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# Landscape and climatic drivers of dengue fever in Lao People's Democratic Republic and Thailand: a retrospective analysis during 2002–2019

Sumaira Zafar · Joacim Rocklöv · Richard E. Paul · Oleg Shipin · Md. Siddikur Rahman · Chamsai Pientong · Sirinart Aromseree · Petchaboon Poolphol · Mayfong Mayxay · Tiengkham Pongvongsa · Nanthasane Vannavong · Hans J. Overgaard · Ubydul Haque

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## Abstract

**Context** Dengue is a major public health threat in the Lao People's Democratic Republic (Laos) and Thailand. Dengue transmission is ecologically complex. Concurrently identifying both climate and landscape-based risk factors for dengue virus transmission is necessary to improve dengue prevention and control efforts in Laos and Thailand.

**Objectives** The objective of this study was to determine how changes in climate (temperature and rainfall), and land use (e.g. built-up areas, agricultural crops, fruit orchards, rubber plantations) and land cover (e.g. evergreen and deciduous forests, permanent and temporary wetlands) affect dengue risk in four provinces in southern Laos and north-eastern Thailand during 2002 to 2019.

**Methods** A conditional autoregressive Bayesian spatiotemporal modeling framework was used to analyze the risk of dengue by spatiotemporal variations in land use and land cover (LULC) and climatic parameters.

**Results** The average annual temperatures in the study area increased by 0.44–0.94 °C during the

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Hans J. Overgaard and Ubydul Haque are Joint senior authors.

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study period. The model indicated that an increase of 1 °C in weekly average temperatures (up to a 29 °C threshold level) increased the average dengue risk by up to 24% in the two Lao provinces and 18.9% in the two Thai provinces. The model suggested that a rainfall increase of 1 mm up to 60 mm increased dengue risk by 1.8–3.2%. A 0.6–1.6% increase in built-up land use increased dengue risk by 1.8–6.9%. Built-up areas and rubber plantations were positively associated with dengue in the Ubon Ratchathani province of Thailand, while wetlands were negatively associated with dengue cases in the Savannakhet province of Laos.

**Conclusions** Changes in dengue risk were clearly related to increases in rainfall and temperature as well as changes in LULC in both Laos and Thailand. These insights may inform community-based dengue control activities by targeting geographically localized areas (microgeographic scale) to deploy dengue control activities more effectively in these highly endemic regions.

**Keywords** Dengue · Vectors · Bayesian · Climate change · Land use and landcover

## Introduction

Dengue fever is the most important vector-borne viral disease in terms of global morbidity and mortality (Rogers and Randolph 2006; Brady et al. 2012; Ebi and Nealon 2016). Half of the global population lives in dengue-risk areas. The burden of dengue in Southeast Asian countries has been estimated to be

21.1 million infections per year (Brady et al. 2012; Stanaway et al. 2016; Zeng et al. 2021). Dengue fever is caused by a Flavivirus consisting of four serotypes (DENV1-4). The virus is primarily transmitted by *Aedes aegypti* and *Aedes albopictus* mosquitoes (WHO 2024). Increased dengue risk is generally associated with unregulated urban development, poor vector control, and globalization (Gubler 2011). There is no effective cure for dengue and vaccines have experienced setbacks, therefore vector control remains the main disease dengue control method. The goals of the 2012–2020 Global Strategy for Dengue Prevention and Control were to reduce global dengue-attributable mortality by 50% and morbidity by 25% (WHO 2024). These goals were not reached. A new set of goals issued by the Global Vector Control Response for 2017–2030 aims to reduce global mortality and morbidity due to vector-borne diseases, including dengue, by at least 75% and 60%, respectively (WHO 2024). Despite such global efforts, dengue transmission is increasing, resulting in a historic peak in 2023 of >5 million cases and >5000 dengue-related deaths reported globally (WHO 2023). The failure to reach global goals calls for exploring alternative approaches to vector control.

A better understanding of the spatial and temporal risk factors of dengue, such as local, regional, and global climate factors as well as local environmental and land use factors may support innovative integrated vector management alternatives (WHO 2004). Such vector control initiatives may involve various environmental and landscape management interventions (Overgaard et al. 2003;

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Overgaard 2006). DENV transmission is influenced by environmental factors such as landscape characteristics, climate, and socioeconomic and human factors. For example, mosquito eggs laid in a suitable environment such as household containers or tree holes, can hatch after being submerged in rainwater. Land use and land cover (LULC) characteristics, such as temporary and permanent wetlands, may provide *Aedes spp.* oviposition sites. LULCs were found associated with dengue in Bangladesh (Hashizume et al. 2012) and Malaysia (Cheong et al. 2014). Flooding can transiently reduce the transmission risk by flushing out larvae and pupae, but residual temporary wetlands can increase the risk for extended periods (Liyanage et al. 2016; McClure et al. 2018). Tree crops/plantations such as rubber, palm, and pineapple plantations in South and Southeast Asian countries were positively related to dengue (Ponlawat and Harrington 2005; Calderón-Arguedas et al. 2015; Tangena et al. 2016), as they provide natural oviposition sites for *Ae. albopictus* (Ponlawat and Harrington 2005; Calderón-Arguedas et al. 2015; Brown et al. 2018). Rice wetland crops are also suspected of hosting dengue vectors, but no clear evidence has been reported (Jamieson et al. 1994; Yasuoka and Levins 2007; Sarfraz et al. 2012). *Aedes spp.* can adapt to modified bio-ecological settings and changes in LULC can support their proliferation (Powell and Tabachnick 2013; Pereira-Dos-Santos et al. 2020), making disease control difficult.

The complexity of using climate and environmental data for dengue control requires advanced modelling capabilities and models that can detect spatiotemporal heterogeneity of relevant factors. Several studies have used multivariate zero-inflated Poisson regression model to assess the impact of climate and environmental variables on DENV transmission and proposed prioritize high-risk areas for control strategies in Bhutan, Vietnam, Australia, and Thailand (Vannavong et al. 2017; Tsheten et al. 2020; Akter et al. 2021; Colón-González et al. 2021). Several Bayesian modeling frameworks have been used to model the spatiotemporal dengue risk due to climate (Lowe 2015; Phung et al. 2018; Bett et al. 2019; Tsheten et al. 2020; Colón-González et al. 2021) and LULC change (Martínez-Bello et al. 2017; Lim et al. 2020; Valentine et al. 2020; Ye and Moreno-Madriñán 2020; Akter et al. 2021). Results indicate significant impacts of climate variations on

dengue, especially temperature. Most of these studies used few LULC variables and averaged data across short study periods of three to 6 years (Phung et al. 2018; Tsheten et al. 2020; Ye and Moreno-Madriñán 2020; Akter et al. 2021), except two with more than 10 years (Bett et al. 2019; Lowe et al. 2021), which ultimately restricts the temporal estimation of dengue risk.

