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Impact of climate change on dengue fever epidemics in South and Southeast Asian settings: A modelling study

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A B S T R A C T

The potential for dengue fever epidemic due to climate change remains uncertain in tropical areas. This study aims to assess the impact of climate change on dengue fever transmission in four South and Southeast Asian settings. We collected weekly data of dengue fever incidence, daily mean temperature and rainfall from 2012 to 2020 in Singapore, Colombo, Selangor, and Chiang Mai. Projections for temperature and rainfall were drawn for three Shared Socioeconomic Pathways (SSP126, SSP245, and SSP585) scenarios. Using a disease transmission model, we projected the dengue fever epidemics until 2090s and determined the changes in annual peak incidence, peak time, epidemic size, and outbreak duration. A total of 684,639 dengue fever cases were reported in the four locations between 2012 and 2020. The projected change in dengue fever transmission would be most significant under the SSP585 scenario. In comparison to the 2030s, the peak incidence would rise by 1.29 times in Singapore, 2.25 times in Colombo, 1.36 times in Selangor, and >10 times in Chiang Mai in the 2090s under SSP585. Additionally, the peak time was projected to be earlier in Singapore, Colombo, and Selangor, but be later in Chiang Mai under the SSP585 scenario. Even in a milder emission scenario of SSP126, the epidemic size was projected to increase by 5.94%, 10.81%, 12.95%, and 69.60% from the 2030s–2090s in Singapore, Colombo, Selangor, and Chiang Mai, respectively. The outbreak durations in the four settings were projected to be prolonged over this century under SSP126 and SSP245, while a slight decrease is expected in 2090s under SSP585. The results indicate that climate change is expected to increase the risk of dengue fever transmission in tropical areas of South and Southeast Asia. Limiting greenhouse gas emissions could be crucial in reducing the transmission of dengue fever in the future.

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1. Introduction

Dengue fever, a mosquito-borne infectious disease, is becoming a growing health concern worldwide. In the past fifty years, reported cases of dengue fever have increased more than thirty times, with transmissions mainly occurring in tropical regions that have warm and wet climates (Bhatt et al., 2013; Ebi & Nealon, 2016). In addition to the rapid population growth and frequent national travel that accelerate the rising dengue fever transmission, climate change is also a potential contributor to the increased incidence of dengue fever and its geographical expansion, as global warming could create more favourable environments for mosquito breeding and the spread of the disease (Lowe et al., 2021).

Ambient temperature and rainfall are two critical factors that regulate the environmental suitability for the transmission of most mosquito-borne infectious diseases, such as Zika and dengue fever. Previous laboratory and field research has quantitatively estimated the impact of temperature on vector traits, demonstrating a positive association between normal ambient temperature and vector traits like biting rate and extinct incubation rate (Mordecai et al., 2017; Yang et al., 2009). The primary focus of rainfall on the vector-borne disease transmission is on the aquatic stage. Typically, a moderate rainfall can create more breeding sites for mosquitoes, leading to a higher risk of disease spread (Nuraini et al., 2021). On the other hand, heavy rainfall can be disruptive to the vectors due to the flushing-out effect (Benedum et al., 2018).

Several studies have projected the transmission potential of dengue fever under climate change based on the association between meteorological factors and disease transmission (Caldwell et al., 2021; Taghikhani & Gumel, 2018). According to the studies, the future may show an increasing trend in disease transmissibility and vectorial capacity (Kakarla et al., 2020; Ngonghala et al., 2021; Taghikhani & Gumel, 2018). The increased transmission risk highlights not only an increased dengue fever incidence, but also geographic expansions to non-epidemic areas (Baylis, 2017; Butterworth et al., 2017). Due to the intricate influence of meteorological factors on disease transmission, the patterns of disease epidemics, such as the epidemic size and peak time, may be subject to a change under global warming (Liu-Helmersson et al., 2016; Sadeghieh et al., 2021). For instance, a longer duration of dengue fever epidemics was expected in the future due to a prolonged environmental-favourable period for the dengue fever vector in Europe (Liu-Helmersson et al., 2016). In addition, spatial heterogeneity suggests a variability in the projections of dengue fever transmission across different regions. Compared to temperate areas, tropical regions like South and Southeast Asia are expected to maintain a more favourable condition for dengue fever vectors in the future (Davis et al., 2021), and dengue fever transmission in the future may thus behave differently.

To examine the impact of climate change on dengue fever epidemics, our study employed a compartmental model parametrized with temperature and rainfall variability to simulate dengue fever epidemics under projected greenhouse gas emission scenarios. The epidemics were projected from the 2030s to the end of the century in four settings, including Singapore, Colombo (Sri Lanka), Selangor (Malaysia), and Chiang Mai (Thailand). We evaluated the changes of key characteristics of dengue fever epidemics, including peak incidence, peak time, epidemic size, and outbreak duration. The findings of this study could assist in the prevention and control of dengue fever spread under climate change.

