Climate warming is expanding dengue burden in the Americas and Asia

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Abstract Climate change poses significant threats to public health, with dengue representing a growing concern due to its high existing burden and sensitivity to climatic conditions. Yet, the quantitative impacts of temperature warming on dengue, both in the past and in the future, remain poorly understood. In this study, we quantify how dengue responds to climatic fluctuations, and use this inferred temperature response to estimate the impacts of historical warming and forecast trends under future climate change scenarios. To estimate the causal impact of temperature on the spread of dengue in the Americas and Asia, we assembled a dataset encompassing nearly 1.5 million dengue incidence records from 21 countries. Our analysis revealed a nonlinear relationship between temperature and dengue incidence with the largest marginal effects at lower temperatures (around 15°C), peak incidence at 27.8°C (95% CI: 27.3 - 28.2°C), and subsequent declines at higher temperatures. Our findings indicate that historical climate change has already increased dengue incidence 18% (12 - 25%) in the study region, and projections suggest a potential increase of 40% (17 - 76) to 57% (33 - 107%) by mid-century depending on the climate scenario, with some areas seeing up to 200% increases. Notably, our models suggest that lower emissions scenarios would substantially reduce the warming-driven increase in dengue burden. Together, these insights contribute to the broader understanding of how long-term climate patterns influence dengue, providing a valuable foundation for public health planning and the development of strategies to mitigate future risks due to climate change.

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Introduction

Anthropogenic climate change is a major health threat that is already causing significant morbidity, mortality, and economic loss through its effects on biological processes and ecological systems[1,2]. Describing the causal relationship between climate and biological processes is necessary to anticipate and respond to health hazards and attribute harms to fossil fuel emissions as part of climate accountability and justice efforts[3,4,5]. Changing temperatures and increasingly frequent extreme weather events are generally expected to drive changes in the global burden and distribution of infectious diseases[6]. However, the implications of warming for vector-borne diseases remain particularly unclear and are often difficult to estimate compared to other climate-associated risks due to data sparsity and confounding by climate-independent factors[7,8,9].

By building from a biological understanding of the temperature sensitivity of ectothermic mosquito vectors, we can better understand the relationship between temperature and cases of vector-borne diseases that pose particularly significant health threats[10]. Prior experimental work has measured transmission-relevant mosquito traits (e.g., biting rate, survival, development time) across a temperature gradient and used these values to estimate relative R_0, a measure of transmission intensity, as a function of temperature[11,12]. Across mosquito-borne diseases, we expect a nonlinear and unimodal relationship between temperature and transmission[11,13]. Dengue, vectored by *Aedes aegypti* and *Aedes albopictus*, is expected to present a growing risk with warming temperatures relative to other vector-borne diseases due to its particularly warm thermal optimum (29 and 26°C for the two mosquito vectors, respectively)[14,15,16]. However, relative transmission risk metrics cannot be translated directly into cases, morbidity, and mortality, the outcomes most relevant to quantifying health costs of climate change, because of complexities and nonlinearities of infectious disease dynamics and the potential for additional covariates to modulate the relationship[17,18]. We therefore aim to directly estimate the quantitative relationship between cases and temperature in the field over space and time, while controlling for potentially confounding variation in other factors.

In addition to considering temperature, studies to estimate drivers of disease burden may incorporate several additional covariates including El Niño Southern Oscillation (ENSO), urban infrastructure, age structure, human mobility, and immunity (based on past exposure)[19,20,21,22,23,24]. Several other covariates have been identified as important and potential confounders in existing analyses (e.g., vector control, serotype changes, and global trade and migration), but many of these variables are difficult to measure and report in a standardized manner[19,25,26]. The field of applied econometrics has developed a set of causal inference tools for quantifying causal effects of hypothesized drivers in complex systems where randomized-controlled trials are impractical or unethical (such as for estimating large-scale impacts of climate change). These tools, called panel regression, allow us to account for spatiotemporal variation in unmeasured covariates and focus on the relationship between anomalies in both temperature and dengue cases[6]. Further, because deviations in temperature from the average conditions in a given space and time are plausibly random, we can interpret our result as a causal estimate[27].

Previous work has addressed impacts of temperature on dengue transmission, but has not been able to conclusively quantify the relationship at a large scale. Statistical models have generally considered dengue across smaller geographic areas, either within a single geographic region (e.g., a district, island, or city)[28,23,29] or across multiple administrative subunits (e.g., municipalities or districts) within a single country or province[30,31,19]. The relationship between weather and disease may not be consistent globally. For example, a meta-analysis found that population density, precipitation, and prior disease burden (and resulting immunity) may modulate the reported correlation between dengue and temperature[32], and urban infrastructure (particularly water supply) may alter the effects of precipitation and drought[24]. We therefore examine whether covariates like average dengue incidence, continent, health expenditure, and population density significantly moderate the relationship between dengue and temperature.

After deriving a causal estimate of the relationship between dengue and temperature and determining that it is robust across regions with endemic transmission in East Asia and Central and South America, we apply our model to attribute historical dengue burden to existing climate change–one of the first vector-borne disease climate attribution studies ever done–and to forecast how dengue burden may change by mid-century under different emissions scenarios[5,33]. The distribution of dengue is generally expected to expand while the burden increases under climate change, but prior studies have focused on more limited geographic regions[26,34,35]. By building from a nonlinear dengue-temperature relationship that is well-supported by previous mechanistic experimental work and leveraging a global dataset encompassing a large temperature gradient, we expect to find both increases in dengue in regions where temperature warms toward the thermal optimum and declines in warmer tropical regions where the thermal optimum for transmission is exceeded[36,37].

Here, we assess the impact of temperature on dengue in the Americas and Asia. Specifically, we (i) capture the causal nonlinear relationship between temperature and dengue incidence, (ii) assess the impact of socioeconomic and environmental covariates on this relationship, and (iii) estimate the change in dengue incidence due to historical and future warming. To do so, we assembled a dataset of dengue incidence, climate, and covariates (Fig. 1). We then use future climate scenarios and our temperature-dengue response function to project future changes in incidence.

Results

Thermal sensitivity of dengue We find that dengue incidence responds nonlinearly to temperature, increasing up to a peak at 27.8°C(95% CI: 27.3 - 28.2) and declining at higher temperatures (Fig. 2). This dengue - temperature response corresponds to a marginal effect of temperature that is highest at low temperatures (15-20°C), declines to zero at 27.8 °C, and becomes negative at higher temperatures. The general shape and nonlinearity of this relationship is consistent across a range of alternative model specifications, including higher degree polynomials, varied lags of temperature, alternative fixed effects and weightings, and removing Brazil, which makes up 74% of the spatial units in our dataset (Fig. 2, Fig. S4). These results are consistent with previous mechanistic models based on laboratory-derived mosquito thermal performance curves, which predicted maximum transmission at 29°C for *Ae. aegypti* and 26°C for *Ae. albopictus*[14].

The impacts of temperature changes on dengue incidence are likely to be heterogeneous based on existing conditions, including serotype dynamics in the location, population immunity levels from previous exposure, availability of vector breeding habitat, the dominant vector species with *Ae. aegypti* having a slightly warmer temperature optimum, living conditions and exposure to vectors, and public health response. We focused on investigating whether the thermal sensitivity of dengue incidence varied spatially over large continental regions, with country health expenditure, with population density, and with average dengue incidence. We found the largest variation in thermal responses between continental regions, and smaller variations by health expenditure, population density, and existing dengue incidence (Fig. 3). For all responses, we see larger positive marginal effects at low temperatures, a decline to zero around 27-30 °C, and negative marginal effects at higher temperatures. The temperature responses differed slightly in the exact optimum temperature and the magnitude of the marginal impacts at low temperatures. The temperature response for Asia displayed a slightly higher optimum temperature than the Americas, and smaller marginal impacts at low temperatures, although support in the lower temperature range was limited for Asia given the observed temperature distribution. For health expenditure, we originally hypothesized that higher expenditure might enable countries to better limit transmission resulting in lower marginal effects of temperature, but instead found slightly larger impacts in higher health expenditure countries, although confidence intervals overlapped. For population density, we similarly see overlapping estimates among all terciles, although slightly higher median estimates for high population density follow by intermediate and low population density, consistent with higher transmission rates in high density areas. Finally, for dengue incidence, one possibility was that higher incidence locations might have more immunity and more health infrastructure for dealing with dengue transmission resulting in lower marginal impacts, while a competing hypothesis was that places with higher incidence might have more interactions between serotypes and thus more severe cases of dengue likely to be reported as well as the other environmental and socioeconomic condition conducive to transmission so more suitable temperature would lead to larger marginal effects. Again we see overlapping confidence intervals between different terciles of dengue incidence, but some evidence supporting the second set of hypotheses.

Historical and future impacts of climate change To quantify the impact of existing climate change, we estimate the change in dengue incidence under observed temperatures for 1995-2014 compared to a counterfactual of global circulation models (GCMs) without anthropogenic forcing. We estimate that on average over the locations included in the study, 18% (95% CI: 12 - 25%) of existing dengue incidence is due to anthropogenic climate change already (Fig. 4, Table S3). The estimates vary both within and between countries, with cooler areas in Bolivia, Peru, Mexico, Brazil, and Colombia seeing 30-40% of existing dengue from climate change and warmer countries like Thailand and Cambodia having little impact from existing warming. These impacts equate to a large number of dengue cases and affected populations: while some of these cooler countries where a larger portion of existing dengue is due to climate change have relatively low current dengue burdens, other countries like Brazil, El Salvador, and Indonesia with intermediate average temperatures (22-26°C) have high current burdens of dengue and 10-30% of that existing burden is estimated to be due to climate change (Fig. 4).

