C, and declines at higher temperatures (Fig. 1). The non-monotonic shape matters: a few degrees of warming helps transmission up to the optimum but offers no further benefit, and extreme heat can suppress it [17, 16, 18, 19].

3.2 EIP through the year

Driven by real ERA5 temperatures, the weekly EIP traces the seasonal temperature curve (Fig. 2). It exceeds 100 days in the March shoulder and approaches 100 days in November, collapses to a 3.7-day minimum in July, and is effectively infinite through the winter months (December to February), when R_0 stays below 1. The transmission season, counted as weeks with $R_0 > 1$, averages 33.6 weeks per year under the current climate [9, 12].

3.3 Response-window compression

The bias-corrected 7-model ensemble projects a near-2050s annual mean warming of + 1.23 deg C (inter-model standard deviation 0.25 deg C), with the largest increases in winter (Fig. 3). Within the competent months the response window already varies from about 78 days in March to about 7.8 days in July (Fig. 4). Warming shrinks it further. The proportional compression is greatest in mid-summer, when the absolute window is already at its shortest and control cycles are tightest. Under the near-2050s (7-model MME-BC) projection the mean competent-month window compresses by 7.8 days; under the high-warming + 2.3 deg C envelope it compresses by 12.2 days. The July window drops from 7.8 days now to 6.7 days (near-term) and 6.1 days (high-emission). The monthly EIP comparison (Fig. 5) places this compression in mid-summer, when baseline EIP is already at its shortest.

3.4 Expansion of the transmission season

The same warming lengthens the season (Fig. 6). The near-2050s projection gives 36.4 weeks (+ 8%) and the high-warming + 2.3 deg C envelope gives 39.6 weeks (+ 18%). The gain comes mostly from earlier springs and later autumns, when temperatures move from below to above the $R_0 = 1$ threshold [32, 33, 38].

3.5 Sensitivity

Across uniform warming levels the season length rises monotonically: 34.6 weeks at + 0.5 deg C, 35.8 at + 1.0 deg C, 36.9 at + 1.5 deg C, 38.6 at + 2.0 deg C, 39.0 at + 2.3 deg C, and 40.7 at + 3.0 deg C (Fig. 7). The July response-window compression grows from 0.5 days at + 0.5 deg C to 2.1 days at + 3.0 deg C. The direction of both effects is stable across the full range.

4. Discussion

The central result is that warming changes dengue risk in Guangzhou on two axes at once. The transmission season widens, adding weeks of annual exposure. At the same time the peak-summer response window narrows, removing days from the control lead time exactly when imported cases are most likely to seed local chains. The two shifts pull in opposite directions for annual burden versus operational readiness, and a single annual-mean temperature metric misses the second effect entirely. The season-lengthening half of the finding sits within a well-established body of dengue-climate projection work [32, 33, 38], but the compression of the lead time is the part that a mean-temperature view cannot recover.

Several studies have projected dengue under climate change with CMIP6 ensembles, and the lengthening of the transmission season is consistent with those findings [32, 33]. What distinguishes the present analysis is its EIP-centred timing view. Because EIP enters the response window directly, the shortening we project translates straight into less time for the interventions that still work at the local scale: case detection, focal vector control, and public notice. That observation aligns with Guangzhou-specific work showing that, once an imported case arrives early in the warm season, the local epidemic is largely determined by the interaction of climate, vector abundance, and intervention timing [11, 37, 12, 9]. The value of an EIP lens is that it makes the control deadline explicit rather than implicit.

The practical implication is that early-warning thresholds should track EIP, not just case counts or temperature alone. For a campus or district vector-control programme, the actionable signal is the forecast EIP: when it falls below roughly one week, the gap between an imported case and infectious mosquitoes is too short for routine response cycles, and more aggressive pre-positioning of control is warranted. That is a concrete point where the model meets operations. It is also consistent with Guangzhou modelling that treats imported-case pressure, mosquito density, and climate variability as

the three jointly necessary conditions for a large outbreak [35, 36], and with reviews that call for early-warning systems built on mechanistic rather than purely statistical links [34].