2. Materials and methods

2.1. Data

We collected weekly dengue fever incidence data between 2012 and 2020 in four locations named Singapore, Colombo, Selangor, and Chiang Mai from official surveillance reports (Wang et al., 2022). The data sources were noted in Supplementary Table A1. Daily mean temperature and total rainfall data over the same time period were retrieved from the National Centers for Environmental Information (NCEI), which provides weather data recorded by one or more weather stations in each setting. The projected monthly mean temperature and total rainfall data for the 2030s, 2050s, 2070s, and 2090s under three Shared Socioeconomic Pathways (SSP) scenarios (i.e., SSP126, SSP245, and SSP585 for low, middle, and high greenhouse gas emissions, respectively) were collected from 11 general circulation models (GCMs) in Phase 6 of the Coupled Model Intercomparison Project (CMIP6) via the WouldClim website (Supplementary Table A2). GCMs selection was based on previous studies (Hamed et al., 2022). Location-specific projected daily mean temperature series were calculated by adding the differences between the projected and nine-year averaged monthly mean temperature to the nine-year averaged daily mean temperature. The ratio between projected and nine-year averaged monthly total rainfall was multiplied by observed nine-year averaged daily rainfall in the corresponding month to get the projected daily rainfall series. Details in temperature and rainfall projections are noted in Supplementary Methodology (Supplementary material).

2.2. Disease transmission model

This study employed a SEI-SEIR compartment model to investigate the dynamics of dengue fever and to evaluate the impact of temperature and rainfall on disease transmission (Caldwell et al., 2021), as illustrated in Fig. 1. The model incorporates the following equations:

$$\frac{dS_v}{dt} = EFD(T)*pEA(T)*MDR(T)*\frac{1}{\mu_v(T)}*\left(1-\frac{N_v}{K(T,R)}\right)*N_v - \frac{b(T)\beta_v(T)I_h}{N_h}*S_v - \mu_v(T)*S_v \tag{1}$$

$$\frac{dE_v}{dt} = \frac{b(T)\beta_v(T)I_h}{N_h}*S_v - (\gamma_v(T)+\mu_v(T))*E_v \tag{2}$$

$$\frac{dI_v}{dt} = \gamma_v(T)*E_v - \mu_v(T)*I_v \tag{3}$$

$$\frac{dS_h}{dt} = (\mu_n + ie)*N_h - \frac{b(T)\beta_h(T)I_v}{N_h}*S_h - (\mu_h + ie)*S_h \tag{4}$$

$$\frac{dE_h}{dt} = \frac{b(T)\beta_h(T)I_v}{N_h}*S_h - (\gamma_h + \mu_h + ie)*E_h \tag{5}$$

$$\frac{dI_h}{dt} = \gamma_h*E_h - (\sigma_h + \mu_h + ie)*I_h \tag{6}$$

$$\frac{dR_h}{dt} = \sigma_h*I_h - (\mu_h + ie)*R_h \tag{7}$$

In this model, the total vector population (N_v) was separated into Susceptible (S_v), Exposed (E_v), and Infected (I_v) compartments, while the total human population (N_h) included Susceptible (S_h), Exposed (E_h), Infected (I_h), and Recover (R_h) compartments. The parameters used in this model were summarized in Table 1, and the temperature-dependent parameters were shown in Table 2.

The temperature and rainfall-dependent carrying capacity (K) was modeled as:

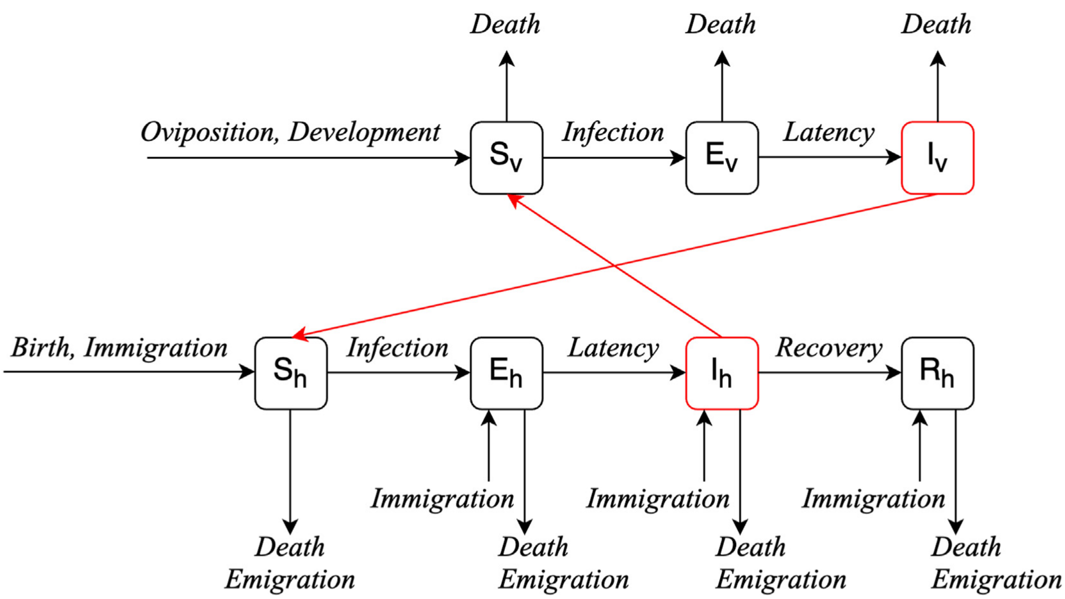

Fig. 1. Model framework for dengue fever transmission. S_v, susceptible vector; E_v, exposed vector; I_v, infected vector; S_h, susceptible human; E_h, exposed human; I_h, infected human; R_v, recovered human.