Future warming will also play a role in determining dengue incidence. On average in the study region, we predict a 57% (95% CI: 33 - 107%) increase in dengue incidence under SSP3-7.0. While some low elevation equatorial areas will warm beyond the peak temperature and are projected to see small declines in dengue incidence due to climate change, the majority of locations are projected to see increases in dengue incidence under all climate scenarios (Fig. 5, Fig. S5). Some cooler regions of Mexico, Peru, Bolivia, and Brazil are predicted to see over 150% increases in dengue incidence due to climate change under all climate scenarios. Many of the largest cities in the Americas are located in these cooler regions where large increases in dengue are projected. Among the 21 countries included in the study, only one country (Cambodia) is projected to see declines in dengue incidence under all three climate scenarios while 17 countries are projected to see increases under all scenarios. Despite the estimated increases in dengue in the majority of locations even under the most optimistic (low emissions) scenario (SSP1-2.6, Fig. S5), we find that these increases would be on average 7% (95%CI: 1 - 20%) larger under the high emissions scenario (SSP3-7.0), with some countries seeing up to 30% greater increases in dengue incidence in SSP3-7.0 compared to SSP1-2.6 (Fig. 5b, Table S3). These estimates are largely similar when using continent-specific temperature responses, which showed the greatest difference between temperature responses, with the largest differences in projected impacts in Asia where no countries are predicted to have see significant declines in dengue under future climate scenarios due to the slightly higher estimated temperature where dengue incidence peaks (Fig. S6).

Discussion

A wide range of existing literature documents that temperature affects dengue transmission[32,14,18,38], but quantifying the exact nature of this relationship has been challenging due to the confounding effects of multiple other drivers[19,24,26]. Yet, understanding this relationship precisely is critical for projecting impacts under climate change to better anticipate future changes and design adaptations to meet them. Here, we aim to comprehensively quantify the temperature-dependence of dengue transmission using human case data. We find clear nonlinear effects, consistent with the thermal biology of the vectors[11]. Increases in temperature have the largest marginal impact at low temperatures (15-20°C) and become negative at very high temperatures (¿27.8°C), allowing us to identify geographic regions where temperature change is likely to have the largest impact.

Based on these marginal effects of temperature, we estimate that 18% of the current dengue burden in the study region is due to increases in temperature from existing climate change, and up to 40% of dengue incidence due to climate change in some cooler countries. Projecting forward, we expect the impacts of climate change to be even larger by the mid-century, with 40 - 57% increases in dengue incidence overall in the study region depending on the scenario. While dengue is expected to increase under all climate scenarios, climate mitigation still has large benefits, with estimated increases in incidence 7% smaller overall under the lowest emissions scenario, and some countries seeing 30% smaller increases.

We project that most areas will see increases in dengue transmission due to climate change in contrast to malaria, which is projected to decline in sub-Saharan Africa by mid-century due to climate change-driven temperature increases[39]. These divergent impacts are consistent with the differences in thermal biology between malaria and dengue, with malaria predicted to have a cooler optimum temperature around 25°C compared to the 27.8°C optimum inferred here for dengue[11]. Relative to other health impacts of climate change, especially direct heat-related mortality, which is predicted to increase the most in already warm regions[40], the impacts on dengue are projected to be largest in relatively cool regions while the hottest regions in our study are projected to see declines in dengue incidence due to climate change (Fig. 5). In fact, our study likely underestimates these future warming-driven dengue increases in cool areas as many such regions do not yet have consistent dengue transmission and/or reporting, and thus are not included in our dataset.

While our results highlight the benefit of climate mitigation in reducing the projected increases in dengue incidence, the projected increases under all scenarios suggest that climate adaptation will also be necessary even in the best case (Fig. 5). Moreover, the consistency of the estimated dengue-temperature relationship across places with both high health expenditures and high existing dengue incidence (Fig. 3) suggests that even the locations most likely to have existing public health systems able to withstand the impacts of temperature are still strongly affected.

Although this work presents the most globally comprehensive (spanning 21 countries), quantitative estimate of temperature impacts on dengue to date, our estimates are constrained by the set of locations with available sub-annual, sub-national dengue data, which are primarily located in tropical areas of the Americas and southeast Asia. The study omits both other tropical areas with endemic dengue (notably south Asia and sub-Saharan Africa, Fig. S1) and cooler temperate regions that do not have consistent dengue transmission. As a result of the latter, our estimates focus on the impact of temperature changes in intensification of dengue incidence rather than invasion of dengue into new regions. Taken together, this suggests that our estimated change in dengue case from climate change will be conservative due to the omitted dengue-endemic regions and the temperate regions where dengue transmission occurs sporadically and could expand (including recently in California, Texas, and Florida, USA). Some of the excluded areas may be at or above the optimum temperature for dengue transmission and see declines in dengue incidence due to climate change, but the majority will see increases with future warming. In addition to focusing on endemic regions, our projections center on the effect of changes in monthly average temperature rather than any of the myriad of other impacts expected with climate change, including altered precipitation patterns, changes in temperature variability, increased extreme weather events, and behavioral adaptation to climate change. Further, our temperature response is estimated from real dengue dynamics in the field, and in doing so, implicitly incorporates complexities like serotype dynamics, vector control, policy, and population growth and mobility. Our projections assume that these other factors will not change in a way that alters the estimated dengue-temperature response (i.e., in a way that is interactive with temperature). Finally, our projections focus solely on temperature's impacts on dengue incidence, and the landscape of dengue transmission in the future will also be impacted by a range of other factors including urbanization, migration, the emergence of new serotypes, and/or potential medical advances in treating or preventing dengue in a way that could either reduce or exacerbate the future temperature effects.

Our study contributes in several important ways to the growing body of literature attributing climate impacts on health[5]. First, it makes quantitative predictions for how dengue burden will change under climate warming at the local, sub-national scale across a major swath of its endemic range, which can be used to develop targeted public health planning and responses and compare the consequences of different emissions scenarios. Second, it is among the first studies to attribute changes in infectious disease to climate change—expanding on the attribution literature centered on more direct effects such as heat waves, storms, and fires—providing a road map for future studies on other ecological and health impacts[33,41,39]. Third, this work provides a rare demonstration that theoretical models based on laboratory experiments can capture the thermal biology of complex infectious disease systems, reinforcing the idea that such models can be used to predict climate responses in places with limited existing data. Finally, attribution studies like this one are increasingly used in litigation aimed at holding governments and fossil fuel companies financially accountable for negative societal effects of carbon emissions due to climate change.

Methods

Dengue Case Data To obtain a comprehensive global dataset of dengue cases at the sub-annual and sub-national scale, we searched the Pan-American Health Organization (PAHO) and Project Tycho databases, Ministry of Health websites, and published literature. For Project Tycho, we selected "Dengue" for condition, "Month" as the interval type, and downloaded data for any country with >2 years of data at admin level 1 (state or province) or below. For all countries with endemic cases listed on the WHO website, we found their Ministry of Health (or equivalent) website and navigated to any relevant tabs or databases reporting health data. If we still could not locate relevant data, we searched the following on Google: "[country name] immunological bulletin OR dengue". Additionally, we searched the literature using the same query for references to data sources; however, these were typically not publicly available. We found 25 datasets from 21 countries that span an average of 11 years (Table S1). We excluded datasets that spanned less than 2 years and trimmed our data to the end of 2019 to avoid confounding effects of COVID-19. We aggregated weekly data to monthly as follows: if a week spanned two months we split the cases into months based on the number of days within that week that fell into each month. To obtain incidence from the raw case counts, population size was obtained by summing population count within each administrative boundary (see "Subnational boundaries") in the midyear of the time series, using population counts from WorldPop[42] on available on Google Earth Engine[43]. In total, our dataset consisted of roughly 1.5 million monthly observations of dengue incidence at the first or second administrative level.

Subnational boundaries We matched the names of the subnational administrative units with those in shapefiles downloaded from the Humanitarian Data Exchange[44] except for Taiwan, which was downloaded separately[45]. Because case data in Costa Rica is reported for socioeconomic regions, which does not fall cleanly in administrative level 1 or 2, a shapefile of administrative boundaries within Costa Rica was manually modified to correspond to socioeconomic regions. We used the district (administrative level 3) shapefile and aggregated to six socioeconomic regions based on a mapping from canton (administrative level 2) to socioeconomic region[46]. Four districts (admin level 3) in socioeconomic regions different from the rest of their cantons are switched to the correct socioeconomic region.

Historical temperature data To obtain downscaled daily temperature values with consistent performance across regions, we compared ERA5 daily climate reanalysis product[47] to Global Historical Climatology Network (GHCN) station observations in the countries included in this study. We found that ERA5 temperatures were on average downward biased relative to GHCN station observations, with large (up to 10°C) negative biases at high elevations (Fig. S7). To avoid this differential bias in the ERA5 product, we debias using WorldClim, a high resolution climatology product with monthly average temperature from 1970 - 2000[48]:

$$\widetilde{ERA5}_{idmy} = ERA5_{idmy} - \overline{ERA5}_{im} + WorldClim_{im} \tag{1}$$

where $\widetilde{ERA5}_{idmy}$ is the debiased daily temperature, $ERA5_{idmy}$ is observed ERA5 temperature in location i on day d in month m and year y, $\overline{ERA5}_{im}$ is the month- and location- specific ERA5 climatology over 1970 - 2000 and $WorldClim_{im}$ is the WorldClim climatology over the same time period. We calculate $\overline{ERA5}_{im}$ from monthly average temperature in ERA5 monthly products, and use $ERA5_{idmy}$ from the daily average temperature product available on Google Earth Engine[43]. We find that this correction reduces the mean error between satellite-based temperature estimates and ground-based measurements from the GHCN, especially at higher elevation sites (Fig. S7). We calculate higher powers of debiased temperature data ($\widetilde{ERA5}_{idmy}$) for each day and grid cell before calculating administrative unit - month population-weighted averages using the subnational boundaries described above and WorldPop population estimates[42]. We use the same population-weighted average approach to calculate monthly average precipitation from ERA5.