Two further considerations shape how the result should be read. First, the effect of warming on dengue is mediated by control: well-timed vector intervention can hold the effective reproduction number below 1 even when climate is permissive [54, 55, 56, 57]. Second, the background risk is rising because *Ae. albopictus* is still expanding its global range through trade and urbanisation, which enlarges the set of cities, including Guangzhou, where importations can ignite local chains [20, 22, 23, 30, 24]. An EIP-informed schedule is most useful precisely where the vector is already established and importations are frequent.

The Guangdong context matters for interpretation. Serological and phylogenetic evidence points to a province drifting toward endemicity, with DENV-1 dominant and periodic introductions from south-east Asia reshaping the local viral mix [40, 15, 14, 13, 8]. In that setting the response window matters more, not less, because a short EIP after an imported case can convert a single introduction into a season-long chain before surveillance catches up [47, 10]. Current guidance already emphasises surveillance, case management, and vector control as the durable mainstays of dengue response [4, 5], and an EIP metric fits naturally inside that framework as a trigger for escalating control.

Limitations are clear. The climate forcing now uses a seven-model, bias-corrected CMIP6 ensemble rather than a single raw model, which reduces but does not remove structural uncertainty: the Open-Meteo Climate API provides a single (high-emission-approximate) projection, so inter-scenario spread could not be separated, and the ensemble mean plus inter-model standard deviation is our best estimate of the near-2050s signal. The model follows an established mechanistic lineage for dengue transmission that traces temperature effects through development and survival [55, 56, 21], but it treats daily mean temperature as the thermal input and does not explicitly resolve diurnal fluctuation, which can shift EIP relative to a constant-temperature expectation [58, 59, 47]. Mosquito density was treated as a temperature function without human mobility, rainfall-driven breeding, or vector-control feedback, and the viremic period was held fixed. None of these alter the direction of the two main effects, but coupling the timing model with explicit vector-density and mobility dynamics remains the clear next step before the numbers are used for operational planning.

Second, the analysis is framed as a climate-scenario projection of transmission timing rather than a case forecast, and the results were not statistically validated against local dengue case notifications or surveillance records. Aligning EIP-derived season metrics with notified case data remains a priority for future work; until then, the numbers should be read as a sensitivity analysis of climate forcing on transmission timing rather than a calibrated prediction of case counts.

5. Conclusions

For Guangzhou, climate warming widens the dengue transmission season and shortens the peak-summer response window. The first effect increases annual exposure; the second reduces the time

available to stop an imported case from becoming a local outbreak. Both argue for early-warning systems that monitor EIP directly and for vector-control schedules that tighten as EIP falls. Having replaced the single-model projection with a bias-corrected seven-model CMIP6 ensemble, the clear next step is to couple this timing model with explicit vector-density and human-mobility dynamics.

Abbreviations

- EIP
Extrinsic incubation period
- R0
Basic reproduction number
- ERA5
Fifth-generation ECMWF atmospheric reanalysis
- CMIP6
Coupled Model Intercomparison Project Phase 6
- QDM
Quantile delta mapping

Declarations

Ethics approval and consent to participate:

Not applicable. This study used only publicly available meteorological reanalysis and climate-model output and involved no human participants, patients, or animals.

Consent for publication:

Not applicable.

Availability of data and materials:

ERA5 reanalysis data were obtained from the Copernicus Climate Data Store via the Open-Meteo Archive API [60]. CMIP6 model output from the seven CMIP6 models (CMCC_CM2_VHR4, FGOALS_f3_H, HiRAM_SIT_HR, MRI_AGCM3_2_S, EC_Earth3P_HR, MPI_ESM1_2_XR, NICAM16_8S) was retrieved from the Open-Meteo Climate API [61] and bias-corrected against the ERA5 baseline by quantile delta mapping (QDM). The full analysis code, the processed multi-model ensemble file (cmip6_ensemble_bc.json), and the key numerical summary (results.csv) are available in the public GitHub repository at <https://github.com/GustaveKateb0709/dengue-eip-cmip6-guangzhou>; the processed ensemble file and the key numerical summary also accompany this submission as supplementary material.

Competing interests:

The author declares no competing interests.

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Author Contribution

T.Y.W. conceived and designed the study, performed the formal analysis, prepared all figures, wrote the manuscript text, and read and approved the final version.