Table 1
Summary of the parameters in the SEI-SEIR model.

Parameter	Definition	Values	Range	Sources
μ_n	Human natural birth rate (per 1000 people)	Singapore: 9.26 Colombo: 15.65 Selangor: 16.50 Chiang Mai: 10.36	8.50–10.10 14.24–17.32 15.40–17.30 9.18–11.75	Worldbank (https://data.worldbank.org/indicator/SP.DYN.CBRT.IN)
μ_h	Human death rate (per 1000 people)	Singapore: 4.84 Colombo: 7.04 Selangor: 5.10 Chiang Mai: 6.83	4.50–5.20 6.90–7.18 4.91–5.31 6.46–7.26	
ie	Immigration/emigration rate	0.001	0.001–0.005	Worldbank (https://data.worldbank.org/indicator/SM.POP.NETM?end=2021&start=1960)
$1/\gamma_h$	Intrinsic incubation period (days)	5.9	gamma (μ=5.9, σ=0.5)	Chan and Johansson (2012)
$1/\sigma_h$	Human infectivity period (days)	5.0	gamma (μ=5.0, σ=0.5)	
b	Biting rate (day^{-1})	Temperature-dependent	Table 2	Mordecai et al. (2017)
EFD	Eggs laid per female per day			
pEA	Probability of mosquito egg to-adult survival			
MDR	Mosquito. egg to adult development rate (day^{-1})			
μ_v	Vector mortality rate			
β_h	Probability of mosquito infectiousness			
β_v	Probability of mosquito infection			
γ_v	Virus extrinsic incubation rate (day^{-1})			
K	Carrying capacity	Temperature and rainfall dependent		Caldwell et al. (2021)

Table 2
Temperature-dependent parameters.

Trait	Function	c (in 10^{-4})		Tmin (°C)		Tmax (°C)	
		mean	95% CI	mean	95% CI	mean	95% CI
EFD	Briere	85.6	[37.80, 141.00]	14.58	[8.08, 20.60]	34.61	[34.00, 35.77]
pEA	Quadratic	−59.90	[-68.20, −51.30]	13.56	[12.56, 14.51]	38.29	[37.54, 39.02]
MDR	Briere	0.79	[0.58, 0.99]	11.36	[7.19, 15.03]	39.17	[39.00, 39.54]
b	Briere	2.02	[1.20, 2.80]	13.35	[8.27, 17.41]	40.08	[40.00, 40.28]
$1/\mu_v$	Quadratic	−1480	[-2060, −980]	9.16	[6.69, 12.33]	37.73	[35.68, 39.89]
β_h	Briere	8.49	[5.07, 12.00]	17.05	[12.56, 21.26]	35.83	[35.06, 36.69]
β_v	Briere	4.91	[3.33, 6.41]	12.22	[5.61, 17.76]	37.46	[35.70, 39.29]
γ_v	Briere	0.67	[0.36–1.09]	10.68	[3.86, 18.33]	45.90	[39.73, 52.92]

*Briere function: $cT(T-T_{\min})(T_{\max}-T)^{1/2}$; Quadratic function: $c(T-T_{\max})(T-T_{\min})$; T means daily mean temperature, $T_{\max}$ and $T_{\min}$ mean the maximum and minimum temperatures for each trait; c is the rate constant. The parameters were assumed based on Mordecai et al., 2017.

$$K(T,R) = \frac{EFD(T_o)*pEA(T_o)*MDR(T_o)*\mu_v(T_o)^{-1} - \mu_v(T_o)}{EFD(T_o)*pEA(T_o)*MDR(T_o)*\mu_v(T_o)^{-1}} * N_{v.max} * e^{\frac{-E_A*(T-T_o)^2}{\theta*(T+273)*(T_o+273)}} * f(R) \tag{8}$$

where T_0 was set to 29.00 °C, the activation energy (E_A) was set as 0.05, and the θ (Boltzmann constant) was set as 8.617e-05 eV/K based on previous research (Huber et al., 2018). $N_{v.\ max}$ refers to the maximum vector-to-host ratio, and was set to two for the four locations in this study.

2.3. Rainfall function selection

According to previous research, the most suitable rainfall function might vary among locations (Caldwell et al., 2021). Therefore, the relationship between rainfall and carrying capacity was modeled using three different rainfall functions ($f(R)$) (Caldwell et al., 2021):

$$f(R_{\text{Briere}}) = c^*R^*(R - R_{min})^*\sqrt{(R_{max} - R)}^*z \tag{9}$$

$$f(R_{\text{Quadratic}}) = c^*(R - R_{min})^*(R - R_{max})^*z \tag{10}$$

$$f(R_{\text{Inverse}}) = \frac{1}{R}^*z \tag{11}$$

These functions were modeled with 14-days cumulative rainfall (mm), and a value of less than 1 mm or more than 123 mm was set as cut-off value (Benedum et al., 2018). The parameter c was set as 0.79e−4 and −59.90e−4 for the Briere and Quadratic functions, respectively. The scaling factor z has a range of 0.15–0.25, 0.015–0.025, and 0.30–0.70 for Briere, Quadratic, and Inverse functions, respectively. Models with the above-mentioned different rainfall functions and scaling factors were constructed to simulate daily dengue fever cases in each location between 2012 and 2020. The nine-year average total population for Singapore, Colombo, Selangor, and Chiang Mai were 5,551,545, 2,393,667, 6,223,810, and 1,719,512, respectively. The initial proportions were set as $S_v = 0.95$, $E_v = 0.03$, $I_v = 0.02$, $S_h = 0.50$, $E_h = 0.003$, $I_h = 0.002$, and $R_h = 0.495$. We set a burn-in period of 365 days to ensure the model's invariance to the initial status. Subsequently, the weekly dengue fever cases simulated from 2013 to 2020 were compared to those observed. The location-specific model with the lowest Akaike information criterion (AIC) value was selected for further analysis (Supplementary Methodology).