Climate scenario temperature projections To estimate the change in dengue transmission under future climate change, we use projected temperature from the Coupled Model Intercomparison Project Phase 6 (CMIP6)[49] under different scenarios. In keeping with recommendations from the latest IPCC report[50] and Hausfather et al.[51], we use SSP3-7.0 as a high baseline emissions scenario, and SSP2-4.5 and SSP1-2.6 as medium and low emissions scenarios, respectively. We also consider the historical-natural projections as our counterfactual for historical temperature absent anthropogenic forcing to understand how climate change has already impacted dengue transmission. Of the 39 global climate models (GCMs) available from the CMIP6, we follow recent guidance on excluding "hot models" and limit to models with transient climate response (TCR) in the likely range (1.4 - 2.2°C)[51] using existing TCR calculations for the GCMs[52]. We further limit to models that have monthly temperature available for projections for all three future climate scenarios specified above, resulting in 22 GCMs included in this analysis. A full list of included models and scenarios can be found in Supplementary Table S2.

Given known biases in average temperatures and unreliable daily temperature anomalies in GCMs[53,54] we use the delta change method[55] to calculate temperature under future climate scenarios as follows. We determine the estimated change in temperature from the current period to the mid 21st century as

$$dT_{imgvs} = \overline{T}_{imgvs} - \overline{T}_{imygv0} \tag{2}$$

for location i, month of the year m, model g, variant v and scenario s, where $\overline{T}_{imygvs}$ is the average of monthly temperatures within a specified period (2040 - 2059 for future scenarios, 1995 - 2014 for the historical-natural scenario) and $\overline{T}_{imygv0}$ is the average from the historical scenario for 1995 - 2014. We match variants between scenarios for each GCM when calculating dT, defaulting to the first variant available for all of the desired scenarios run for a GCM, or if no variant is available for all scenarios, a single variant for future scenarios and a separate variant for the historical-natural scenario. Details on variants used for each GCM and scenario are in Supplementary Table S2.

To calculate estimated temperature under different scenarios, we then add the estimated temperature change to debiased daily temperature data ($\widetilde{ERA5}_{idmy} + dT_{imgvs}$), and then aggregate to monthly temperatures as described above. To compare scenarios, we use observed temperatures from 1995 - 2014 for all locations.

Data extraction for moderators For each country, health expenditure per capita expressed in international dollars at purchasing power parity in 2010 was from WHO Global Health Expenditure Database was downloaded from World Bank Open Data[56]. For the Gini index and health expenditure, we selected the year that is the average of all time series midpoints (2010). If this was missing, we took health expenditure from the closest date. We calculated population density using total population from WorldPop[42] (as described above) and diving by the area of the administrative unit. To estimate average dengue incidence at the administrative units, we calculate annual average dengue incidence in the our case data, and scale by the ratio between observed country-level average annual dengue incidence in the case data and country-level incidence estimates (1990 - 2017) from the Global Burden of Diseases[57] to account for potential differences in disease detection rates between countries while still allowing for variation in dengue incidence within countries.

Estimating dengue-temperature responses To obtain an overall estimate of temperature dependence on dengue we used a panel regression. Our model takes the form

$$\log(\text{dengue}_{i,c,m,y}) = f(\text{temp}_{i,c,m,y}) + \text{precip}_{i,c,m,y} + \mu_i + \tau_{c,y} + \sigma_{c,m} + \epsilon_{i,c,m,y} \quad (3)$$

where i is unit, c is country, m is month, and y is year. This model includes an administrative unit fixed effect to control for differences between locations that are consistent over time, a country-year fixed effect to account for country-level patterns over time, and country-month fixed effect to remove seasonal patterns in dengue and temperature. The main specification included population weighting and used cubic polynomials of temperature with 1-3 months of lags, but we also considered functional forms with up to degree 5 and lags from 0 to 4 months. We also tested sensitivity of model estimates to including quadratic effects of precipitation rather than linear, no weighting of estimates, removing Brazil from the sample, fixed effects for country - month - year rather than country - month and country - year, and fixed effects for unit - month rather than country - month (Fig. S4). All models were run as Poisson regressions with the 'fixest' package in R[58]. For countries that had data from multiple sources, we removed any duplicate years from the earlier data source and treated each country-data source as a different "country" for the purpose of fixed effects to allow for potentially different reporting rates between data sources.

To understand how this relationship varies spatially, we interacted the estimated temperature relationship with administrative unit-level covariates including continental region, health expenditure, population density, average dengue incidence:

$$\log(\text{dengue}_{i,c,m,y}) = A_{i,c} \times f(\text{temp}_{i,c,m,y}) + \text{precip}_{i,c,m,y} + \mu_i + \tau_{c,y} + \sigma_{c,m} + \epsilon_{i,c,m,y}, \quad (4)$$

where $A_{i,c}$ is the covariate value for unit i in country c. For continent we divided into Asia and the Americas and for the remaining covariates, we split into terciles with health expenditure terciles being defined at the country-level due to availability of health expenditure data, and population density and dengue incidence terciles defined at the administrative-units. We defined these terciles only accounting for administrative units that reported dengue during the study.

We calculate confidence intervals on estimated temperature responses and marginal effects using stratified bootstraps and analytic confidence intervals based on the Delta method. Stratified bootstraps were conducted using countries as the strata, and sampling administrative units with each country with replacement, then using the full time series for each sampled administrative unit in the bootstrap sample. Bootstrapped confidence intervals were only slightly wider than analytic confidence intervals calculated with the delta method (Fig. S4, so alternative model specifications and models with heterogeneous effects are shown with analytic confidence intervals, while main model estimates and continent-specific estimates used in projections are bootstrapped.

Attributing existing dengue burden and projecting future impacts Using the estimated temperature relationship $f(\text{temp}_{i,c,m,y})$, we calculate the change in dengue incidence due to temperature changes as

$$\% \text{ change in dengue}_{s,i,c,m,y} = \exp(f(\text{temp scenario}_{s,i,c,m,y}) - f(\text{temp observed}_{i,c,m,y})) - 1, \quad (5)$$

where s indexes the scenario of interest (SSP1-2.6, SSP2-4.5, SSP3-7.0, historical-natural forcing). We use debiased monthly ERA5 data for observed temperatures and monthly climate projections (described above) for scenario temperatures. We estimate the percent change in dengue for the specified GCMs (22 for future scenarios, 10 for historical - natural forcing, see Table S2) using 50 of the bootstrapped estimated temperature response to incorporate uncertainty from both the model estimates and the climate scenarios. For each GCM and bootstrap, we calculate the average percent change in dengue over the 20 years of temperature data for each administrative unit. To estimate administrative unit-specific effects, we then calculate medians and 95% confidence intervals over 1100 estimates from the GCMs and bootstraps. Similarly, to estimate country-level and overall effects, for each bootstrap and GCM we calculate a population-weighted average of the administrative unit averages, then calculate the median and 95% CI over the 1100 estimates for each scenario. To compare the between two future climate scenarios (particularly between SSP1-2.6 and SSP3-7.), we use the scenario temperatures in equation 5 instead of observed temperatures. We project future impacts using both the main model bootstrapped estimates and the continent-specific estimates.

Data availability Data is available upon request and code to replicate all results in the main text and supplementary materials will be made available at https://github.com/marissachilds/global-dengue-temperature.

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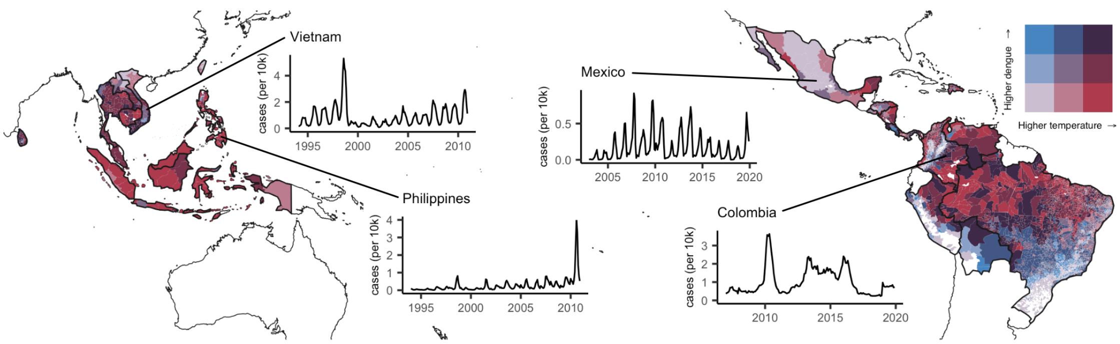

Figure 1: **Subnational data on dengue and temperature from 21 countries.** Darker red indicates warmer temperatures and darker blue indicates higher incidence of dengue. Insets show four examples of epidemic dynamics in different countries.