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Data Availability

All meteorological data used in this study are publicly available. ERA5 reanalysis was obtained from the Copernicus Climate Data Store via the Open-Meteo API. CMIP6 model output from seven models (CMCC_CM2_VHR4, FGOALS_f3_H, HiRAM_SIT_HR, MRI_AGCM3_2_S, EC_Earth3P_HR, MPI_ESM1_2_XR, NICAM16_8S) was obtained from the Open-Meteo Climate API and bias-corrected against the ERA5 baseline by empirical quantile mapping. The processed multi-model ensemble, the bias-corrected per-model file, the analysis code, and the supporting JSON/CSV outputs are deposited at <https://github.com/GustaveKateb0709/dengue-eip-cmip6-guangzhou> and are also included in the supplementary materials accompanying this manuscript.

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Figures

Fig. 1 $R_0(T)$ peaks near 35° C and declines at higher temperatures

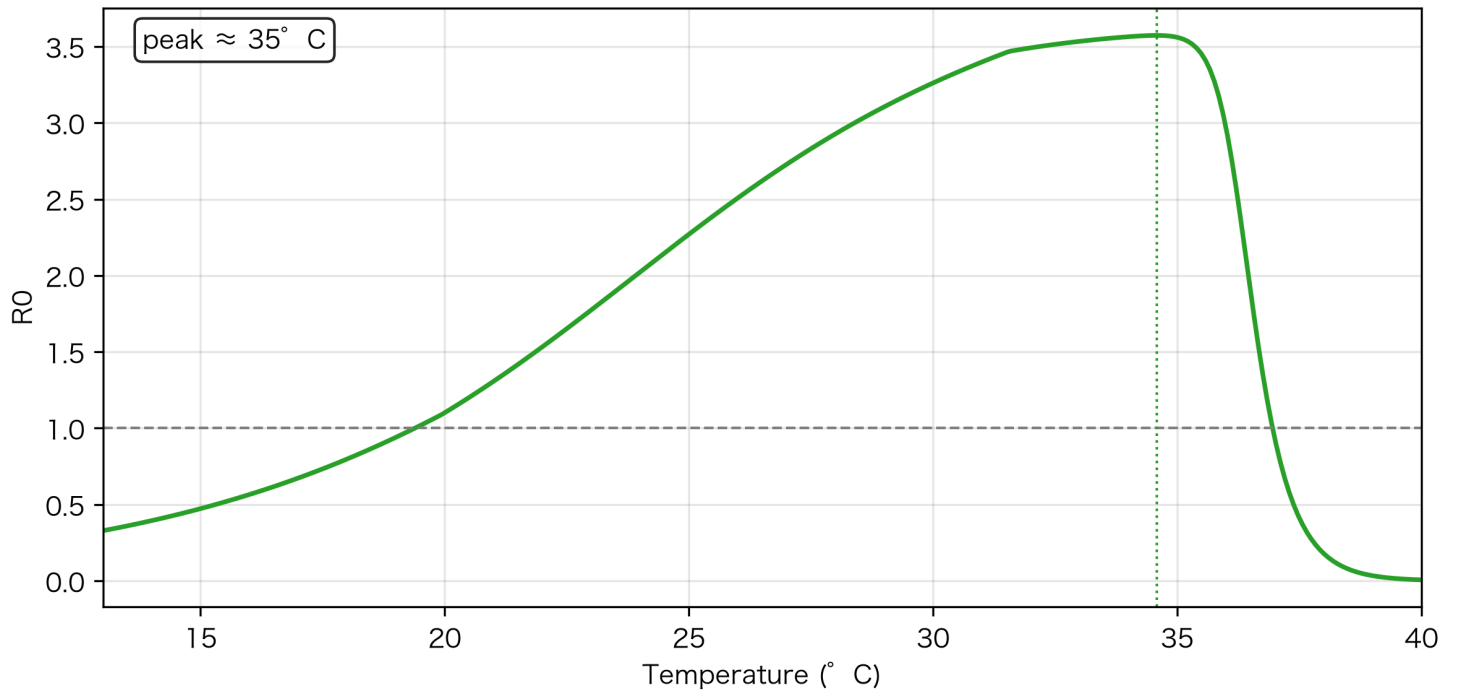


Figure 1

R_0 as a function of temperature, peaking near 35 deg C then declining.