2.4. Projecting dengue fever transmission under climate change

To simulate dengue fever incidence in the future, the study utilized location-specific temperature and rainfall projections. The total population (N_h) was set as 100,000 in each location, with an initial status of $S_v = 2^*N_h - 150$, $E_v = 100$, $I_v = 50$, $S_h = N_h - 15$, $E_h = 10$, $I_h = 5$, $R_h = 0$. We characterized the peak dengue fever incidence (i.e., the peak daily new dengue fever cases in a year), peak time (i.e., number of days between the first day of a year and the day with peak incidence), epidemic size (i.e., the final population in the Recover compartment), and outbreak duration (i.e., the number of consecutive days with daily new cases exceed the outbreak cut-off values in a year). For Singapore, Colombo, and Selangor, an outbreak was defined as daily dengue fever cases exceeding 100 cases, while a cut-off value of 10 cases was used to define a dengue fever outbreak in Chiang Mai due to the relatively moderate dengue fever epidemic status in this location.

2.5. Uncertainty and sensitivity analysis

To perform uncertainty and sensitivity analysis, the study utilized Latin Hypercube Sampling (LHS) and partial rank correlation coefficients (PRCCs) (Marino et al., 2008; Okais et al., 2010). A total of 29 fixed parameters and their corresponding ranges are presented in Tables 1 and 2. PRCCs range from −1 to 1, with a higher value indicating a more significant impact on the model output. We determined the PRCCs between each fixed parameter and the transmission characteristics of dengue fever, such as epidemic size and peak incidence. The projected dengue fever transmissions under all climate change scenarios were determined through 1000 iterations of simulation, and the uncertainty was also assessed. To test the impact of projection uncertainty of climate change scenarios on disease transmission, five (i.e. ACCESS-CM2, EC-Earth3-Veg, INM-CM5-0, MICRO6, and MPI-ESM1-2-HR) out of the 11 GCMs were randomly selected to generate a new set of temperature and rainfall projections, and the simulated transmission dynamics were compared with the original results. All statistical analyses were conducted using R 4.0.2 software with the *deSolve* package.

3. Results

From 2012 to 2020, four locations including Singapore, Selangor, Colombo, and Chiang Mai reported a total of 684,639 cases of dengue fever. Among these locations, Selangor reported the highest number of dengue fever cases at 409,704, with the highest dengue fever incidence of 72.35 cases per 10,000 people per year, followed by Colombo with 52.11 cases per 10,000 people per year. Singapore and Chiang Mai showed relatively lower dengue fever incidences by 25.34 and 22.90 cases per 10,000 people per year. The average mean temperature in these locations was around 28.0 °C, with average daily rainfall ranging from 2.89 mm to 8.10 mm over the study period, as shown in Table 3. The Quadratic rainfall function with a scale factor z of 0.015 showed the lowest AIC in all four locations (AIC for Singapore: 8415.65, Colombo: 7548.35, Selangor: 8540.74, and Chiang Mai: 4343.24), and was used for further analysis.

According to the simulation results, the peak incidences of dengue fever generally increased in the four study settings under different climate change scenarios, as depicted in Figs. 2 and 3. Dengue fever transmission showed less noticeable change over this century under SSP126, whereas a remarkable increase in peak dengue fever cases was found under SSP245 and SSP585 scenarios (Fig. 2). In comparison to the 2030s, the peak dengue fever incidence in Singapore was projected to increase by 1.19 times from 593 cases per day to 707 cases per day under SSP245, and 1.29 times from 615 cases per day to 796 cases per day under SSP585 by the end of this century. A similar rising trend was observed in Selangor, in which the peak dengue fever incidence would increase from 487 cases per day in 2030s to 668 cases per day (1.37 times) in 2090s under SSP245, and from 503 to 684 (1.36 times) under SSP585. Colombo would show an increase in the peak incidence by 2.25 times

Table 3
Dengue fever situation and climate conditions in the four study locations from 2012 to 2020.

	Total number of cases	Mean annual incidence (/10,000)	Daily mean temperature (°C) [a]	Daily rainfall (mm)[a]
Singapore	126,962	25.34	27.87 (27.29, 28.42)	6.28 (2.73, 9.00)
Colombo	112,757	52.11	28.06 (27.35, 28.75)	6.89 (1.06, 10.00)
Selangor	409,704	72.35	28.17 (27.47, 28.82)	8.10 (2.37, 11.94)
Chiang Mai	35,216	22.90	26.91 (25.56, 28.62)	2.89 (0, 4.43)

[a] Daily mean temperature and rainfall were shown as mean and the first and the third quartile over the study period.