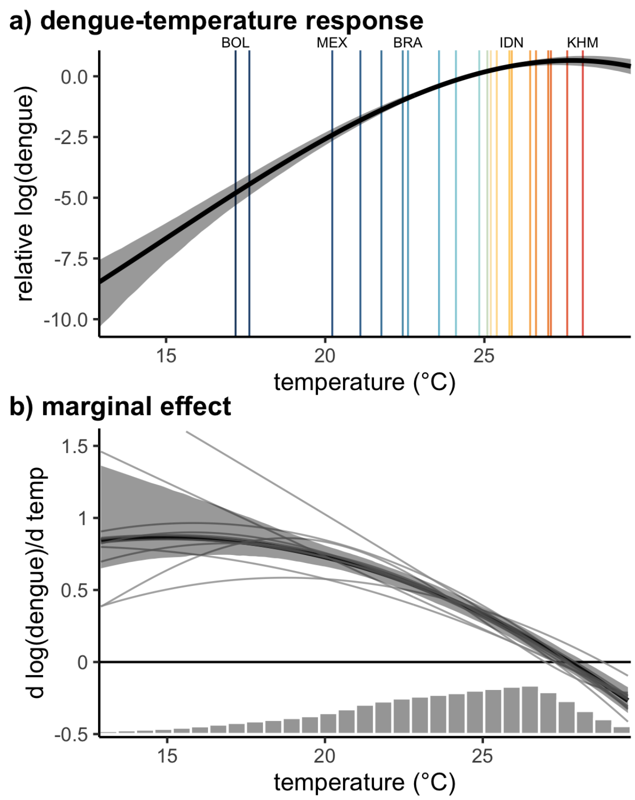

Figure 2: **Effect of temperature on dengue.** (a) Global nonlinear relationship between dengue cases and temperature and (b) the slope of that relationship indicating the marginal effect of temperature on dengue incidence. Main panel regression model fit in black with 95% confidence interval in gray shading. Vertical lines in (a) indicate country mean temperatures, with labels highlighting the coldest and warmest countries as well as the three highest population countries in the sample: Bolivia (BOL), Mexico (MEX), Brazil (BRA), Indonesia (IDN), and Cambodia (KHM). Thin gray lines in (b) represent variations on the main model using alternative specifications. Histogram in (b) shows the distribution of observed monthly temperatures. Model estimates are restricted to the 1st to 99th percentiles of the observed temperature distribution.

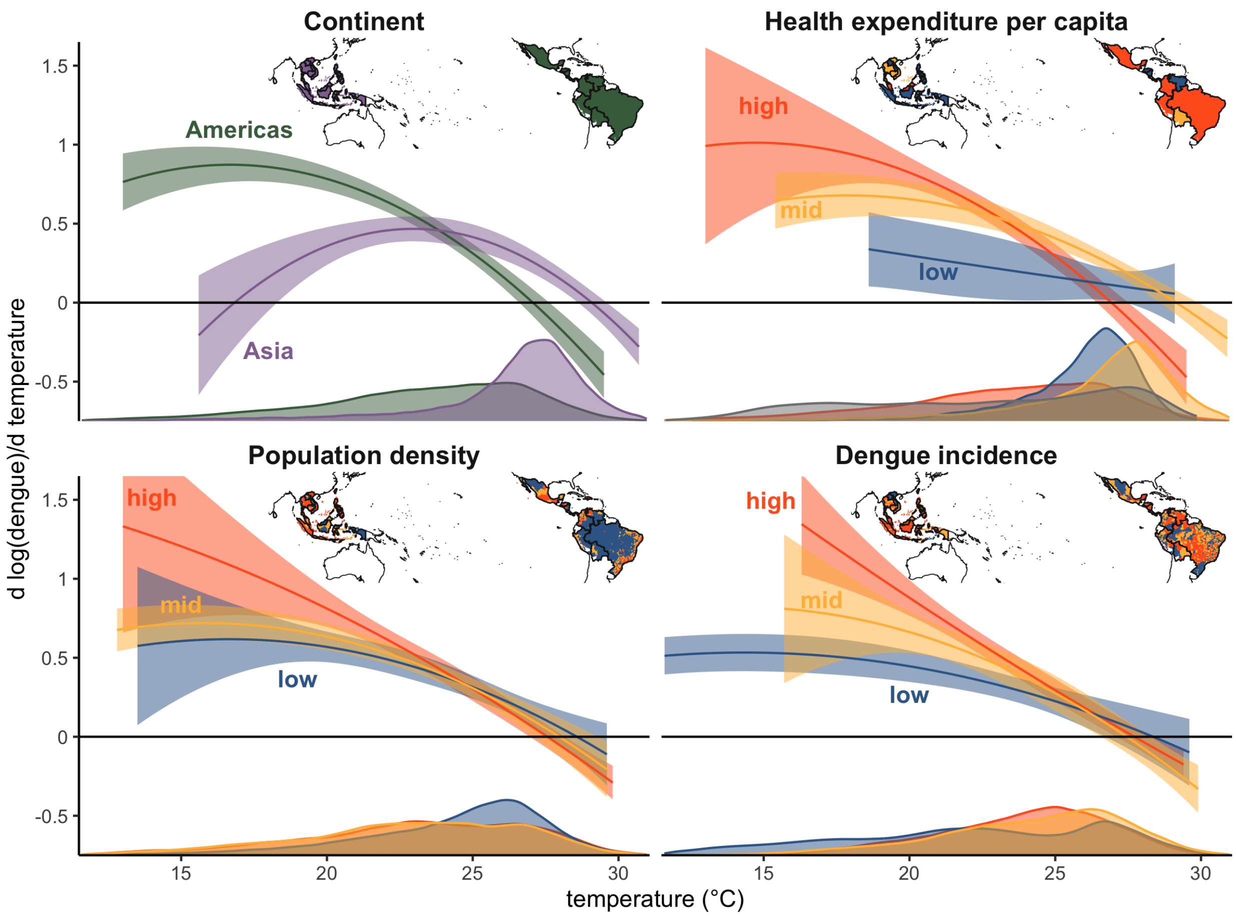

Figure 3: **Spatial heterogeneity in the dengue-temperature relationship.** Marginal effect of temperature on dengue incidence by (a) continental region, (b) health expenditure tercile, (c) population density tercile, and (d) dengue incidence tercile. Dengue incidence and population density are subnational covariates, and continent and health expenditure are country-level covariates. Lines are the mean estimates and shaded areas are 95% confidence intervals, with estimated marginal effects trimmed to the 1st to 99th percentiles of the observed temperature distribution for each tercile or continental region. Where relevant, confidence intervals were truncated for visibility. Density plots show the distribution of monthly temperatures for each tercile or continental region and inset maps depict the spatial units included in each tercile for the different covariates, with colors matching those of the estimated marginal effects in each panel.

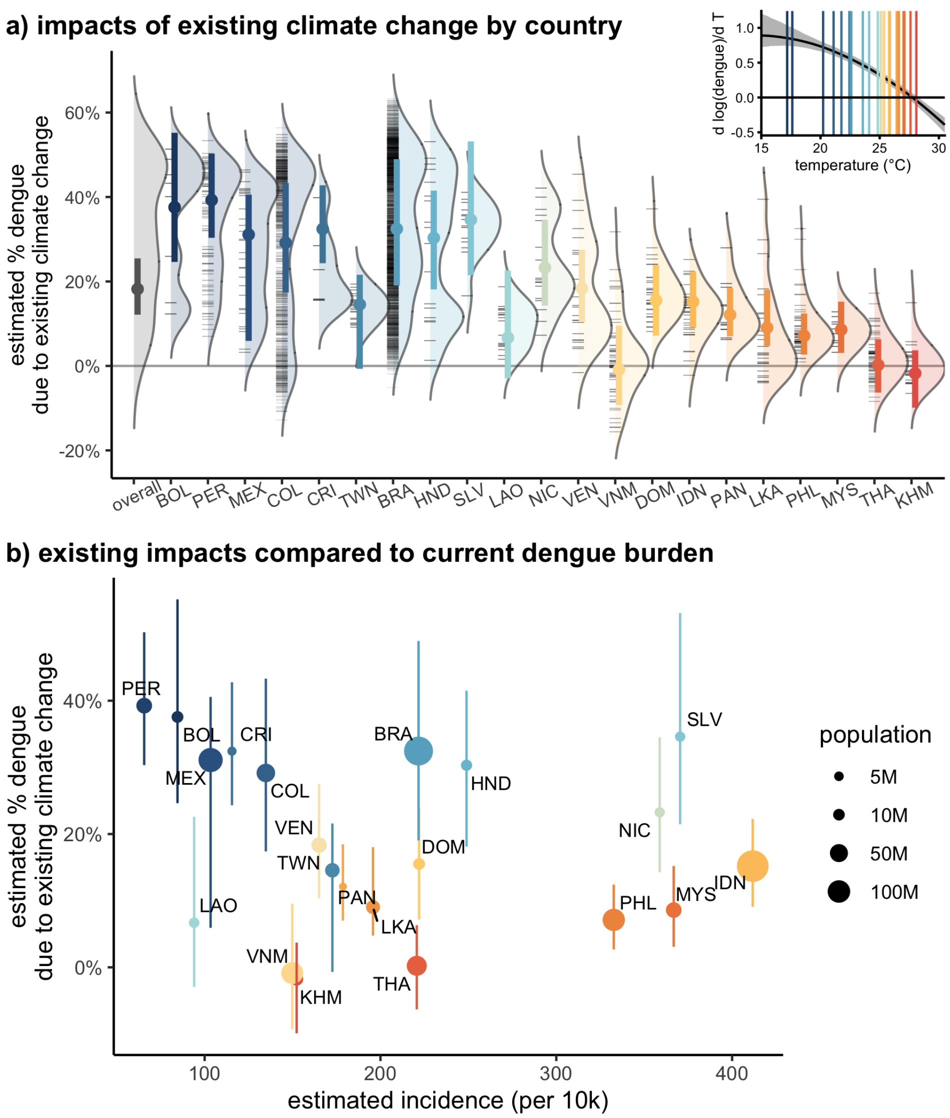

Figure 4: **Climate change has already contributed to increases in dengue.**(a) Distributions show estimated median percent of the dengue burden that is attributable to anthropogenic climate warming across administrative units within each country, estimated as the average % change between observed and counterfactual climate from 1995-2014. Black tick marks indicate individual unit median values, and colored points and bars show the median and 95% CI of the population-weighted average estimate by country. Countries are ordered by current average temperatures with warmer countries to the right. Only administrative units with reported dengue are included in the distributions and country averages. Inset: marginal effect of temperature on dengue from the main model specification, with country-average temperatures indicated with vertical lines matching the colors in the main panel. (b) Climate change to date has already increased dengue transmission. These impacts are largest in cooler countries where current incidence is low, but impacts are also substantial in moderate temperature countries with high current dengue burdens (e.g., Brazil, Honduras, El Salvador, and Nicaragua). Point colors (indicating temperature) are the same in (a) and (b) and point sizes in (b) indicate population size. Line ranges are 95% CIs as in (a).