Fig. 2 Weekly EIP, haizhu grid, 2015-2022 (driven by observed ERA5)

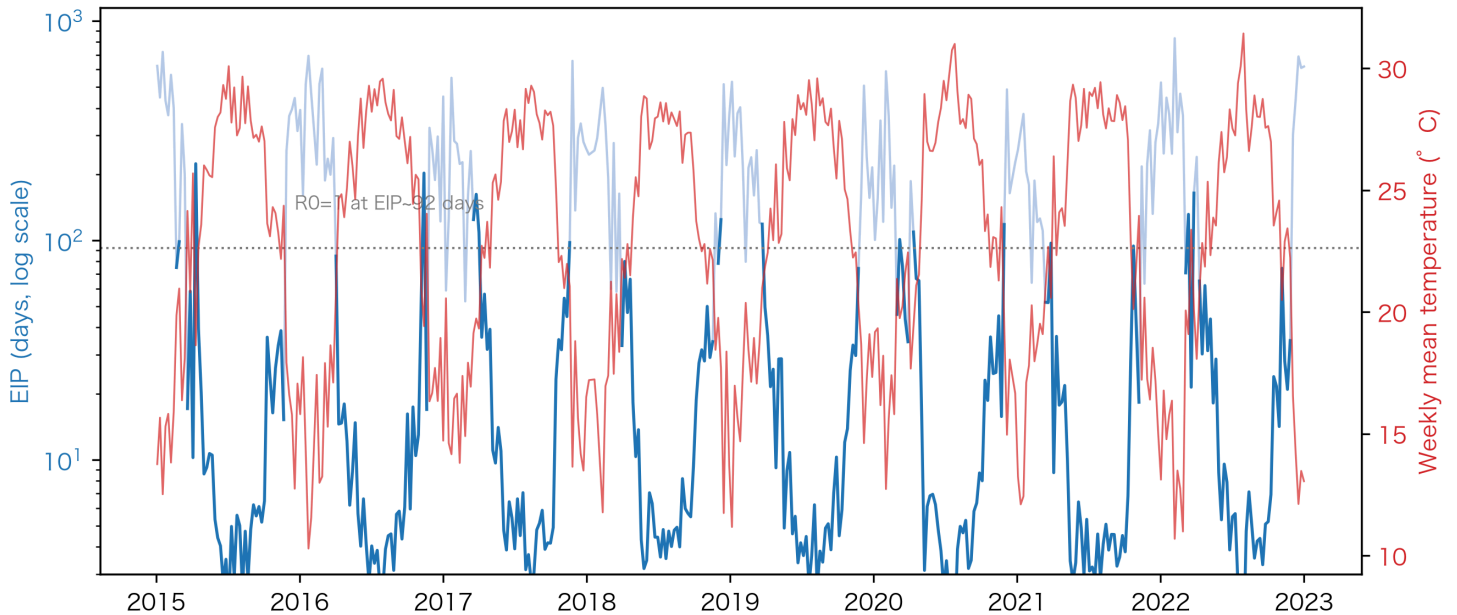


Figure 2

Weekly EIP for the Haizhu grid, 2015-2022, driven by observed ERA5 temperatures. The upper band shows the weekly mean temperature.