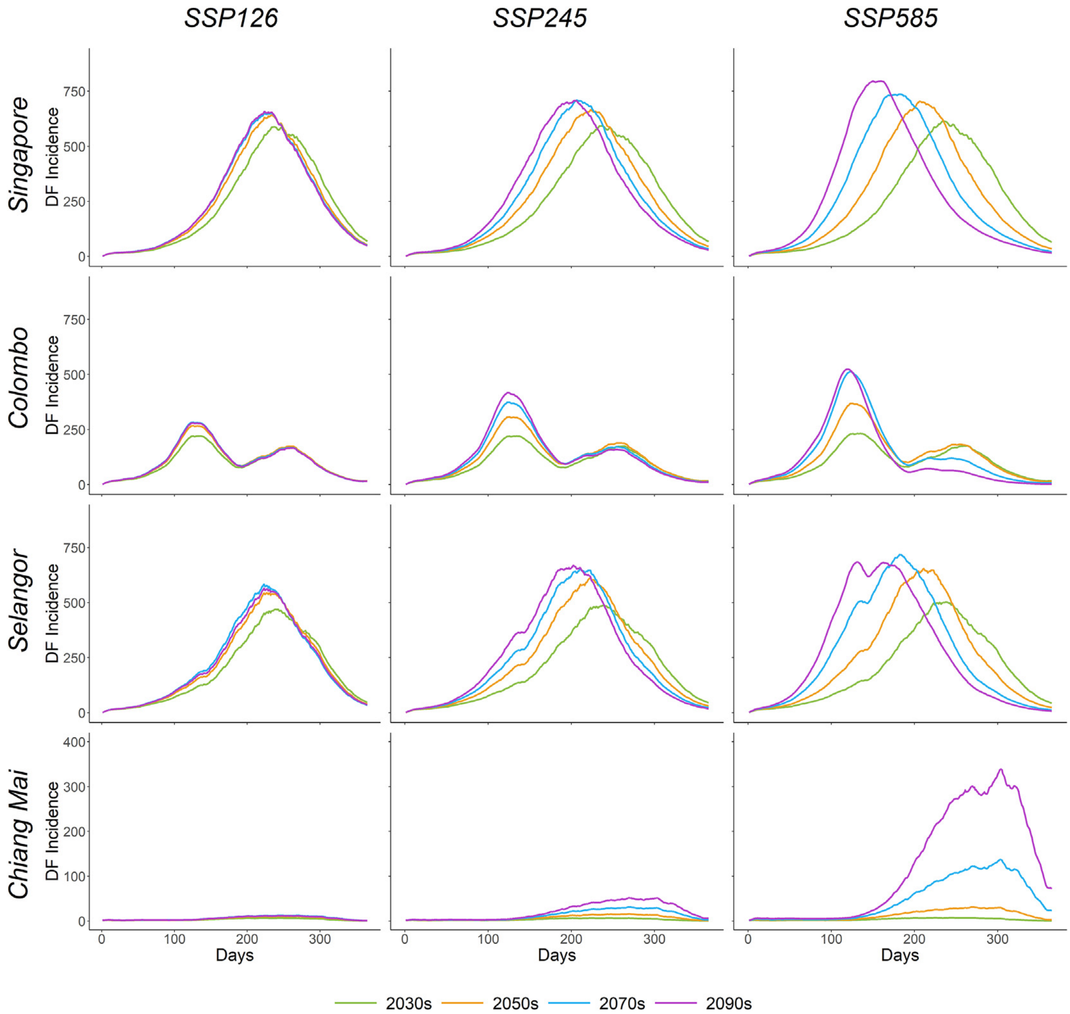

Fig. 2. Projected dengue fever incidence under climate change scenarios.

in this century under SSP585, and the double-peak pattern would be less pronounced. The most significant increase was projected in Chiang Mai, with a more than 10-fold increase in peak dengue fever cases by the end of this century under the middle-to-high emission scenario.

As shown in Figs. 2 and 3, the epidemic peak of dengue fever consistently appeared earlier in a year in Singapore, Selangor, and Colombo. Compared to the 2030s, the peak time in Singapore would be 13 days, 29 days, and 84 days earlier in 2090s under SSP126, SSP245, and SSP585, respectively. Similarly, Selangor would experience a 106-day earlier dengue fever peak in 2090s compared to the 2030s under SSP585. In contrast, the peak time was projected to be 80 days later in Chiang Mai in 2090s compared to 2030s under SSP585. Regardless of the SSP scenarios, the peak time in Colombo would have less remarkable changes with about 15 days earlier from 2030s to 2090s.

Our study projected obvious increases in the dengue fever epidemic size and duration, as shown in Figs. 2 and 3. The epidemic size was projected to increase by 5.94%, 10.81%, 12.95%, and 69.60% from the 2030s–2090s under SSP126 for