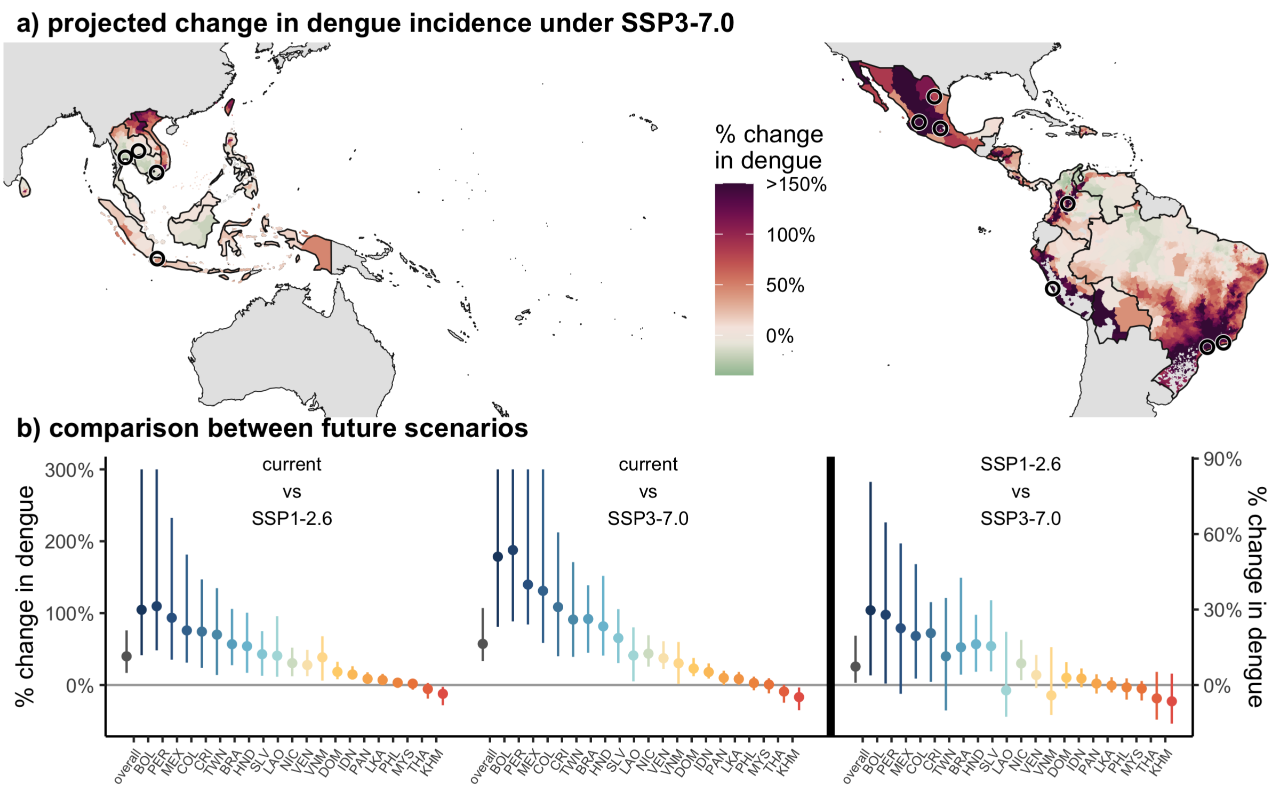

Figure 5: **Estimated impacts from climate change for 2040-2059 are widespread and largest in more temperate regions, but few places will become too warm.** (a) Most locations are expected to see an increase in dengue under climate change, with a small fraction of locations seeing slight declines due to temperatures exceeding the current predicted optimal temperature. Many of the areas where large increases are predicted (shown in dark red), especially in the Americas, are areas with large cities and high population density. Black circles show cities over 5M in population. Administrative units are colored by the median percent change in dengue incidence under the high emissions scenario at mid-century (SSP3-7.0 in 2040-2059) compared to current temperatures (1995-2014). (b) Across all future climate scenarios, dengue incidence is predicted to increase for a majority of countries, with the largest increases in cold countries (left panel), and these impacts are estimated to be up to 30% larger under the highest emissions scenarios compared to the lowest (right panel). Countries retain ordering by average temperature, and country colors are consistent across all figures. Points show median estimates and lines show 95% CIs. Confidence intervals are truncated to 300% for visibility.

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Supplemental Information

January 8, 2024

Table S1: Raw dengue data sources and information. MoH = Ministry of Health

Country	Spatial resolution	Number of administrative units	Original temporal resolution	Start date	End date	Data source
BOL	Admin 1	9	weekly	12/1/13	12/31/19	PAHO
BRA	Admin 2	5570	weekly	1/1/01	12/31/19	MoH DATASUS
COL	Admin 2	1122	weekly	1/1/07	12/31/19	MoH SIVIGILA
CRI	Admin 1	6	weekly	1/1/12	12/31/19	MoH
DOM	Admin 2	32	weekly	1/1/07	12/31/18	MoH DIEPI
HND	Admin 1	18	weekly	1/1/17	6/30/19	PAHO
IDN	Admin 1	34	monthly	1/1/00	12/31/17	Tycho
KHM	Admin 1	25	monthly	1/1/98	12/31/10	Tycho
LAO	Admin 1	18	monthly	1/1/98	12/31/10	Tycho
LKA	Admin 2	25	monthly	1/1/10	12/31/19	MoH Epidemiology Unit
LKA1	Admin 1	9	monthly	1/1/96	12/31/04	Tycho
MEX	Admin 1	32	weekly	1/1/03	12/31/19	MoH
MYS	Admin 1	16	monthly	1/1/93	12/31/10	Tycho
NIC	Admin 1	17	monthly	1/1/00	12/31/04	Tycho
NIC	Admin 1	17	weekly	1/1/04	12/31/19	PAHO
PAN	Admin 1	13	weekly	1/1/18	12/31/19	PAHO
PER	Admin 2	196	weekly	1/1/10	12/31/19	CDC Peru
PHL	Admin 2	87	monthly	1/1/94	12/31/10	Tycho
SLV	Admin 1	14	monthly	1/1/00	8/31/09	Tycho
THA	Admin 1	77	monthly	1/1/93	12/31/10	Tycho
THA	Admin 1	77	monthly	1/1/11	12/31/19	MoPH
TWN	Admin 2	22	weekly	1/1/05	12/31/19	Taiwan NIDSS
VEN	Admin 1	25	monthly	1/1/99	3/31/05	Tycho
VEN	Admin 1	25	weekly	1/1/17	12/31/19	PAHO
VNM	Admin 1	63	monthly	1/1/94	12/31/10	Tycho

Table S2: GCM scenarios and variants included in projections.

	GCM	historical-natural	future
1	ACCESS-CM2	r1i1p1f1	r1i1p1f1
2	ACCESS-ESM1-5	r1i1p1f1	r31i1p1f1
3	AWI-CM-1-1-MR		r1i1p1f1
4	BCC-CSM2-MR	r1i1p1f1	r1i1p1f1
5	CAMS-CSM1-0		r1i1p1f1
6	CESM2	r1i1p1f1	r4i1p1f1
7	CESM2-WACCM		r1i1p1f1
8	CNRM-CM6-1	r1i1p1f2	r1i1p1f2
9	CNRM-ESM2-1		r1i1p1f2
10	FGOALS-f3-L		r1i1p1f1
11	GFDL-ESM4	r1i1p1f1	r1i1p1f1
12	GISS-E2-1-G	r1i1p1f2	r1i1p3f1
13	GISS-E2-1-H		r1i1p1f2
14	IITM-ESM		r1i1p1f1
15	KACE-1-0-G		r1i1p1f1
16	MCM-UA-1-0		r1i1p1f2
17	MIROC-ES2L		r1i1p1f2
18	MIROC6	r1i1p1f1	r1i1p1f1
19	MPI-ESM1-2-HR		r1i1p1f1
20	MPI-ESM1-2-LR		r1i1p1f1
21	MRI-ESM2-0	r1i1p1f1	r1i1p1f1
22	NorESM2-LM	r1i1p1f1	r1i1p1f1

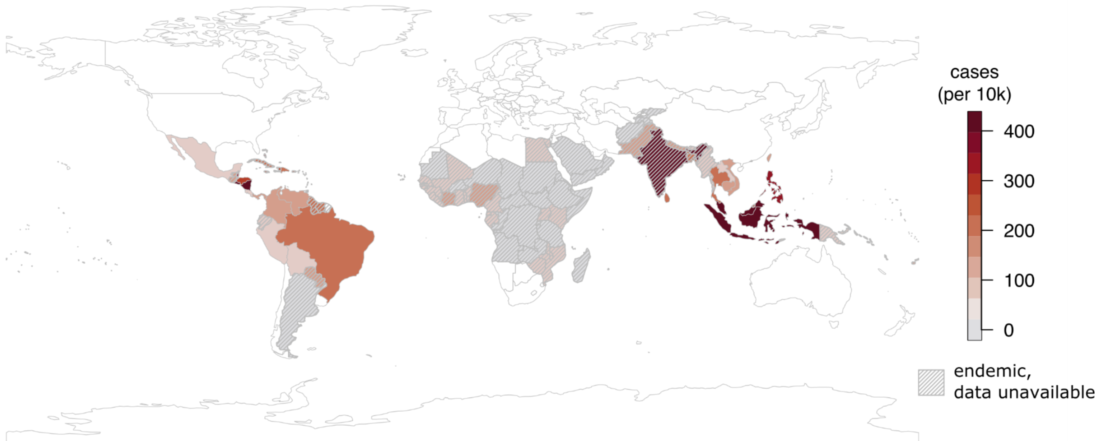

Figure S1: **Availability of dengue data in endemic areas.** Shading indicates no subnational subannual data was available for that country. Dengue cases are annual estimates (Zeng et al. 2021).