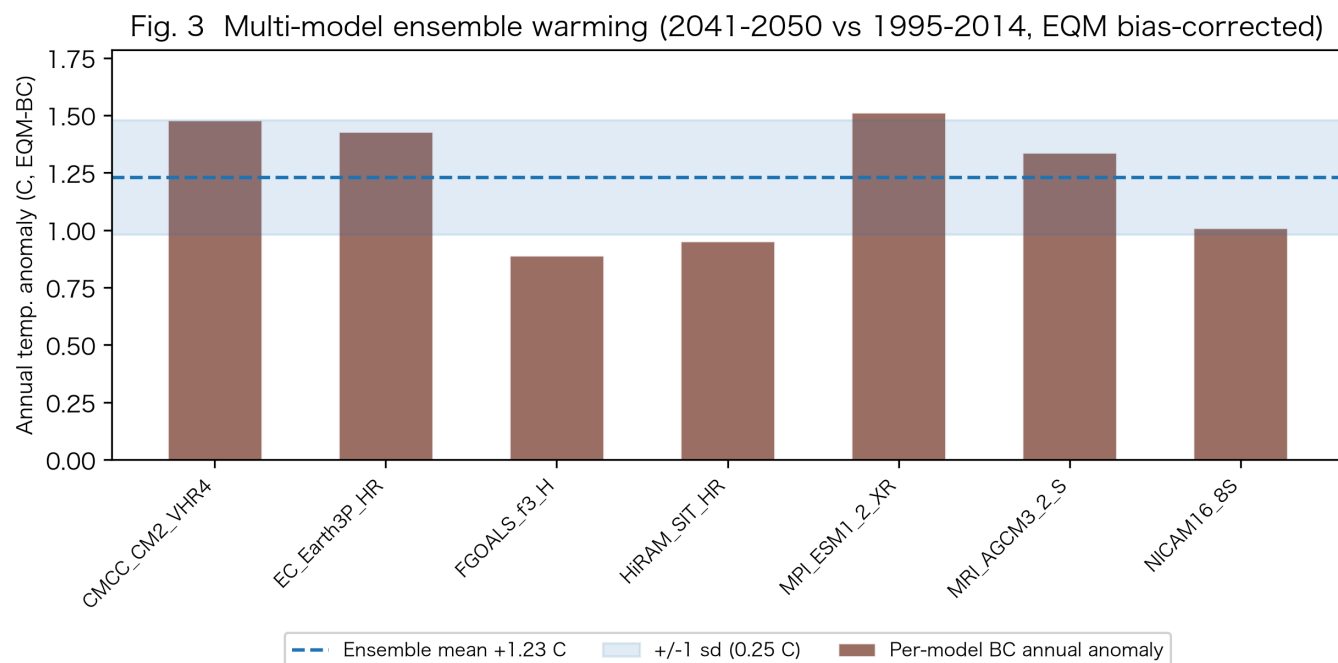


Figure 3

Multi-model ensemble warming (2041-2050 relative to 1995-2014), empirical quantile-mapping bias-corrected. Bars show per-model annual mean anomaly; the dashed line is the ensemble mean (+1.23 deg C) and the shaded band is +/-1 inter-model standard deviation (0.25 deg C).