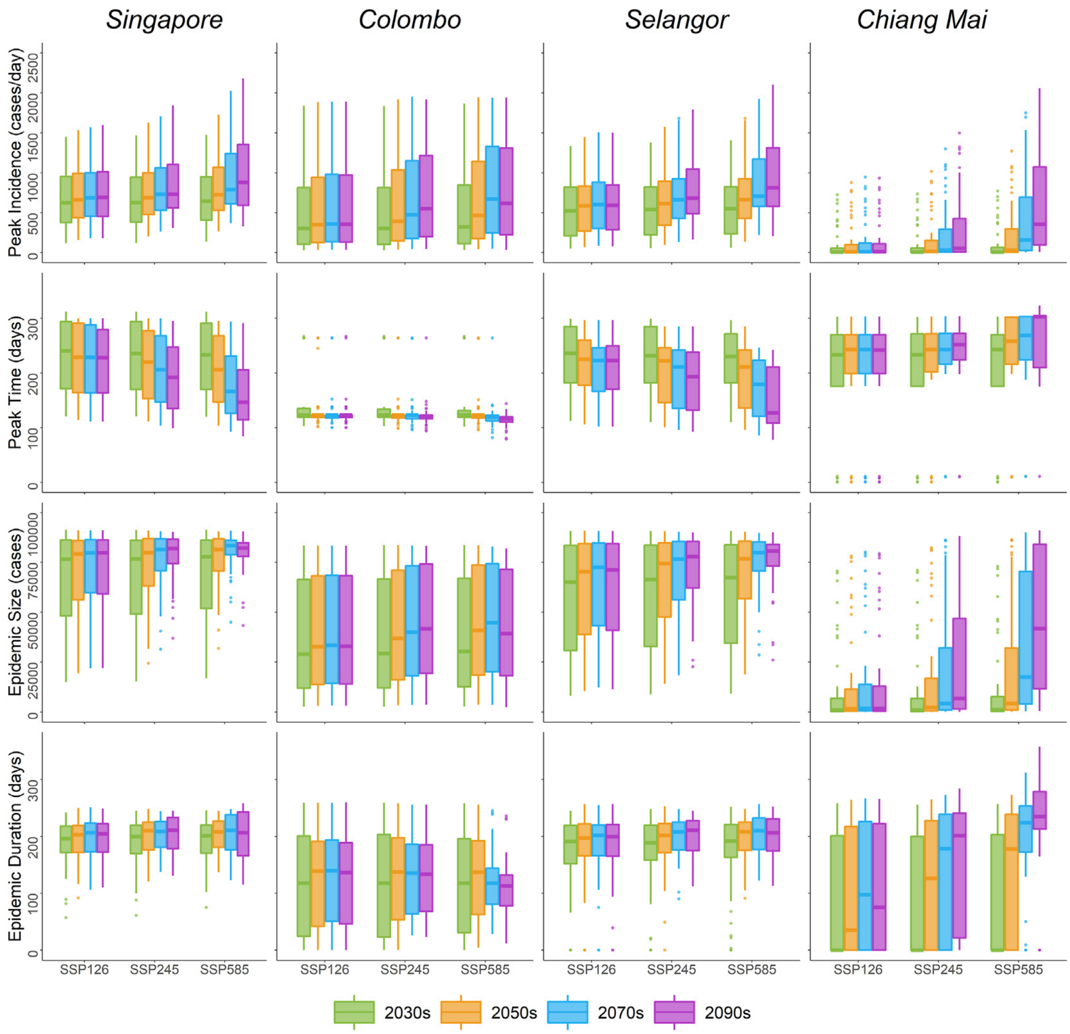

Fig. 3. Uncertainty analysis of the key dengue fever epidemic characteristics.

Singapore, Colombo, Selangor, and Chiang Mai, respectively. A similar rising trend was found under SSP245, while SSP585 showed the most apparent increase in epidemic size. Under the high emission scenario, the epidemic size would increase by 8.02%, 16.29%, 27.00%, and 32.17 times for Singapore, Colombo, Selangor, and Chiang Mai, respectively, from the 2030s–2090s. The outbreak duration in Singapore and Selangor would be around 200 days in 2030s under SSP126, and it was expected to increase by approximately 10 days in 2090s under SSP126 and SSP245, while a slight decline was projected in 2090s under SSP585. Similarly, the outbreak duration would increase by 20 days in Colombo from 2030s to 2090s under low and middle greenhouse gas emission scenarios, while a slight decrease trend was found since 2070s under SSP585. Despite the significant uncertainties (Fig. 3), a prolonged dengue fever epidemic duration was also projected in Chiang Mai.

The sensitivity analysis showed that the dengue fever transmission was mainly sensitive to several temperature-dependent parameters (Fig. 4, Supplementary Fig. A1). The biting rate (b), probability of mosquito infectiousness (β_h), and the mosquito mortality rate (μ_v) were the influential drivers of the final epidemic size and peak incidence. In addition, the results accounting the variability of projected temperature and rainfall from a new set of GCMs only showed a slight difference in terms of the projected epidemic curves in different SSP scenarios (Supplementary Fig. A2).

4. Discussion

Global warming, as a result of climate change, is likely to develop a more favourable living environment for the dengue fever vector. This study utilized a mathematical model to project the transmission of dengue fever in four South and Southeast Asian settings under climate change scenarios. The model simulation projected an increase in peak incidence and epidemic size of dengue fever, along with an earlier peak time and a prolonged outbreak duration in the future generally. The biting