Table S3: Projected percent change in dengue incidence for countries under different climate scenarios. Numbers are median estimates followed by 95% CIs.

country	current vs no anthropogenic forcing	current vs SSP3-7.0	current vs SSP2-4.5	current vs SSP1-2.6	SSP1-2.6 vs SSP3-7.0
overall	-18.2% (-25.5- -12.1%)	57.3% (33.3-107.1%)	54.2% (27.6-98.3%)	39.9% (16.8-76%)	7.3% (0.9-19.6%)
BOL	-37.6% (-55.2- -24.6%)	178.5% (80.9-917.8%)	151.2% (69.1-754.4%)	104.7% (41.5-461.5%)	29.7% (3.8-80.7%)
PER	-39.3% (-50.3- -30.3%)	187.7% (88.5-389.3%)	162.8% (75-363.7%)	109.6% (48.2-306.1%)	27.9% (0.6-64.6%)
MEX	-31.1% (-40.6- -5.9%)	139.7% (84.2-354.5%)	132.4% (66.9-280.3%)	93.5% (35.2-232.5%)	22.6% (-3.5-56.3%)
COL	-29.2% (-43.3- -17.4%)	131% (58.5-305%)	111.4% (48.5-264.6%)	75.9% (31.1-181.4%)	19.5% (2.6-48%)
CRI	-32.4% (-42.8- -24.3%)	108.5% (40-212.3%)	95.7% (50.8-189.8%)	74.3% (23.8-146.9%)	20.6% (1.3-32.9%)
TWN	-14.6% (-21.6-0.7%)	91.1% (39.1-171%)	89% (27.5-162.1%)	70.1% (13.9-134.7%)	11.4% (-10.1-34.6%)
BRA	-32.4% (-49- -19%)	91.8% (44.8-138.8%)	81.4% (23.7-150.6%)	56.8% (27.6-105.9%)	15% (4.1-42.6%)
HND	-30.3% (-41.5- -18.1%)	81.7% (40.9-151.8%)	68.8% (31.9-129.5%)	54% (17-100.6%)	16.2% (5.3-27.9%)
SLV	-34.6% (-53.2- -21.5%)	65.3% (30.5-105.6%)	56.7% (21.4-94.6%)	42.9% (12.8-74.9%)	15.5% (5.4-33.7%)
LAO	-6.7% (-22.6-2.9%)	41.1% (5.1-80.2%)	45.1% (9.3-75.9%)	40.7% (11.5-95.7%)	-2.1% (-12.6-21.1%)
NIC	-23.3% (-34.5- -14.3%)	43.7% (25.6-69.2%)	39.9% (20.7-62.8%)	30.5% (12.2-52%)	8.6% (1.9-17.9%)
VEN	-18.3% (-27.5- -10.3%)	37.3% (22.3-60.9%)	34.8% (21.6-58.9%)	27.8% (12.3-48.9%)	4% (-1.2-12%)
VNM	0.9% (-9.5-9.3%)	30.3% (1.6-59.9%)	40.2% (5.1-71.7%)	38.5% (6.1-67.8%)	-4.1% (-11.9-15%)
DOM	-15.5% (-23.9- -7.2%)	22.9% (12.2-37.6%)	22% (12.4-37.9%)	18.4% (8-32.3%)	2.9% (-1.4-9.1%)
IDN	-15.2% (-22.3- -9.1%)	18.1% (9-30.1%)	17.2% (8.7-28.3%)	14.7% (7.6-26.1%)	2.6% (-0.9-6.6%)
PAN	-12.1% (-18.5- -7%)	9.9% (0.1-19.9%)	9.7% (0.4-18.5%)	8.6% (1.9-17.7%)	0.6% (-3.4-4.3%)
LKA	-9% (-18- -4.8%)	8.4% (0.3-18.2%)	8% (0.4-17.3%)	6.9% (0.9-15.5%)	-0.2% (-3-3.1%)
PHL	-7.1% (-12.4- -2.7%)	2.8% (-7.3-11.7%)	3.2% (-5.6-11.1%)	3.2% (-3.9-9.6%)	-0.9% (-5.8-2.6%)
MYS	-8.6% (-15.2- -3.1%)	0.7% (-11.6-9.4%)	1.2% (-9-9.2%)	1.9% (-6.4-7.9%)	-1.4% (-6.2-1.6%)
THA	-0.2% (-6.3-6.3%)	-9.1% (-24.6-0.3%)	-8.3% (-21.3-1.4%)	-5.6% (-18.9-2.9%)	-5.3% (-13.8-5.2%)
KHM	1.8% (-3.7-9.9%)	-16.8% (-35- -3.4%)	-16% (-33.9- -6%)	-12.2% (-28.1- -2.5%)	-6.5% (-15.4-4.5%)

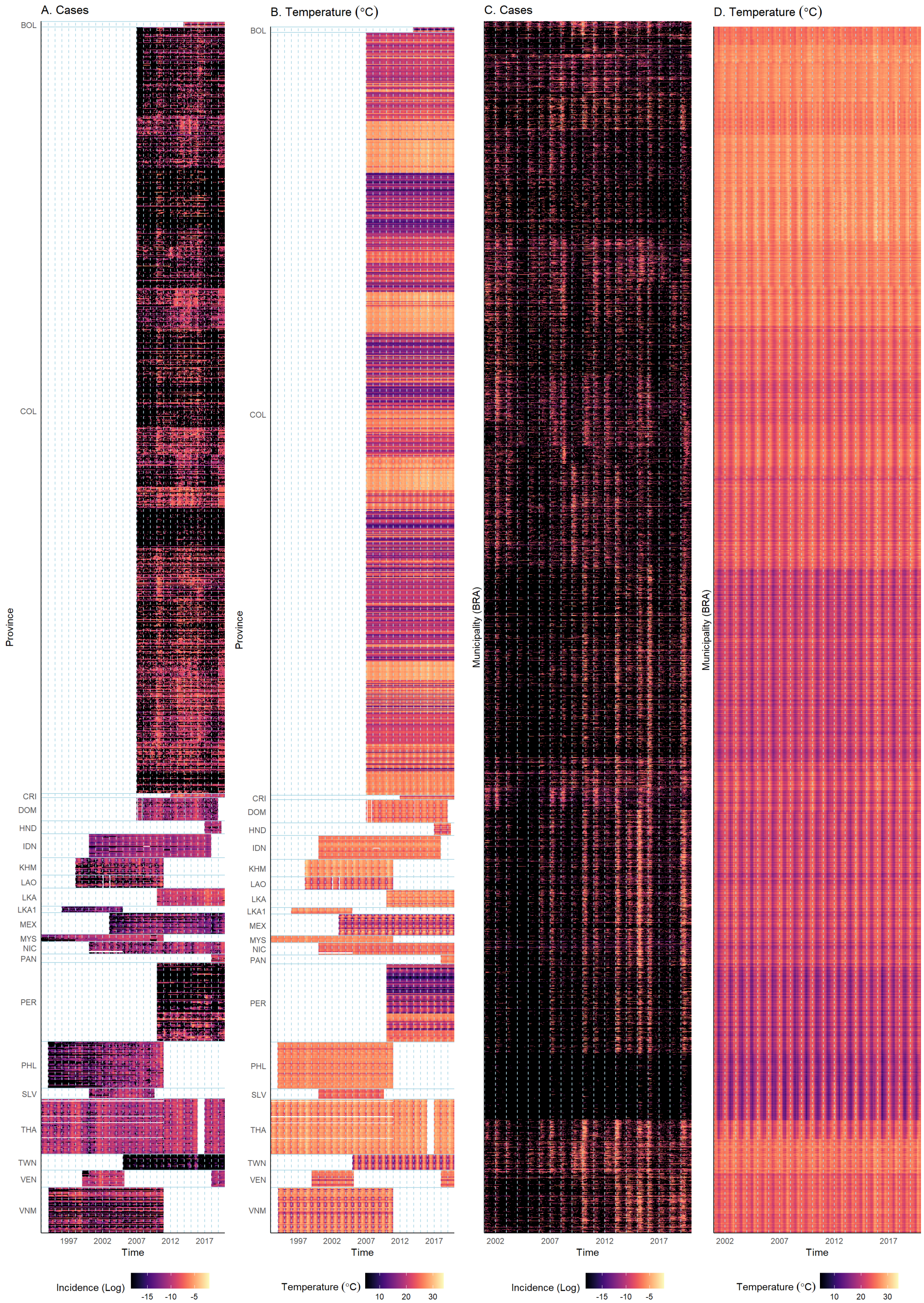

Figure S2: **Heatmap of logged monthly dengue incidence and temperature for subnational administrative units.** Months with no data are indicated in white while months with no cases are indicated in black. Countries are indicated on the left by their three-letter codes and horizontal lines separate spatial units in different countries. Vertical dashed lines separate years.