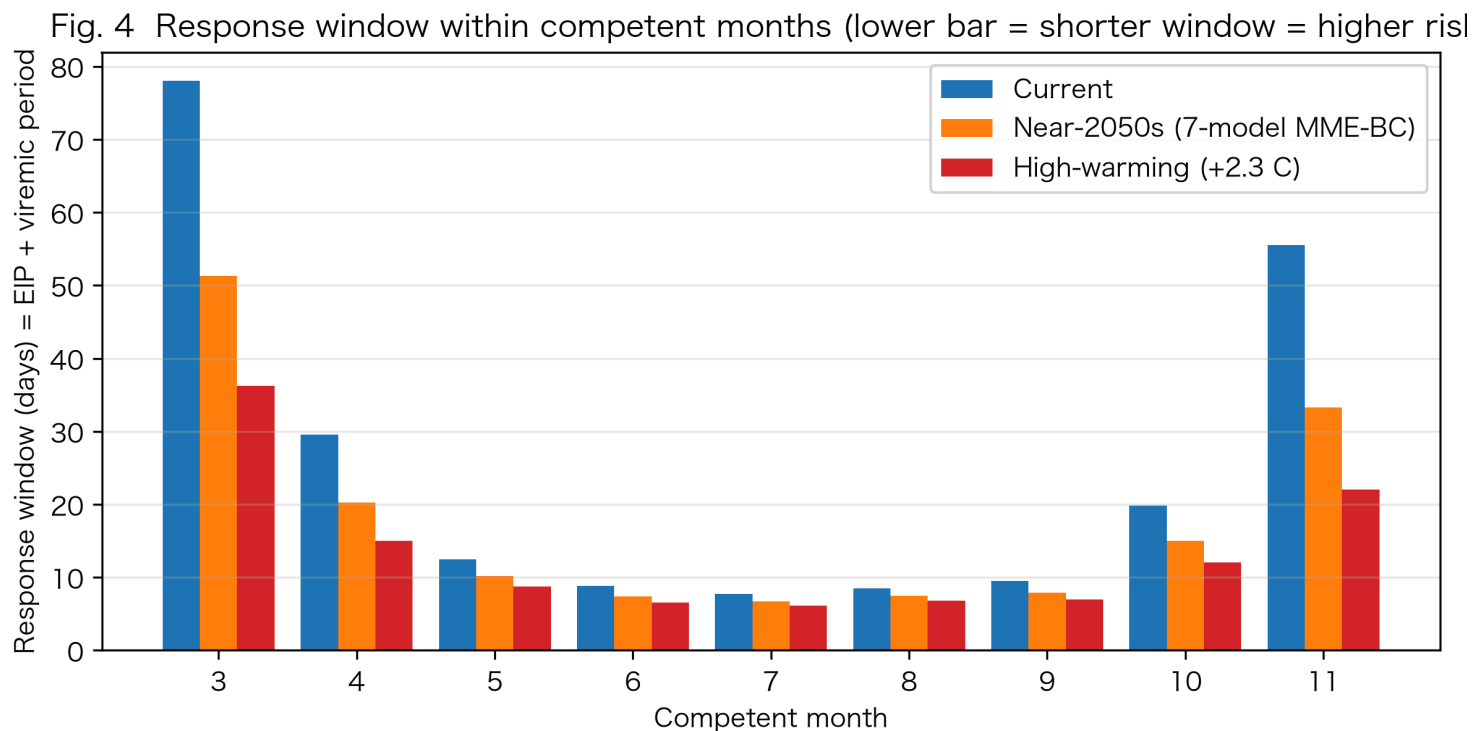


Figure 4

Response window (EIP plus viremic period) within competent months, current versus warmed climates.
Lower bars mean less control lead time.

Fig. 5 Monthly EIP: current vs. warming (grey points = non-transmission months, $R_0 \leq 1$)