Understanding the relationships between spatiotemporal patterns of dengue, climate, and land use are important to overcome the limitations of short-term outbreak management and provide longer temporal estimates of dengue risk for more strategic long-term management. Therefore, the overall purpose of this study was to analyze how the spatiotemporal patterns of dengue, climate, and land use affect dengue risk four provinces in southern Laos and north-eastern Thailand, that have high annual numbers of dengue virus (DENV) infections (Johansson et al. 2009; Tangena et al. 2016, 2017; Thongyuan and Kittayapong 2017; Vongpunsawad et al. 2017; Miot et al. 2020). The specific objectives were to determine the effects of (1) changes in temperature and rainfall, (2) changes in land use (e.g. built-up areas, agricultural crops, fruit orchards, rubber plantations) and (3) changes in land cover (e.g. evergreen and deciduous forests, permanent and temporary wetlands) during 2002 to 2019 (4) and estimation posterior median annual relative risk of dengue per administrative unit in the four provinces.

## Methods

### Study area

This study was carried out in four neighboring provinces along the Mekong River in Laos and Thailand: Savannakhet and Champasak in Laos, and Mukdahan and Ubon Ratchathani in Thailand. These provinces were selected based on potential between-country variations in climate change vulnerability and adaptive capacity, socioeconomic development, poverty, and geographical and ecological diversity. Laos is organized into three administrative subdivisions: province (including one prefecture, the capital Vientiane), district, and village; while Thailand has four administrative divisions: province, district, sub-district, and village. The study area has

a tropical climate with a dry season from November to April and a rainy season from May to October, dominated by the southwest monsoon, with high rainfall, humidity, and temperature (Kottek et al. 2006).

#### Data collection

Daily reported dengue cases were retrospectively collected from governmental sources from 2002 to 2019 from all four provinces, except Savannakhet, where data were available from 2003 to 2019 (Ministry of Public Health—Thailand 2019; Provincial Health Department Laos 2019). Clinical DENV infection manifests itself along different degrees of severity, from dengue fever with signs of hemorrhage and eventually shock. To aid in clinical care, WHO drafted a new categorization in 2009, based on specific biological and physiological measurements generating warning signs for increasingly severe disease prognosis. This new classification was, however, not implemented everywhere. Thus, in Thailand, dengue cases included subdistrict level cases reported as dengue fever (DF), dengue hemorrhagic fever (DHF), and dengue shock syndrome (DSS) (Department of disease control-Thailand 2020). In Laos, dengue cases included district-level cases reported as DF, DHF, and DSS, and after 2009, dengue with warning signs, dengue without warning signs, and severe dengue according to the WHO guidelines (WHO 2019). Population census data of Laos and annual population data of Thailand, from 2002 to 2019, were acquired from official web portals of the National Department of Statistics in each country (National Statistical Office of Thailand 2019; Lao Statistics Bureau 2019). Weekly rainfall data were acquired from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) with a spatial resolution of 0.05 degrees (Funk et al. 2015). Weekly surface air temperature datasets from 2002 to 2019 were obtained from the fifth-generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis (ERA5) of the global climate (Hersbach et al. 2020). LULC were mapped from a series of Landsat satellites (USGS 2021), including ETM+, TM, and Optical Land Imager (OLI) and Thermal Infrared (TIR) images from 2002 to 2019. Sentinel-1 images from 2015 to 2019 were used for flood

inundation mapping (ESA 2019). We aggregated all variables to a weekly time scale.

#### Spatial distribution

The spatial scales of the national dengue reporting are different in the two countries. In Laos, dengue is reported at the district level, whereas in Thailand it is at the sub-district level. The modifiable areal unit problem (MAUP) refers to the change in results when data are combined into larger areal units or a combination of base units (Openshaw 1979). Dengue data were not aggregated on other areal units, which minimizes MAUP errors. The annual number of dengue cases per district (Laos) and sub-district (Thailand) was used to calculate Standardized Morbidity Ratios (SMR) to measure disease risk. The SMR was computed by dividing the observed number of disease cases ( $Y$ ) per district in Laos and per sub-district in Thailand by the expected number of cases ( $E_{kt}$ ). The weekly average incidence rates over the 18 years (2002 – 2019) were calculated and used to estimate the expected number of cases.

#### Climate time-series analysis

The temporal variation in temperatures and rainfall during the study period was identified using the non-parametric Theil Sen's slope method (Sen 1968). The daily rainfall and temperature were aggregated for each week for each district level in Laos and at the sub-district level in Thailand.

#### Land use and land cover mapping

Thirteen LULC classes were delineated from annual Landsat images and ground-truthed through training and well-distributed verification points (approximately 50 to 200 samples in each class/year/province) that were collected from ground surveys, high-resolution Google Earth imagery from 2002 to 2019, Google Street View, visual interpretation of Landsat data, and from published studies. A supervised machine learning algorithm, Random Forest (RF), was used to classify the LULCs. In addition, inundated areas, i.e., flooded areas/temporary wetlands, were also mapped with Sentinel-1 satellite images using the Google Earth

Engine platform. Flooding events and extent for each province are provided in S1 and S2 Tables.

The study used weekly cumulative rainfall (mm), average, minimum, and maximum temperature (°C), land use (i.e., built-up areas, rice crops, sugarcane crops, rubber plantation, cashew plantation, cassava plantation, and coffee plantations), and land cover (orchards, evergreen forest, deciduous forest, disturbed forest, permanent wetland, and flood inundated temporary wetlands) as independent variables and dengue cases as dependent variables in a Bayesian Regression Model.

### Dengue risk modeling

A Bayesian Poisson regression model expressed as

$$Y_{kt} \sim \text{Poisson}(\theta_{kt}) \tag{1}$$

$$\ln(\theta_{kt}) = \beta_0 + \beta_1 x_{kt} + \beta_2 x_{kt} + \log(E_{kt}) + \psi_{ktsub}$$

was used to predict spatiotemporal variations of dengue risk. Here  $Y_{kt}$  is the observed number of dengue cases in district  $k$  ( $k=1, \dots, K$ ) at time period  $t$  ( $t=1, \dots, N$ ), with respect to the independent variables  $x_i$ . The term  $\beta_0$  is the intercept of the model, and  $\beta$  ( $\beta=1,2,\dots$ ) is the regression coefficient for independent variables  $x_i$ .  $X_{kt}=(X_{kt1},\dots, x_{ktp})$  is a vector of  $p$  known covariates for areal unit  $k$  and time  $t$ . ‘ $W$ ’ denotes a symmetric nonnegative  $K \times K$  neighborhood, weight, or adjacency matrix ( $W = w_{kj}$ ). An adjacency matrix is typically assumed to be binary, where  $W_{kj} = 1$  if districts share a border and is zero otherwise. The term  $\psi_{kt}$  is the random effect that captures the spatial autocorrelation in response data  $Y_{kt}$ . To evaluate the study period’s spatial pattern of dengue risk, a spatially autocorrelated first-order autoregressive process model was selected ( $\psi_t = \rho T \psi_{t-1} + t$ ). Spatial autocorrelation was accounted for by the spatial covariate effect and structured spatial random effect.

The R statistical software package CARBayesST was used to fit the model. The above model (Eq. 1) runs three times to get the Markov Chain Monte Carlo (MCMC) samples from three independent chains with the first burn-in samples keeping the results from every 100th iteration (Lee 2020). Regression equations for each province and trace

plots of MCMC are given in S2 and S3 Tables. Additionally, the Gelman–Rubin diagnostic was used to identify the convergence of three MCMC chains, where a value less than 1.1 indicates good convergence (Gelman 2013). The diagnostic model output describes the model fit criterion such as the deviance information criterion, parameter summaries, and the posterior median point estimate (median), and 95% credible intervals.