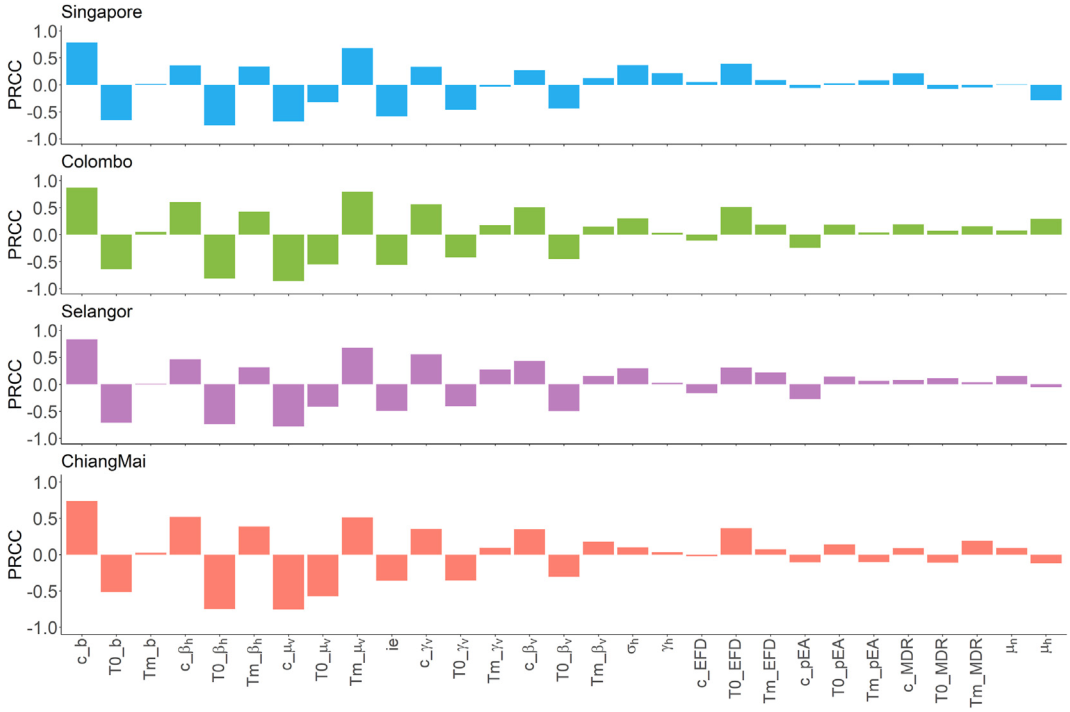

Fig. 4. Sensitivity of the final dengue fever epidemic size in 2030s under SSP126 to fixed parameters in four locations. The bars indicate the partial rank correlation coefficients (PRCC). T_0 represents the minimum temperature, T_m means the maximum temperature.

rate, probability of mosquito infectiousness, and vector mortality were identified as the most influential temperature-dependent parameters affecting the predicted dengue fever incidence.

We showed the peak incidence and epidemic size of dengue fever would increase in the future, consistent with previous research (Huber et al., 2018; Li et al., 2017). Compared with SSP126 that would have relatively conservative temperature elevation, SSP585 with a significant temperature increase was expected for the most remarkable rise in dengue fever incidence. The increase in mosquito activity can be considered as the driving force behind the rising trends, which is directly linked to the elevated ambient temperatures. According to the laboratory and field research, some vector traits such as biting rate and virus transmissibility between host and vector would increase in a warmer environment, while the mosquito mortality rate and the extrinsic incubation period (EIP) would decline at the same time (Mordecai et al., 2017). Of note, the rising trend would be apparent before 2050s, while less noticeable change was predicted from 2070s to 2090s, and this may be due to the different speeds in temperature and rainfall change before and after 2050s.

The study's findings of an earlier peak time of dengue fever epidemic and longer outbreak duration in the future are consistent with some previous studies (Bal & Sodoudi, 2020). As noted earlier, the rising temperature contributes to an accelerated EIP and rapid virus spread, resulting in an earlier peak time. Generally, dengue fever incidence peaks in summer and is lower in the winter seasons. With global warming, the rising temperature in spring and autumn allows a more favourable meteorological condition for survivorship and transmissions of dengue fever virus from *Aedes* spp., and thus outbreak duration is likely to be prolonged with an earlier peak time of epidemic. Nevertheless, we found a delayed peak time in Chiang Mai, and the more apparent temperature and rainfall seasonality in this location may contribute to the inconsistency in the change of peak time among these settings (Wang et al., 2019). Changing in disease outbreak duration was also reported by studies in Australia and Brazil, which showed a decline in dengue fever epidemic duration under climate warming due to high vector mortality rates (Williams et al., 2016), and a shortened outbreak duration for Zika, an infectious disease that shares the same vector with dengue fever (Sadeghieh et al., 2021). These inconsistencies may be due to the threshold effect of temperature on dengue fever vector, which suggests an inverse U-shape association between ambient temperature and dengue fever vector traits, and once the temperature exceeds the optimal threshold, the dengue fever vector mortality increases and the infection risk declines (Paul et al., 2021; Taghikhani & Gumel, 2018). In this study, the dengue fever outbreak duration under SSP585 was projected to decline in 2090s, and this could also be attributed to the beyond optimum temperatures under this scenario. Similar to its epidemic patterns in history, dengue fever in Colombo was projected to have double waves in 2030s and 2050s due to two monsoon seasons in a year. However, the second dengue fever wave in a year would be less significant after 2050s under high emission scenarios, and the dengue fever epidemic duration would decline as well. While the temperature and rainfall patterns in Colombo are expected to remain consistent throughout this century, the degree of elevation in temperature and rainfall under different SSPs could potentially lead to alterations in the climate patterns of the region, ultimately contributing to a less significant second wave in the future.