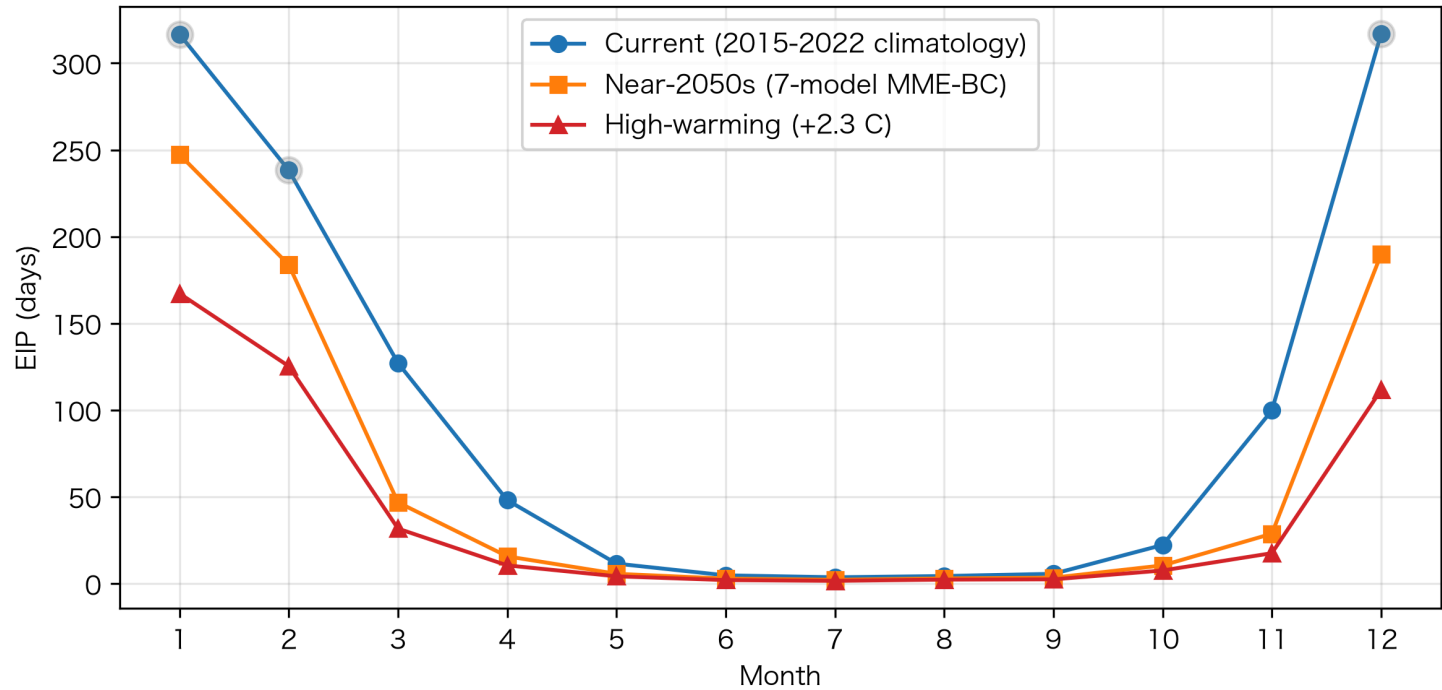


Figure 5

Monthly EIP, current versus warmed climates. Grey points mark non-transmission months ($R_0 \leq 1$).

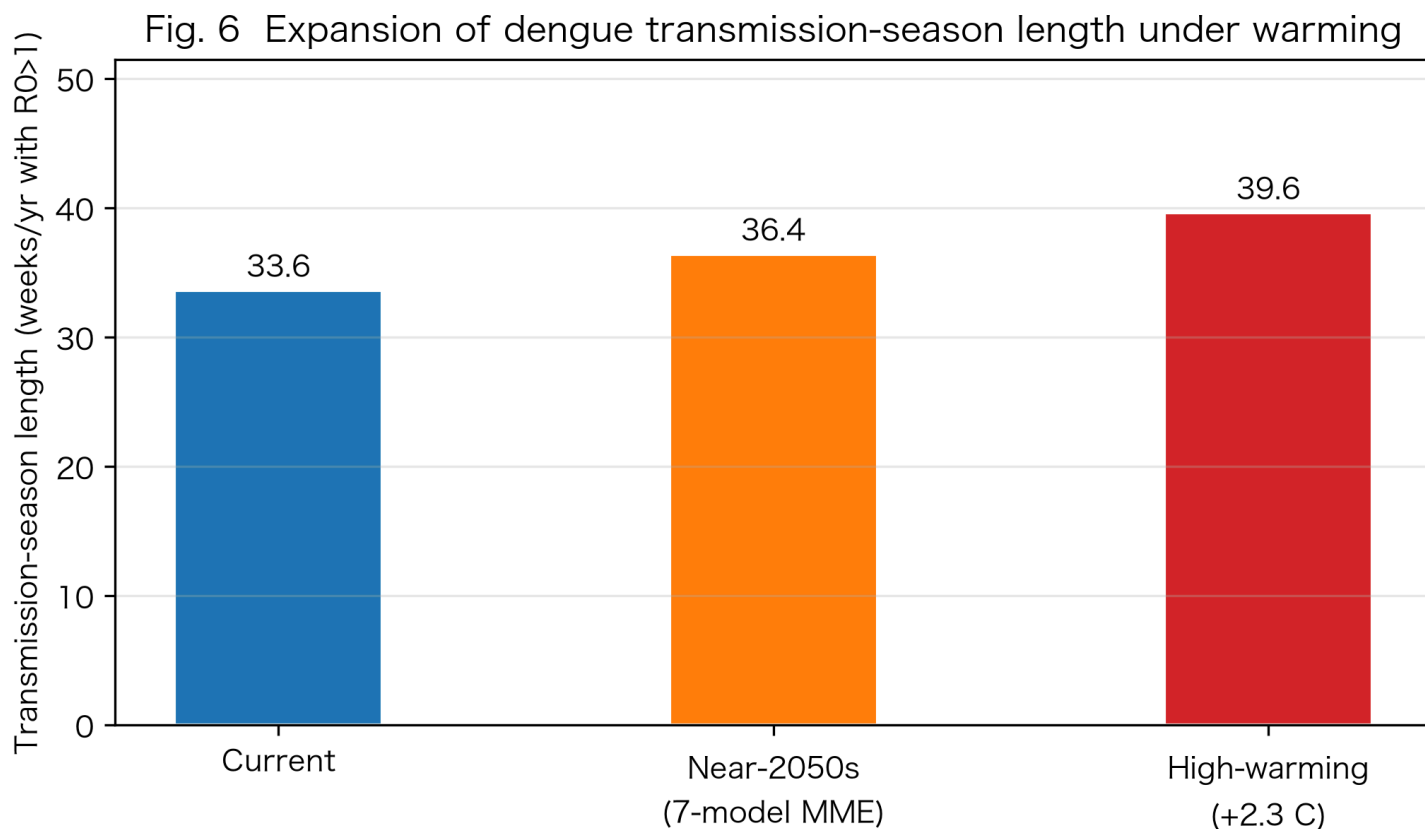


Figure 6

Transmission-season length (weeks with $R_0 > 1$) under current, near-2050s, and high-warming climates.