A locally Weighted Scatterplot Smoothing (LOWESS) was used to analyze the nonlinear effects of lagged average temperatures and rainfall on dengue cases and to identify climate data breakpoints, i.e., the point where one line segment ends and another begins. Such breakpoints were needed to split data into individual segments to fit a linear regression within each segment. A piecewise linear function was used to incorporate the nonlinear relationship of climate variables with dengue cases in the Bayesian model (Choi et al. 2016). For the climate variables, lags of 1 to 15 weeks were used to examine their correlation with dengue cases (dependent variable).

The effects of LULCs and climatic parameters on dengue risk were quantified as posterior median relative risk (PMRR) for a fixed increase ( $\xi$ ) in each covariate value. The relative risks (RRs) were computed from the regression parameters ( $\beta_1, \beta_2 \dots \beta_n$ ) from all chains in the MCMC.

Initially, the PMRR of each independent variable model (climatic and LULC variable) on the response variable (observed weekly dengue cases) was estimated (S2 and S3 Tables). The weekly rainfall average 0–3 week lag and the weekly temperature average 0–3 week lag were combined with LULC to model dengue risk at the provincial level. All possible combinations of LULC with climatic variables were used to estimate the PMRR of dengue. PMRR values were converted to percentages ( $(\text{PMRR} - 1) \times 100$ ) to improve interpretability, making it easier to quantify the relative increase or decrease in dengue risk per 1 km<sup>2</sup> change in climate and land use. The corresponding PMRR values are provided in Table 1. The individual province models with the lowest DIC values were selected. The summary of the fitted models for all provinces is presented in S4 and S5 Tables.

Annual dengue relative risk for each district (Laos) and subdistrict (Thailand) was calculated by dividing

**Table 1** Posterior median relative risks of dengue (PMRR), 2.5th, 97.5th percentiles (the bounds of the 95% credible interval) associated with independent climate and LULC variables of fitted Bayesian spatiotemporal model for data collected in Champasak, Savannakhet, Mukdahan, and Ubon Ratchathani provinces during 2002–2019 (significant estimates in bold letters,  $p < 0.05$ ). Lags are in weeks

Variables 95% credible interval	Champasak, Laos			Savannakhet, Laos			Mukdahan, Thailand			Ubon Ratchathani, Thailand		
	PMRR	2.50%	97.50%	PMRR	2.50%	97.50%	PMRR	2.50%	97.50%	PMRR	2.50%	97.50%
Weekly average temperature lag 0–3 < 28 °C (< 29 °C in Ubon Ratchathani)	<b>1.212</b>	1.158	1.269	<b>1.268</b>	1.163	1.392	<b>1.224</b>	1.184	1.265	<b>1.154</b>	1.096	1.234
Weekly average temperature lag 0–3 > 28 °C (> 29 °C in Ubon Ratchathani)	0.954	0.837	1.098	1.378	0.953	1.967	<b>0.763</b>	0.685	0.848	0.932	0.728	1.188
Weekly cumulative rainfall lag 0–3 < 60 mm (< 50 mm in Ubon Ratchathani)	1.002	0.998	1.007	<b>1.018</b>	1.009	1.027	<b>1.021</b>	1.019	1.024	<b>1.028</b>	1.02	1.034
Weekly cumulative rainfall lag 0–3 > 60 mm (> 50 mm in Ubon Ratchathani)	0.999	0.996	1.002	1.004	0.998	1.011	<b>0.982</b>	0.978	0.986	<b>0.972</b>	0.965	0.98
Built-up area (km <sup>2</sup> )	<b>1.068</b>	1.058	1.077	<b>1.049</b>	1.044	1.054	<b>1.018</b>	1.01	1.027	<b>1.054</b>	1.043	1.065
Rubber plantations (km <sup>2</sup> )	<b>1.001</b>	1.000	1.001	–	–	–	<b>0.978</b>	0.957	0.999	<b>1.009</b>	1.006	1.012
Deciduous forest (km <sup>2</sup> )	–	–	–	<b>0.998</b>	0.997	0.998	<b>0.974</b>	0.968	0.981	–	–	–
Wetlands-temporary (km <sup>2</sup> )	<b>0.966</b>	0.961	0.97	–	–	–	0.980	0.949	<b>1.01</b>	<b>0.947</b>	0.929	0.965
Wetlands-permanent (km <sup>2</sup> )	–	–	–	<b>0.987</b>	0.983	0.992	–	–	–	–	–	–
Rice crop (km <sup>2</sup> )	–	–	–	<b>0.992</b>	0.991	0.993	–	–	–	–	–	–
Cassava plantations (km <sup>2</sup> )	–	–	–	–	–	–	–	–	–	<b>0.998</b>	0.989	<b>1.006</b>
Sugarcane crop (km <sup>2</sup> )	–	–	–	<b>0.995</b>	0.993	0.997	<b>1.005</b>	0.907	<b>1.113</b>	–	–	–

the samples of fitted values  $\{(E(\hat{Y}_{kt}) = E_{kt}\theta_{kt})\}$  with the fixed expected numbers of disease cases  $E_{kt}$ .

$$\text{Dengue Risk } \theta_{kt}(\text{RR}) = E(\hat{Y}_{kt})/E_{kt} \tag{2}$$

The posterior exceedance probability (PEP) distribution indicates the probability that the relative risk exceeds 1 (i.e., an elevated dengue risk), and is defined as  $\phi_{kt}$ ;