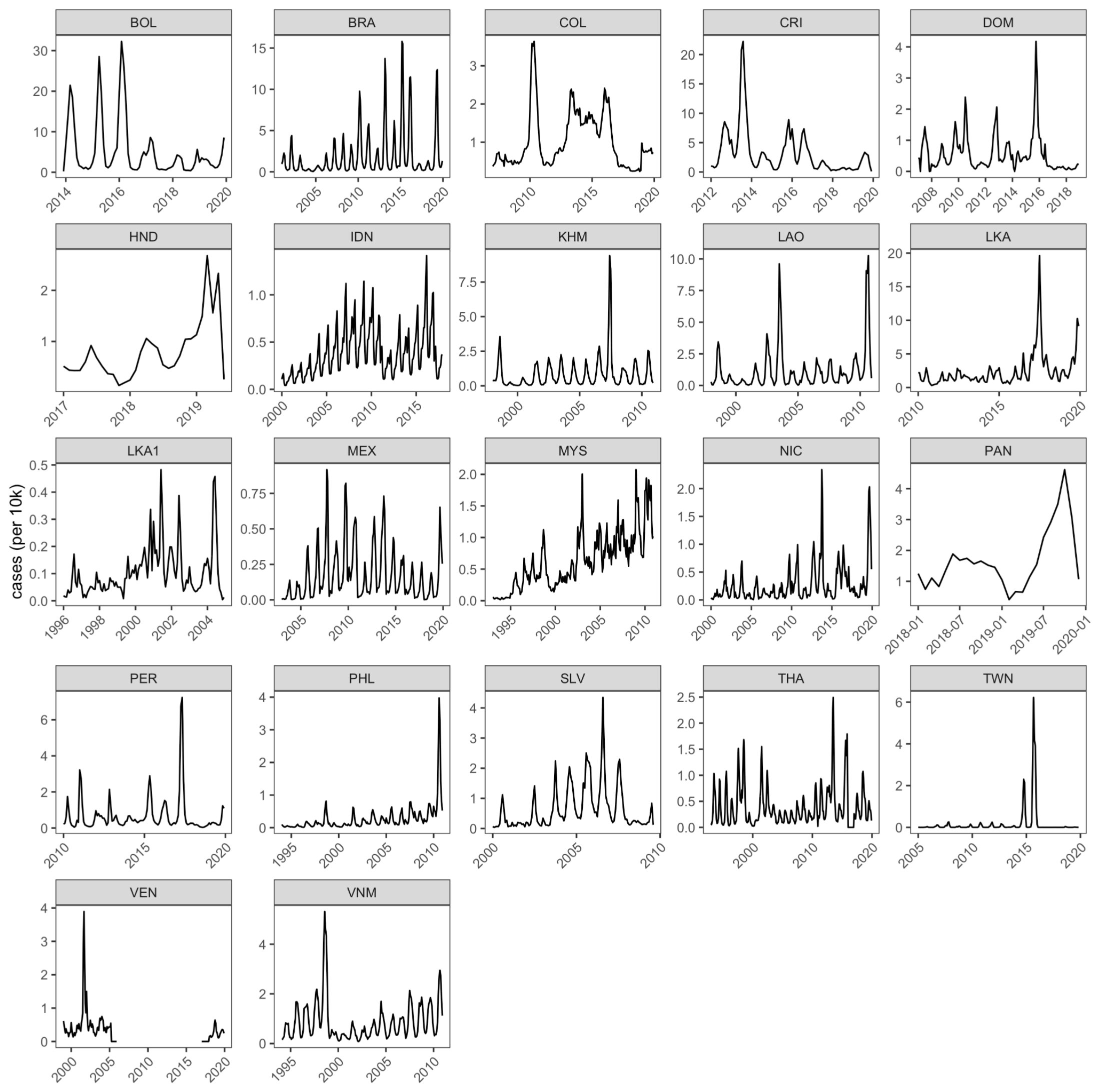

Figure S3: **Epidemic dynamics of dengue in each of 21 countries.** Monthly time series of dengue incidence by country.

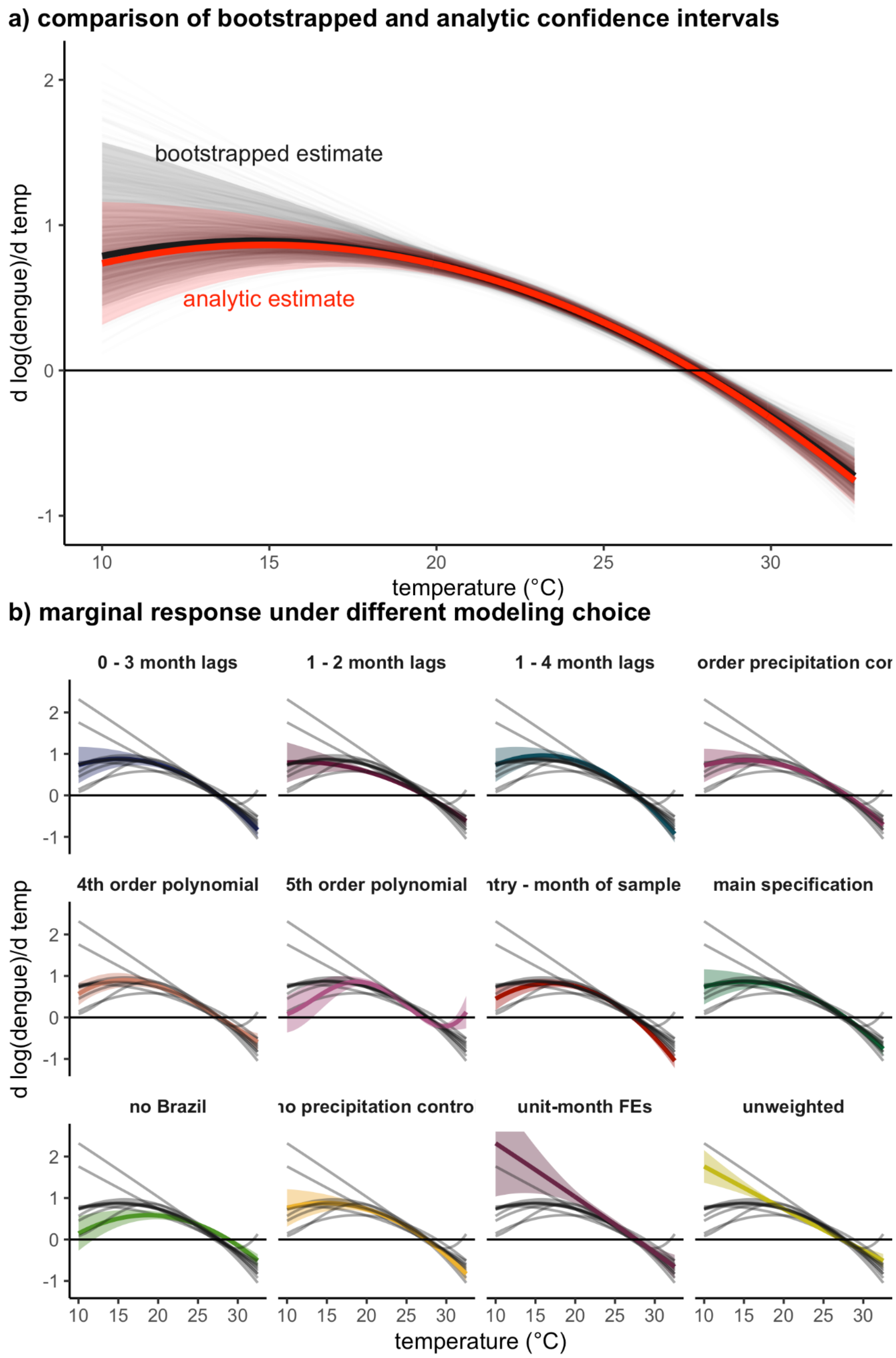

Figure S4: **Sensitivity of results to modelling choices.** (a) Comparison of 95% confidence intervals produced through bootstrapping (gray shaded region) to those produced through an analytic approach (red shaded region). Individual bootstraps are shown in gray lines. (b) The marginal response of dengue to temperature under model variations.