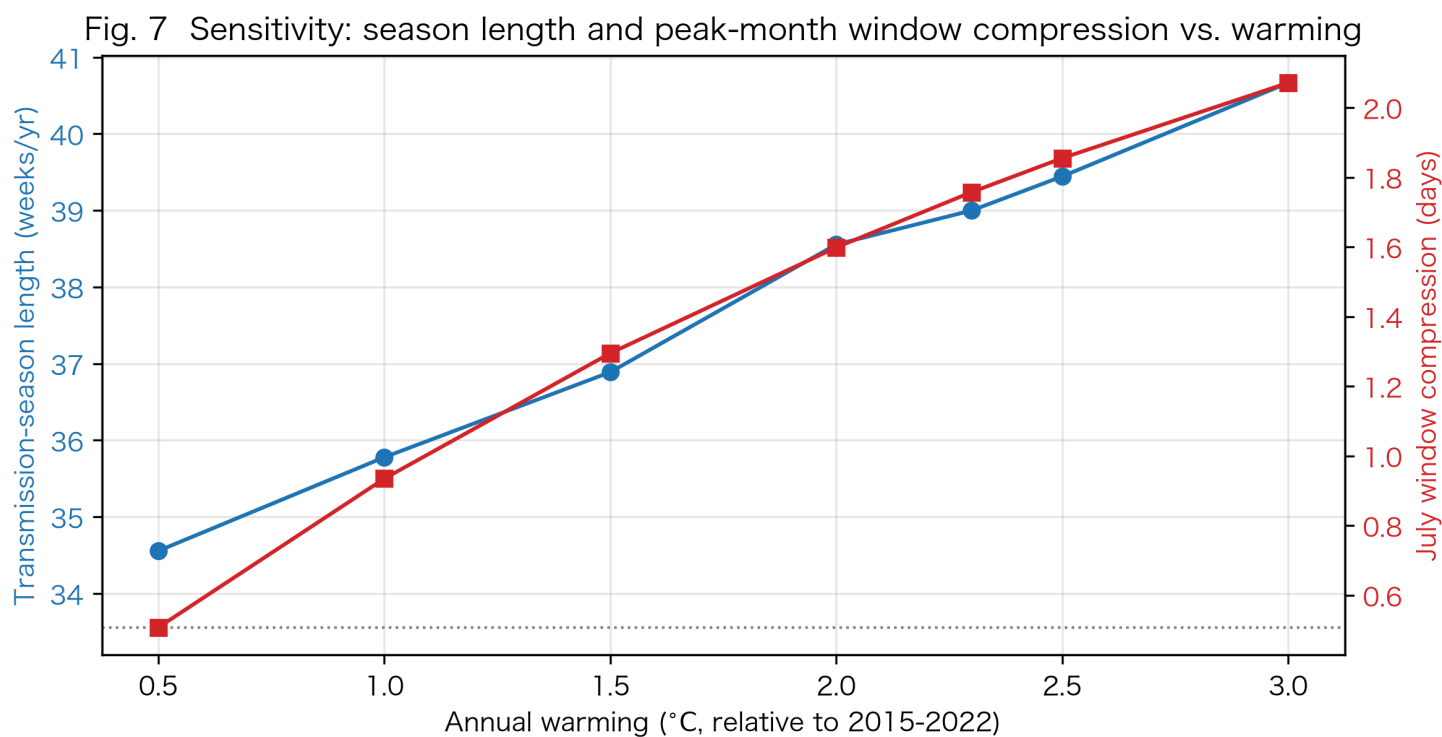


Figure 7

Sensitivity of transmission-season length and July response-window compression to warming.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [cmip6ensemblebc.json](#)
- [era5obs19952014.json](#)
- [results.csv](#)