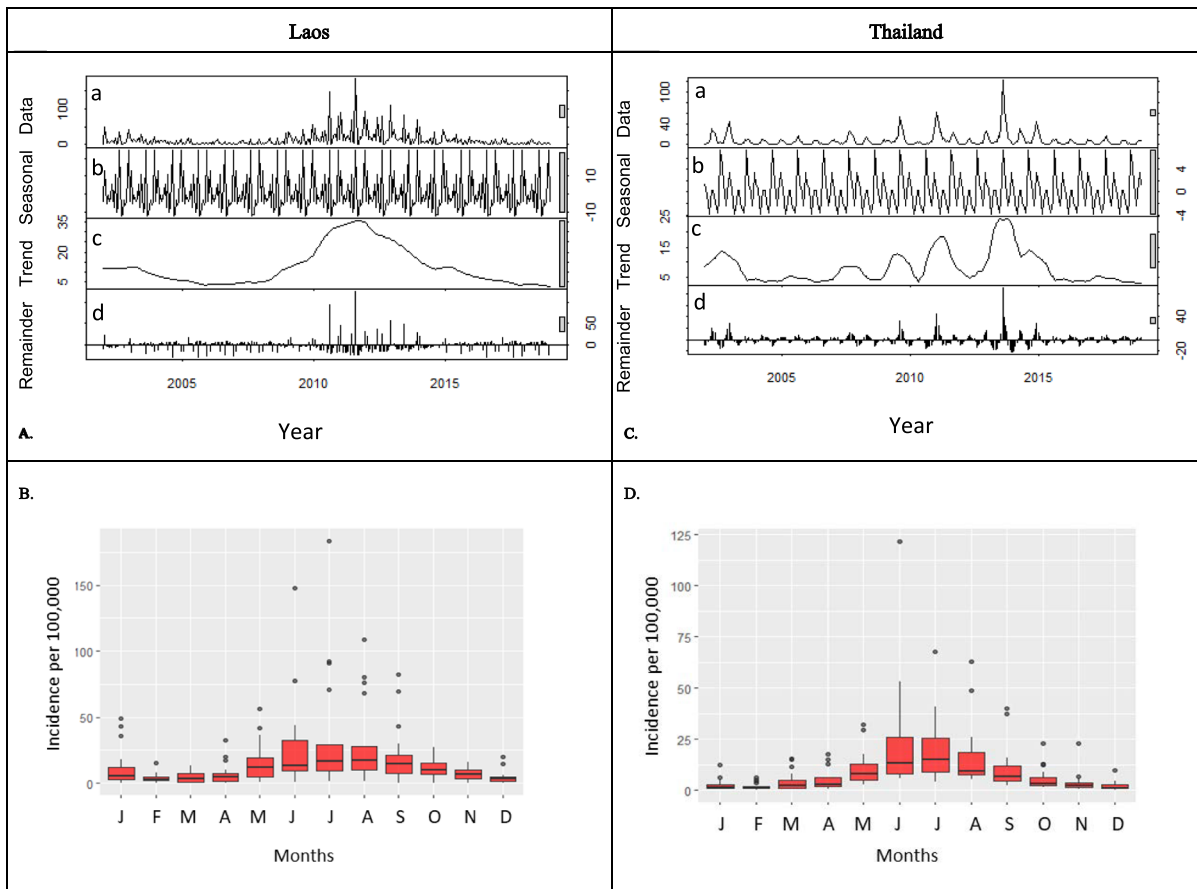
$$\phi_{kt} = P(\theta_{kt} > 1|Y) \tag{3}$$

Higher PEP values suggest a greater likelihood that a specific area experiences elevated dengue risk compared to the baseline.

## Results

### Dengue cases over space and time

A total of 53,782 dengue cases in the two Lao provinces and 42,028 cases in the two Thai provinces were reported during the study period 2002–2019 (S1 Figure) (Ministry of Health, Thailand, 2018). In the Lao provinces, there was an increasing trend of dengue cases up to 2012–2013 and a decreasing trend in the latter period (Fig. 1A and B). Dengue incidences in Thailand have shown significant variability over the years, but a general decrease has been observed since 2014. Dengue incidence in both countries was highest during



**Fig. 1** Seasonal trend decomposition plot of dengue incidence (A and B) and monthly dengue incidence (C and D) in study provinces of Laos and Thailand between 2002 and 2019. Lower case letters in A and B: (a) Observed dengue incidence (per 100,000 people) data over the study period (log scale).

(b) Seasonal pattern of dengue incidence. (c) Long-term trend observed in dengue incidence. (d) Remainder/residual after trend. The scale for each panel is different; the vertical bar present on the right side of each panel indicates the relative variations in components and original time series data

June and August (Fig. 1C and D). In Savannakhet province, the number of cases during the study period was higher than expected ( $SMR > 1$ ), whereas in the Thai provinces and Champasak, the number of cases was lower than expected ( $SMR < 1$ ) (Fig. 2).

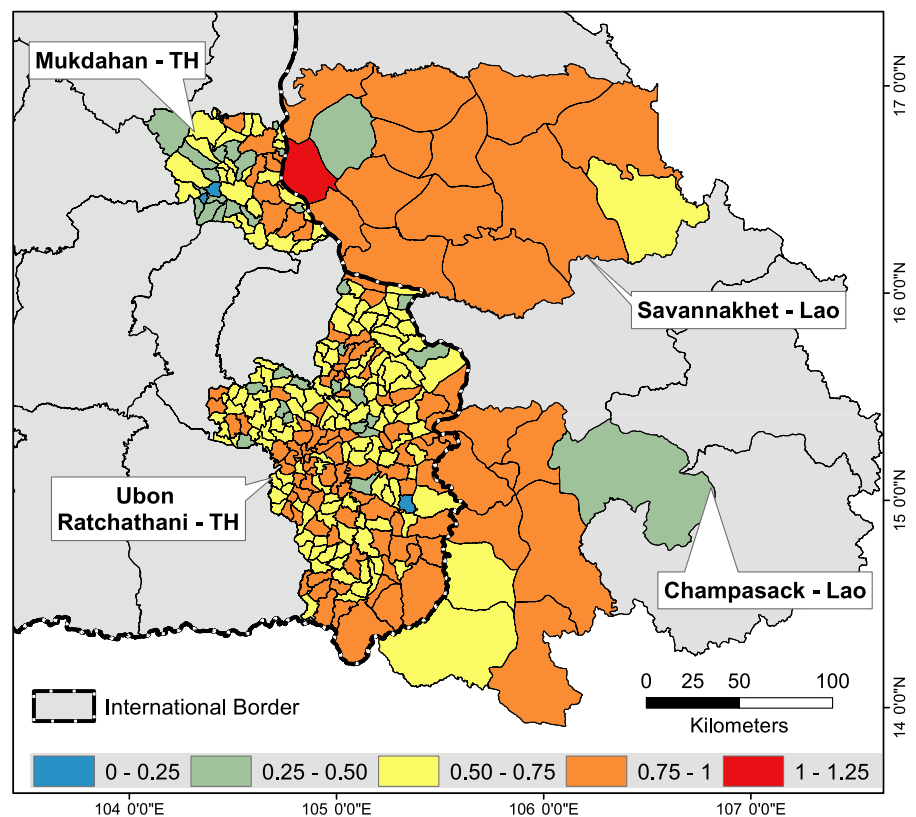
## Climate

The average annual temperatures increased in all provinces during the study period by 0.58 °C in Mukdahan, 0.44 °C in Ubon Ratchathani, 0.78 °C in Champasak, and 0.94 °C in Savannakhet (S2 Figure). During this period, the annual rainfall increased by 22 mm in Ubon Ratchathani and by 24 mm in Champasak, whereas there were no changes in Mukdahan and Savannakhet. The annual number of rainy days decreased in both Thai provinces from 123 in 2002 to 116 in 2019 and in Champasak, it decreased from 140 in 2002 to 110 days in 2019. In Savannakhet, there was no change in the number of rainy days (S3 Figures a–d).