The primary means by which rainfall impacts the transmission of mosquito-borne diseases is through its effect on the aquatic vector, and most prior research has utilized a rainfall-dependent carrying capacity to model the influences. The carrying capacity represents the total amount of immature vector population a system can accommodate based on the available water in this system (Morin et al., 2015). With increased rainfall, a system would be able to carry more aquatic mosquitos and consequently contribute to a rising disease spread potential. However, the flushing away effect and increased density-dependent mortality risk highlight the negative impact of heavy rainfall on disease transmission (Benedum et al., 2018; Morin et al., 2013). This study projected that a moderate increase in rainfall would create more breeding sites for immature vectors, resulting in a larger dengue fever epidemic and an earlier peak incidence. In addition to carrying capacity, other vector traits such as the egg development rate were also suggested to be rainfall-dependent by previous research (Bonnin et al., 2022; Gutierrez et al., 2022; Okuneye & Gumel, 2017). However, since the rainfall-transmission relationship on mosquito-borne diseases is not yet fully understood, models with more comprehensive rainfall functions are needed to improve the disease transmission projections.

Compared to other parameters, the projections were found to be sensitive to the biting rate, probability of mosquito infectiousness, and vector mortality. In line with previous research, these temperature-dependent parameters are expected to have a major impact in shaping dengue fever transmission in the future (Ngonghala et al., 2021; Taghikhani & Gumel, 2018). Biting rate plays a vital role in dengue fever spread due to its impact on both host-to-vector and vector-to-host virus transmission. As a result, the biting rate might have a greater impact on disease projections than other temperature-dependent parameters. The study also found that vector mortality was a sensitive parameter given to its intricate effects on the EIP, biting behavior, oviposition rate, and other vector traits, highlighting its importance in disease incidence projections (Yang et al., 2009). Thus, focusing on these sensitive parameters that dominate dengue fever transmission would help to prevent and control dengue fever transmission more efficiently in the future.

There are several notable strengths to this study. Firstly, the SEIR-SEI model parameter was chosen based on observed incidence data, which greatly improved the precision of the modelling outcomes. Secondly, the study examined the transmission dynamics of dengue fever through the use of both temperature and rainfall projections, leading to more dependable findings than those based solely on temperature-dependent parameters. Thirdly, the study utilized the most recent CMIP-6 climate change data, and its results can serve as a valuable scientific reference for preventing dengue fever spread in the future.

Several limitations of this study should be acknowledged. Firstly, the impact of rainfall on dengue fever transmission was modeled mainly by regulating the carrying capacity, which may differ from the real situation. Since this study mainly focused on projecting the change of dengue fever transmission under climate change, and the rising trend would still be inspiring for dengue fever prevention and control in the future. Secondly, this study projected dengue fever transmission with mean temperature and rainfall only. Although other climate factors such as humidity also help to modulate dengue fever spread, they were not included into this study due to a lack of reliable data (Gutierrez et al., 2022; Xu et al., 2020). Thirdly, this study applied the SEIR-SEI model based on some assumptions such as assuming an infected vector would remain infectious until its death, and there was no vertical transmission and natural protection. Given the complicated virus transmission mechanisms between host and vector, more comprehensive modelling research is expected to achieve more precise projections. Fourthly, this study collected projected temperature and rainfall data from 11 GCMs, and uncertainty may exist even though a sensitivity analysis was conducted. Lastly, the interventions on policies and interventions such as using clean energy, increasing energy efficiency, and implementing carbon pricing mechanism were not studied by modulating their effects in the transmission model. Nevertheless, the effect of these kinds of interventions could actually be proxied by the climate change scenarios. For example, SSP126 is indeed an intervention scenario with intensive emission restriction on reducing the impact from climate change.

5. Conclusion

Our modelling study projected dengue fever transmission in South and Southeast Asian settings under climate change. We demonstrated that climate change reshaped dengue fever epidemics in terms of an increase in peak incidence and outbreak size, especially under high emission scenarios and after the middle of this century. The projections also showed that the seasonal epidemic was likely to arrive earlier with longer duration in a year. Our study thus improves the understanding of the relationship between climate change and dengue fever transmission, providing a useful framework for planning control and prevention strategies for dengue fever epidemics in the future.

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Authors' contributions

Yawen Wang: Conceptualization, Methodology, Formal analysis, Visualization, Writing - Original Draft; Shi Zhao: Methodology, Software, Formal analysis, Investigation, Writing - Review & Editing; Yuchen Wei: Methodology, Software, Formal analysis, Investigation, Writing - Review & Editing; Kehang Li: Writing - Original Draft; Xiaoting Jiang: Writing - Review & Editing; Conglu Li: Writing - Review & Editing; Chao Ren: Writing - Review & Editing; Shi Yin: Writing - Review & Editing; Janice Ho: Writing - Review & Editing; Jinjun Ran: Writing - Review & Editing; Lefei Han: Writing - Review & Editing; Benny Chung-ying Zee: Methodology, Writing - Review & Editing; Ka Chun Chong: Conceptualization, Methodology, Writing - Original Draft, Supervision, Funding acquisition; all authors have read and approved the final paper.

Data sharing

All data used for this study are publicly available. The data sources are listed in the supplementary file.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.idm.2023.05.008.

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