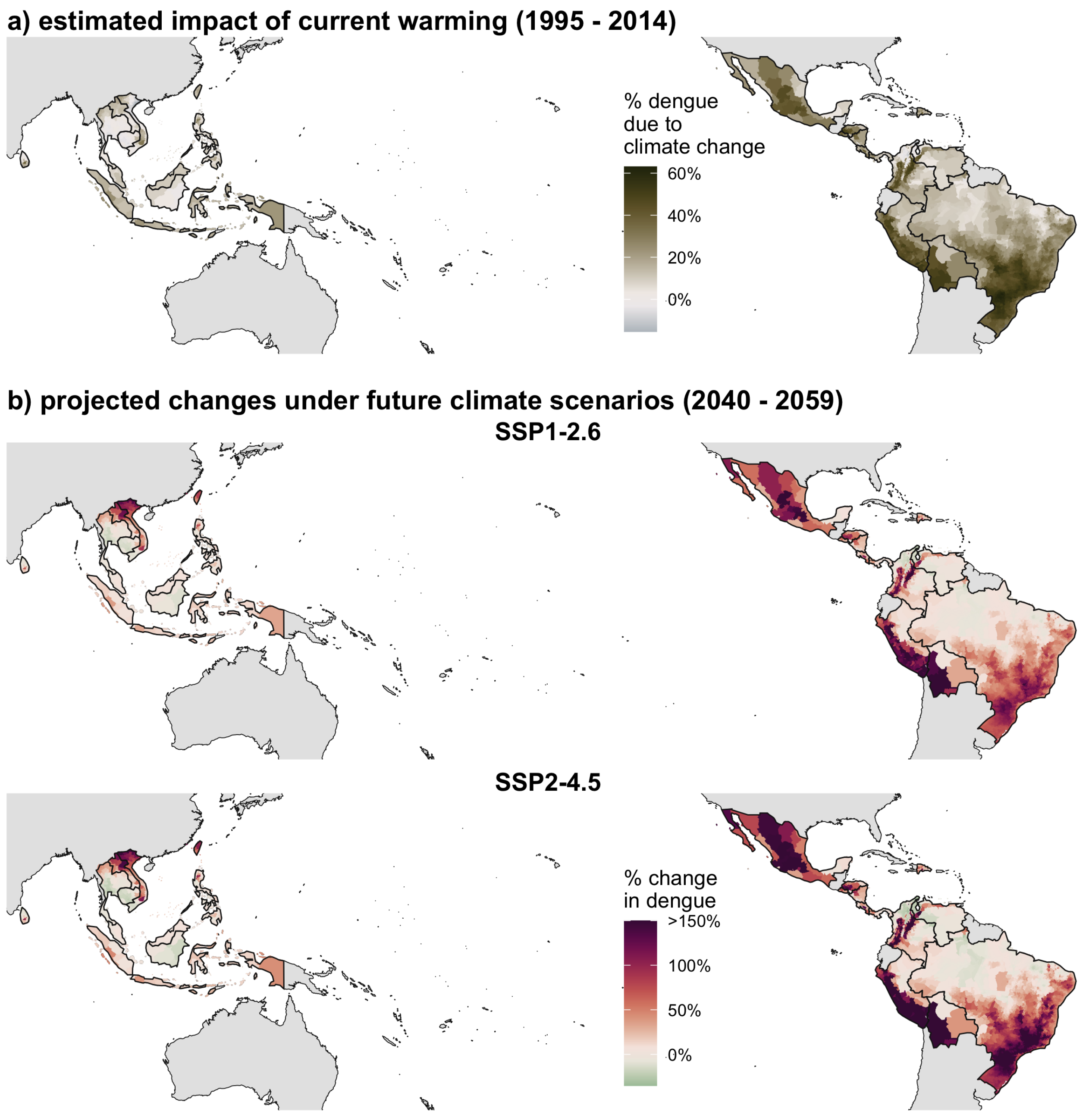

Figure S5: **Maps of impacts of current and future climate warming.** (a) Projected change in dengue under climate scenarios SPP1-2.6 and SPP2-4.5 from 2040-2059. (b) Estimated change in dengue due to current warming (1995-2014) estimated from observed temperatures relative to a model with no anthropogenic forcing.

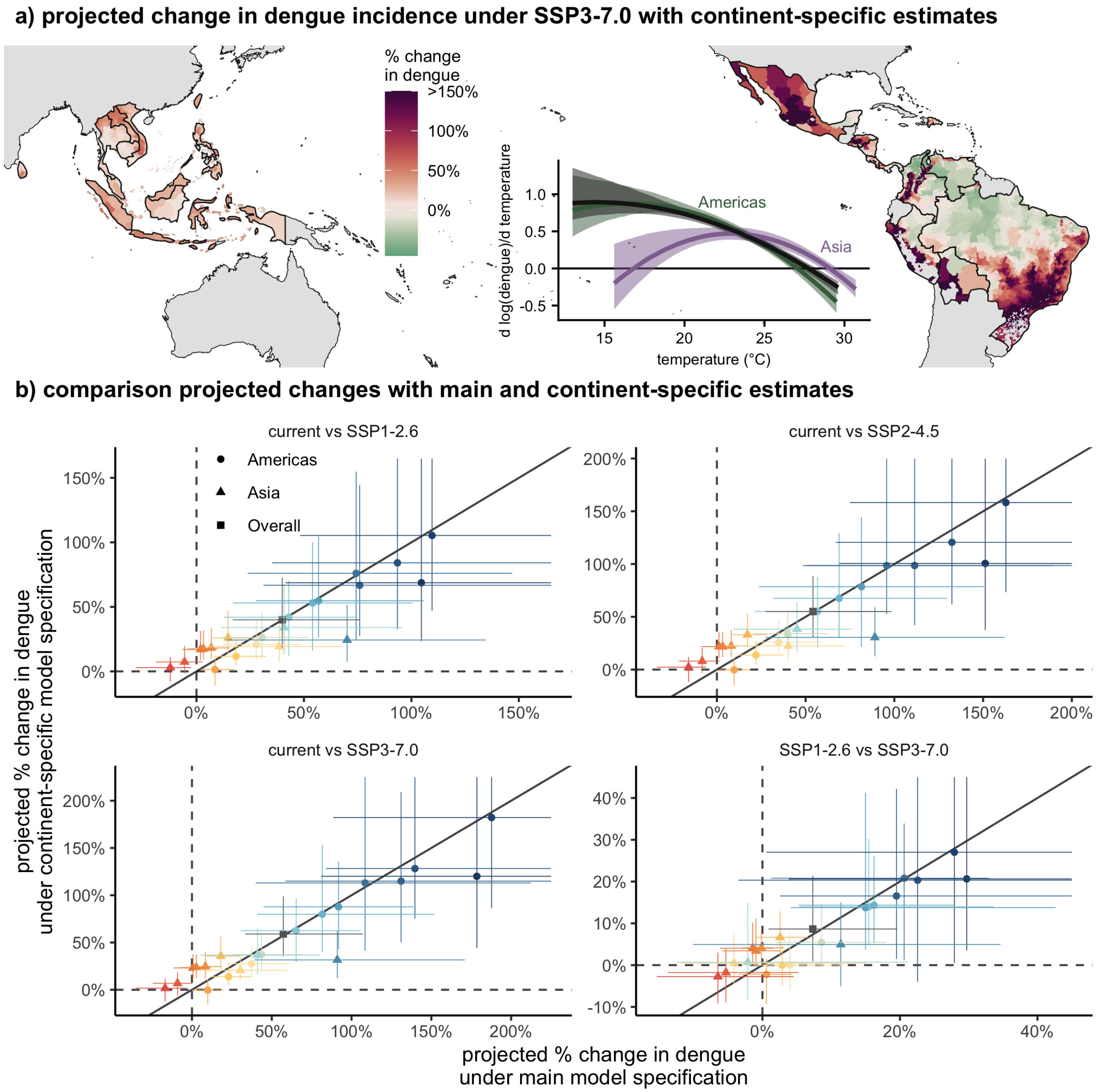

Figure S6: **Projections with continent-speficic temperature responses** (a) Projected change in dengue incidence under climate scenario SSP3-7.0 from 2040-2059 based on continent-specific temperature responses. Inset figure shows continent-specific temperature responses for the Americas (green) and Asia (purple) as well as main specification (black) for comparison, (b) Comparison between country average projected changes with the main model (horizontal axis) and continent-specific model (vertical axis)for different future scenarios. Points are median estimates and line segments indicate 95% CIs. Black diagonal line indicates 1-1. Colors match country colors in Fig. 5.

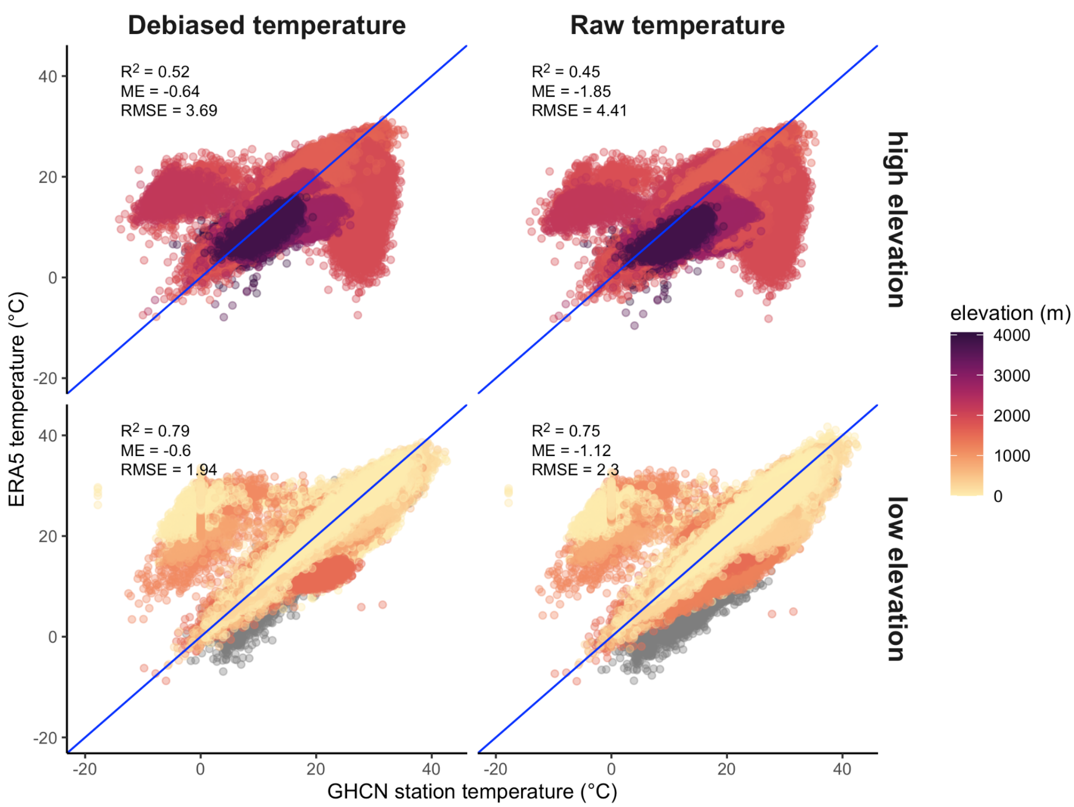

Figure S7: **ERA5 temperature is debiased using WorldClim.** ERA5 temperature is shown against GHCN weather station data. The ERA5 temperature bias, especially prevalent at high elevations, is reduced using monthly WoldClim climatology. Each point is a station-day with points colored by station elevation. High elevation is defined as stations above 1500 meters. Grey points are missing elevation information in the GHCN data set and are included in the low elevation category. R^2 from a linear regression of ERA5 temperature on GHCN station temperature, mean error (ME), and root mean squared error (RMSE) are shown in each panel.