## Dengue cases and climate associations

Lags of 0–3 weeks for average temperature and cumulative rainfall showed the strongest correlations with dengue cases but were non-significant. However, when the four individual lags of 0, 1, 2, and 3 weeks were combined and averaged they were significantly ( $p < 0.05$ ) correlated with dengue cases in all provinces. Thus these average temperature and cumulative rainfall averages were used for further analyses. For the the average 0–3 week lag of the weekly average temperatures, 28 °C was selected as the breakpoint using LOWESS., This breakpoint is the temperature at which there was the initial peak in dengue incidences and beyond which the relationship with dengue incidences became weaker as shown by the increasingly large confidence intervals (Fig. 3a, c, and e). The temperature was thus subsequently analyzed as two variables,  $< 28$  °C and  $> 28$  °C for the analyses combined with LULC variables. Likewise, the 60 mm breakpoint was selected for 0–3 week lagged rainfall, aligning with the first dengue peak and a weakening relationship thereafter (Fig. 3b, d,

**Fig. 2** Average standardized morbidity ratio (SMR) in study provinces of Laos (Lao) and Thailand (TH) over the period 2002 and 2019 ( SMR values are the colour codes shown at the base of the figure ranging from 0 to 1.25.)



and f). Rainfall was then categorized into two groups for further analysis:  $<60$  mm and  $>60$  mm. However, in Ubon Ratchathani, unique breakpoints were identified: 50 mm for rainfall (Fig. 3h) and 29 °C for temperature (Fig. 3g).

#### Land use and land cover

There were considerable changes in LULC in both countries during 2002–2014, and after that, a slow, gradual change took place (S3 Figure and Fig. 4). Deciduous and evergreen forest areas decreased in Savannakhet from 82 to 45%, Champasak from 79 to 62%, Mukdahan from 51 to 38%, and Ubon Ratchathani from 25 to 16%. In 2019, the proportions of rubber plantation area were 12.6% in Mukdahan, 8.8% in Ubon Ratchathani, 4.0% in Savannakhet, and 2.7% in Champasak, represent an increase in all provinces, replacing forest and other agricultural commodities (Fig. 4C, D and S3 Figure). The area of sugarcane increased substantially in northwestern Savannakhet. The rice area increased in all study provinces except in Ubon Ratchathani. The expansion of the built-up area occurred at a slow pace in all provinces over 18 years, with a total 1.6% increase in Savannakhet, 1.3% in Ubon Ratchathani, 0.8% in Mukdahan, and 0.6% in Champasak (Fig. 4). Floods were frequent in all study provinces (S6 Table a-b).

#### Dengue risk

The study uses posterior median relative risk to estimate risks associated with climatic and LULC variables in Laos and Thailand (Fig. 5A). Posterior Exceedance Probability (PEP) measures the probability that the estimated risk exceeds a given threshold, helping to identify areas with elevated spatial risk in the posterior median risk surface. The highest-risk areas are found in most areas in Laos and Thailand, as shown in Fig. 5B.

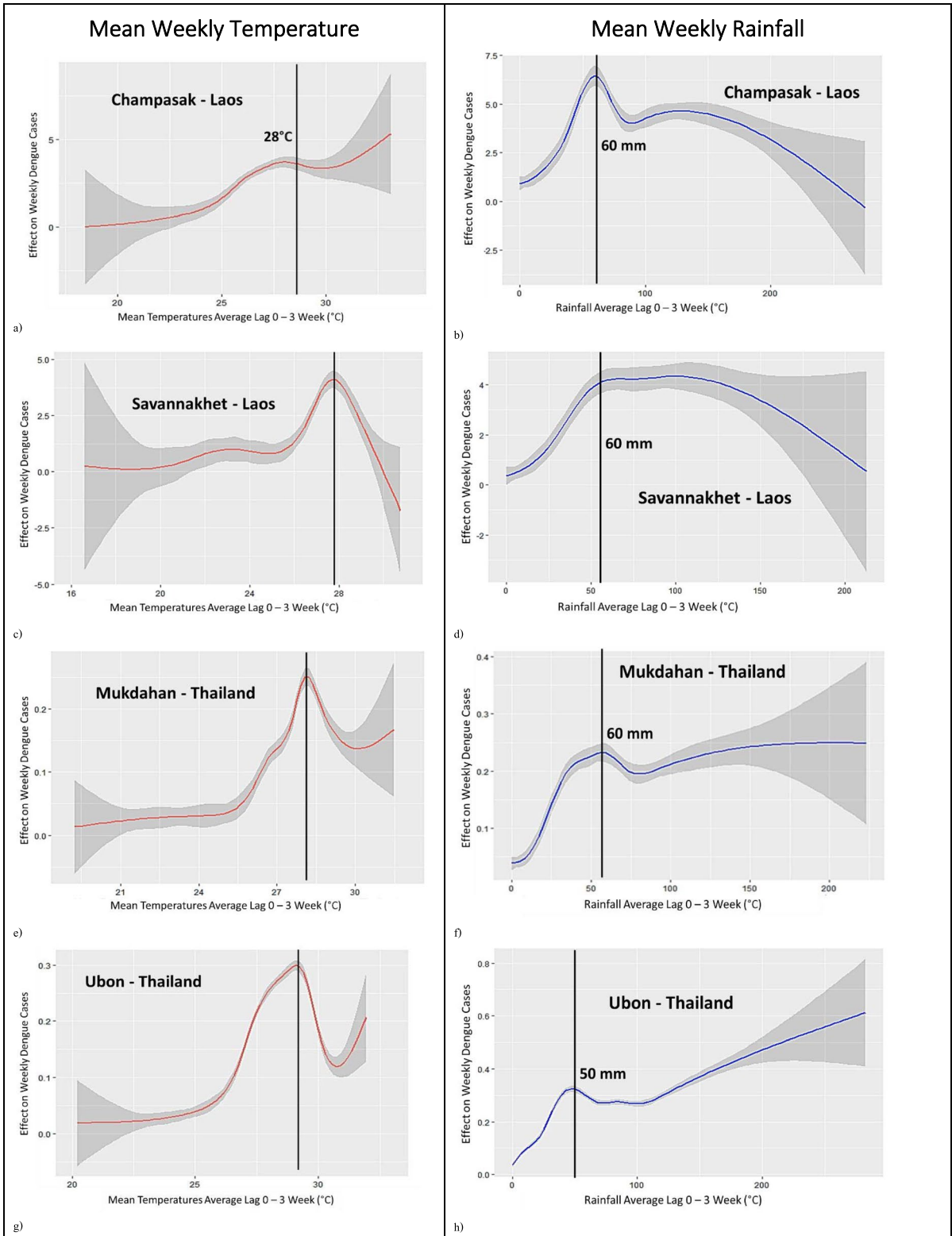
In Champasak (Laos), risk remained high between 2005 and 2008 (2.5–3 PMRR, Fig. 6), and it increased further during outbreaks in 2010 (5.8), 2013 (10.2), and 2019 (6.1). Savannakhet experienced continued dengue risk over the years, with outbreaks in 2003 (8.1), 2010 (2.5), 2013 (6.3), and 2019 (8.1). Dengue risk in Mukdahan (0–1 PMRR, Fig. 6) remained low throughout the study period but started to increase from 2007 (Fig. 6).

In Ubon Ratchathani, risk steadily increased across subdistricts from 1.8 to 5 PMRR during 2002 to 2019. Overall, dengue risk increased in all study provinces, with higher posterior relative risks observed in 2010, 2013, and 2019 (Fig. 6).

#### Dengue risk-associations with climate and LULC

Weekly average temperatures below 28 °C increased dengue risk by 1.21% (range between 1.154 and 1.268) on average in all provinces (Table 1). Weekly cumulative rainfall up to 60 mm in Savannakhet, Ubon Ratchathani, and Mukdahan increased dengue risk by 1.022, while above 60 mm (50 mm in Ubon Ratchathani) reduced it by 0.977 in Mukdahan and Ubon Ratchathani respectively (Table 1).

During the study period, built-up areas increased in all provinces, mostly in major cities. Built-up areas were significantly associated with dengue risk in all provinces. The posterior median relative risks of dengue cases show an increase of 1 km<sup>2</sup> built-up area increased the average dengue risk in Champasak by 6.8%, in Ubon Ratchathani by 5.4%, in Savannakhet by 4.9%, and in Mukdahan by 1.8%. The area of rubber plantations increased in all provinces over the study period but the effect on dengue risk was ambiguous: A 1 km<sup>2</sup> increase in rubber plantation area significantly increased dengue risk in Ubon Ratchathani by 0.9% but significantly decreased dengue risk in Mukdahan by 2.2%. Deciduous forest was related to a decrease in dengue risk by 2.6% in Mukdahan and by 0.2% in Savannakhet. Increases in temporary wetlands (flooding) reduced dengue risk by 3.4% and 5.3% in Champasak and Ubon Ratchathani, respectively, for each 1 km<sup>2</sup> increase in area. Permanent wetlands were found to have a negative effect only in Savannakhet province, where a 1 km<sup>2</sup> increase in area could decrease the risk by 1.3%. Similarly, the impact of rice cultivation was also limited to Savannakhet, with a 1 km<sup>2</sup> expansion reducing dengue risk by 0.8%. In contrast, cassava cultivation was linked to an increased risk of dengue in Ubon Ratchathani, where a 1 km<sup>2</sup> increase in its area could raise the risk by 0.6%. Sugarcane showed a positive association with dengue risk in Mukdahan, with a 1 km<sup>2</sup> expansion potentially leading to an 11.3% increase in risk (Table 1).



◀**Fig. 3** Relationships between weekly dengue cases and climate variables in study provinces of Laos and Thailand (2002–2019) Left panels: average weekly temperature; Right panels: Cumulative weekly rainfall, both with an average 0–3 week lag. **a, b** Champasak, Laos; **c, d** Savannakhet, Laos; **e, f** Mukdahan, Thailand; **g, h** Ubon Ratchathani, Thailand. Vertical lines indicate temperature and rainfall breakpoints

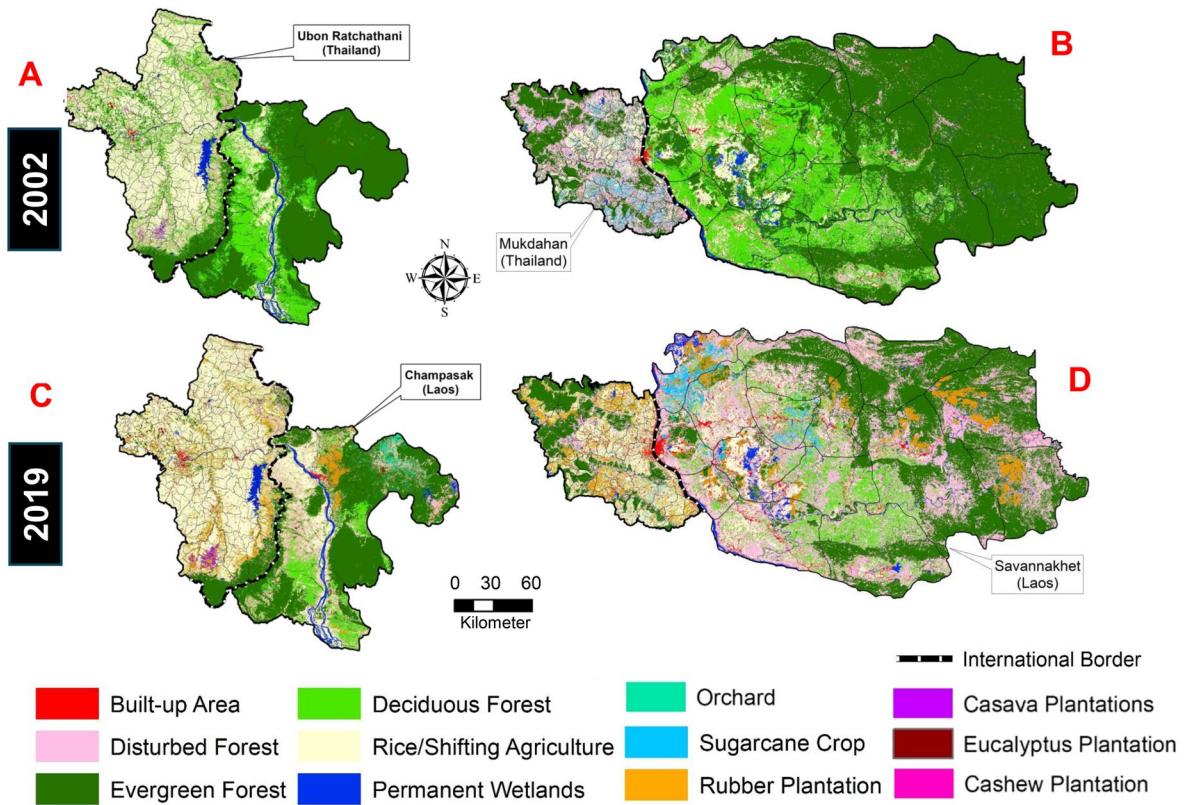
## Discussion

There were notable climatic and land use changes during the 18-year study period, contributing to an increasing relative risk of dengue in several administrative units, particularly in Laos. Among the four provinces studied, Savannakhet exhibited the most favorable combination of spatiotemporal climate and land use factors for dengue transmission. The province had an average standardized morbidity ratio (SMR) > 1 in its most districts throughout the study period, indicating a higher-than-expected number of dengue cases. Additionally, a nearly 1 °C increase in temperature and above-average annual rainfall in the latter years may have further contributed to the heightened dengue risk in this province.

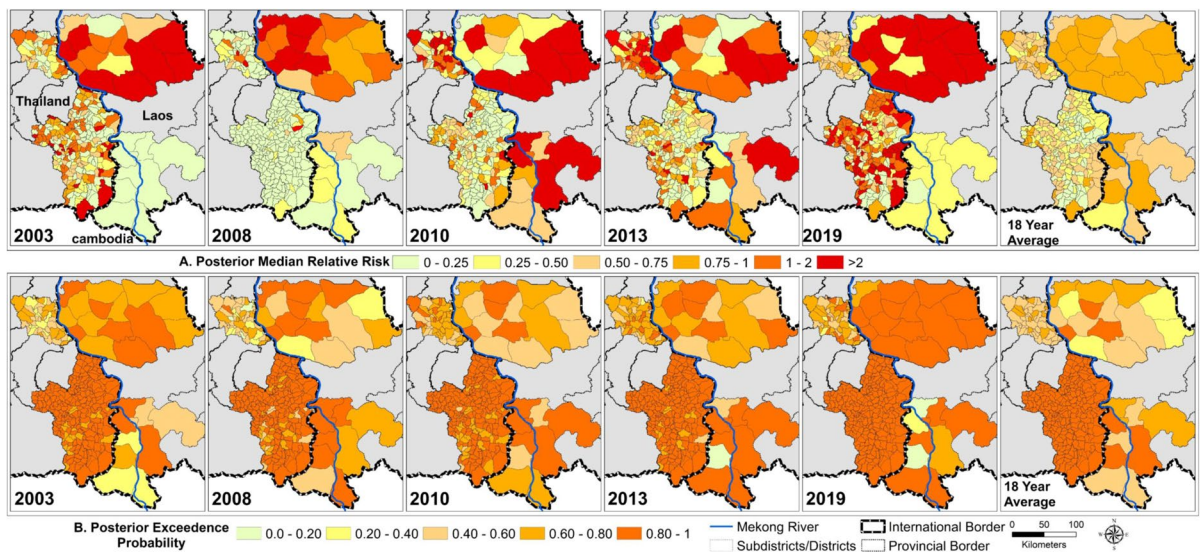
The observed average temperature increased across all provinces by an average of 0.6 °C (range: 0.44–0.94 °C). This temperature increase can elevate dengue risk, as estimated by PMRR. Specifically, a 1 °C increase of temperature was associated with a higher dengue risk, with lag of 0–3 weeks. (S2b Figure). This time correlates with mosquito development time from egg to adult (Reiter 2007; Siraj et al. 2017). In our study, we found that an increase in weekly average temperature of 1 °C increased the dengue risk, ranging from 27% in Savannakhet to 15% in Ubon Ratchathani. This risk was higher than a similar study in Khon Kaen province in northeastern Thailand where a 1 °C increase in weekly maximum temperature increased dengue risk by 5.5% (Phanitchat et al. 2019). We applied a 0–3 weeks lag for the temperature variable to account for the delayed impact of temperature on mosquito development and dengue transmission. In contrast, the Khon Kaen study did not incorporate any lag effect, which may have led to an underestimation of the temperature's impact on dengue risk. Understanding these variations is crucial for tailoring dengue prevention and control strategies to specific regional conditions.

The effect of rainfall on DENV spread was lower than temperature, which has also been shown in other studies (Campbell et al. 2013; Lowe 2015; Phanitchat et al. 2019), and reflects its more complex and delayed effect on mosquito breeding and DENV transmission. We found that a weekly cumulative rainfall of up to 60 mm was suitable for DENV and a 1 mm increase in weekly rainfall increased DENV risk by 1.8–3.2% across the four provinces. In Thailand, inter-annual variations in rainfall and temperature with a lag time of one month were found to be associated with DENV risk (Lowe et al. 2016). Results from Khon Kaen province only showed a 0.4% increased risk associated with a 1 cm increase in monthly rainfall (Phanitchat et al. 2019). Rainfall may create abundant breeding sites for DENV vectors and increase mosquito numbers and disease risk (Rozilawati et al. 2007), but even such direct associations between rainfall and mosquito abundance are not straightforward, complicated by micro-topography, habitat formation, container presence and accessibility, mosquito behavior, etc. (Kampango 2021). The differences observed among these studies, including our own, may indeed be attributed to these complicating factors that were not measured or accounted for in any of the referenced studies.

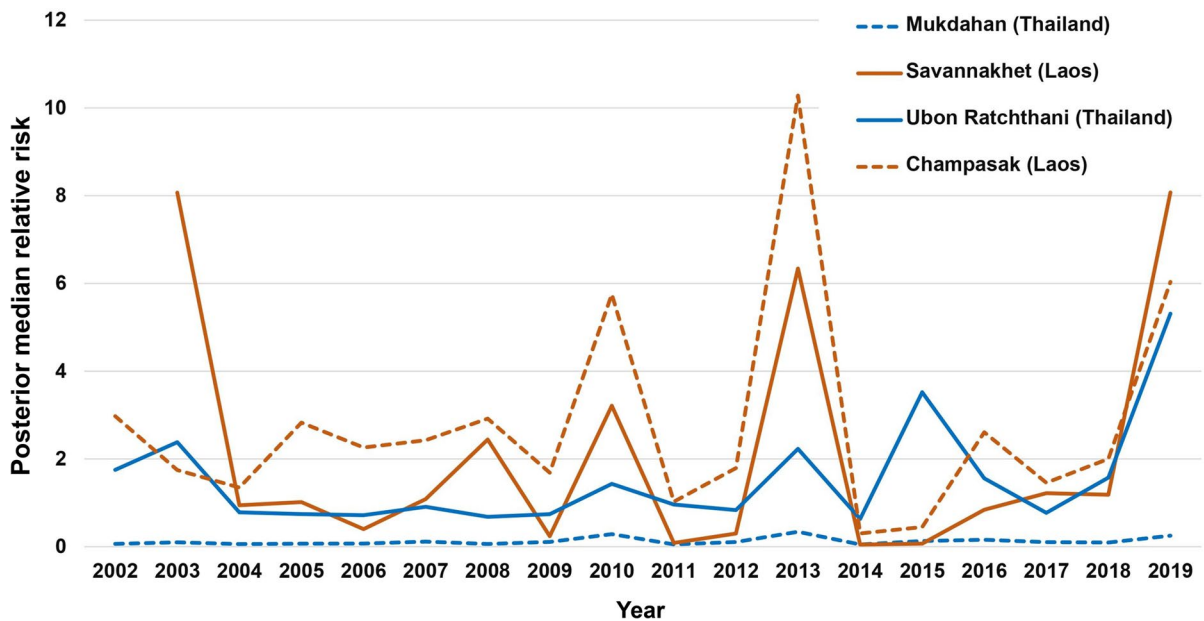
Future studies could integrate unmeasured environmental factors using high-resolution geospatial datasets and advanced modeling techniques. Microtopography, which influences water retention and breeding site formation, can be accounted for by LiDAR-derived digital elevation models (Dhakal 2021) and synthetic aperture radar (SAR) data (Kuntla and Manjusree 2020). These datasets provide fine-scale elevation and surface water accumulation patterns, which can help identify microhabitats suitable for mosquito breeding. Human-made container prevalence, a key factor in vector breeding, can be quantified at household level with high resolution images (e.g. Worldview3 with a resolution of 0.31) using machine learning. Object-based image analysis (OBIA) and convolutional neural networks (CNNs) can help detect water-holding containers in urban and peri-urban settings (Parselia et al. 2019). Citizen science and participatory mapping approaches, such as community-based vector surveillance, could further supplement these remote sensing efforts. For improved spatial and



**Fig. 4** Land use and land cover in study provinces of Laos and Thailand. **A** 2002 LULC for Champasak (Laos) and Ubon Ratchathani (Thailand). **B** 2002 LULC for Savannakhet (Laos) and Mukdahan (Thailand). **C** 2019 LULC for Champasak (Laos) and Ubon Ratchathani (Thailand). **D** 2019 LULC for Savannakhet (Laos) and Mukdahan (Thailand)



**Fig. 5** Dengue risk in study provinces of Laos and Thailand during outbreak years and average over the study period. **A** Posterior median relative risk **B** Posterior exceedance probability



**Fig. 6** Trends in posterior median dengue risk in study provinces of Laos and Thailand (2002 to 2019)

temporal modeling, incorporating microtopography and container prevalence data into geostatistical models (e.g., Bayesian spatial models) or machine learning approaches (e.g., random forests, XGBoost) could refine predictions of dengue risk. Agent-based models which simulate individual mosquito and human interactions with the environment, could also provide insights into how micro-scale factors influence disease transmission in Laos and Thailand. Additionally, the use of climate forecasting models and shared socioeconomic pathways (van den Hurk et al. 2014; Doelman et al. 2018), integrating remotely sensed precipitation data and land-use data, could help predict localized DENV outbreaks under varying rainfall conditions. By incorporating these factors into a multi-scale framework, future research can move beyond broad associations toward more accurate, actionable risk assessments.

Our findings highlight how climate-DENV associations are shaped by landscape structure and physical characteristics, including vegetation cover, urbanization, and heat influx. While built-up areas are well-documented as key drivers of dengue risk (Galli and Neto 2008; Selvarajoo et al. 2020). Our study quantifies this relationship over time, showing that the proportion of built-up areas increased from 1.3% in 2002 to 2.2% during the study period. More

importantly, we provide empirical estimates that each 1 km<sup>2</sup> increase in built-up area corresponded to a 2–7% rise in dengue risk, potentially influenced by population size, development levels, and vector control measures. These results underscore the importance of integrating urban planning and public health interventions to mitigate dengue transmission in rapidly urbanizing regions.

The other land uses selected in our study had variable or negligible effects on dengue risk. However, both permanent wetlands and temporary wetlands (flooded areas) were negatively correlated with dengue risk. The fitted model indicated that a 1 km<sup>2</sup> increase in temporary wetlands or flooding was negatively related and reduced risk by 3.4–5.3% except in Savannakhet province where no effect was observed. Similarly, in Savannakhet, a 1 km<sup>2</sup> increase in permanent wetlands reduced the risk of dengue by 1.3%, while no significant effect was found in the other three provinces. One possible explanation for this negative relationship is that flooding may wash away mosquito larvae and breeding sites, thereby temporarily reducing the mosquito population. These findings are in agreement with study conducted in Thailand (Sarfranz et al. 2012). However, it is also important to consider other factors that could contribute to this effect. For instance, after flooding,

the initial reduction in mosquito populations might be followed by insufficient time or conditions for the mosquito population to rebound before the water recedes or evaporates. Additionally, the presence of natural predators in wetland areas or changes in water quality and chemistry post-flooding could further inhibit mosquito breeding. The lack of host abundance in these areas due to human displacement during floods might also contribute to the reduced dengue transmission risk (Yee et al. 2019; Chang et al. 2014). The study from Puerto Rico (Jesús et al. 2018) found that increase in woody and grassy wetland cover may cause reduction in dengue cases. These findings not only highlight the role of wetlands in potentially mitigating dengue risk but also underscore the importance of specific wetland types, such as woody wetlands, in reducing the incidence of dengue in affected areas. Similar findings were also reported from China (Qi et al. 2015; Cao et al. 2017), Costa Rica (Fuller et al. 2009) and Singapore (Tewari et al. 2023).

We observed negative relationships between deciduous forests and dengue risk, which may be attributed to limited human interaction rather than an inherent protective effect of these forests. While studies such as Tangena et al. (2017) have reported increased exposure to dengue vectors among individuals visiting natural forests in northern Laos, this risk is highly context-dependent. In our study provinces, the sparse population and minimal human activity in deciduous forests likely contributed to their lower observed dengue risk (Tangena et al. 2017). Meanwhile, LULC changes over the past two decades have significantly altered the dengue risk landscape. The decline in deciduous and evergreen forests (S3 Figure) has been accompanied by an expansion of agriculture, settlements, and particularly rubber plantations. These land conversions may have shifted dengue risk toward areas where human-mosquito interactions are frequent.

Rubber plantations have been previously associated with increased dengue risk in India, Laos, Malaysia, and Thailand, likely due to the suitability of these environments for *Ae. albopictus* (Thammapalo 2005; Tangena et al. 2017; Brown et al. 2018). A study from Laos found that individuals living and working near rubber plantations had a 16.2 times higher chance of DENV infection (Tangena et al. 2017). While Ubon Ratchathani

showed a significant positive association, with a 0.9% increased dengue risk with 1 km<sup>2</sup> increase in rubber plantations, Mukdahan exhibited a contrasting trend, with a 2.2% reduction in dengue risk per 1 km<sup>2</sup> increase in rubber plantations. This contradicts previous research and suggests that the relationship between rubber plantations and dengue risk is influenced by local environmental and socio-economic factors. One possible explanation is that the expansion of rubber plantations in Mukdahan replaced deciduous forests (Fig. 4), which had low human activity and thus limited mosquito-human interactions. In contrast, in Ubon Ratchathani, rubber plantations may have replaced land uses with lower mosquito habitat suitability, thereby increasing vector breeding sites and human exposure. These findings highlight the importance of context when assessing the impact of land-use change on dengue risk. While rubber plantations can create favorable conditions for dengue vectors, their actual impact on transmission dynamics depends on factors such as human activity, land cover history, and local climate.

Our study was constrained by the inherent uncertainties of the original dengue data, including under-reporting, misdiagnosis, or misreporting of the symptomatic cases, and the absence of subclinical and asymptomatic infections. Travel-related infections are also common and it has been shown to be important when introduced in the adjacency matrix at a finer spatial scale (Ramadona et al. 2023). However, the impact of importation and mobility is not trivial to quantify. This study could be further improved by incorporating spatial details of each dengue patient, especially their location (house address or location coordinated), along with aggregated data at the district/sub-district level. To improve future research, we recommend that the Laos and Thai governments consider providing more spatially detailed dengue case data for research purposes while ensuring patient privacy. Access to anonymized patient location data at a finer resolution (e.g., village or subdistrict level) would allow for a more precise analysis of local risk factors and transmission dynamics. Additionally, integrating historical entomological surveillance and mobility data—such as human movement patterns—would enhance our ability to assess dengue risk and improve targeted interventions (Wong and Jim 2018; Chen et al. 2019).

## Conclusions

This study detected substantial spatial and temporal heterogeneity in dengue cases, associating to location-specific risk factors such as temperature, rainfall, and increased built-up areas during the study period. With rapid urbanization, population movement, and changes in climatic parameters, these findings are important to understand for adopting and implementing policy to control vectors of dengue fever at the microgeographic scale to improve health for the local population. Urban planning and land use policies should also consider public health implications, with a focus on managing land use changes to reduce mosquito breeding sites. Furthermore, the dynamic nature of dengue epidemiology necessitates continuous monitoring and updating of risk assessments to reflect the latest data on environmental changes and disease patterns. Lastly, public health campaigns should leverage these findings to educate communities about local risk factors and encourage proactive measures. By incorporating these recommendations into policy frameworks, dengue control efforts can become more adaptive and effective, ultimately contributing to the goal of dengue elimination in the Greater Mekong region.

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**Author contributions** SZ: Conceptualization, resources, data curation, formal analysis, visualization, methodology, writing—original draft. HJO: Funding acquisition, project administration, conceptualization, resources, supervision, visualization, writing—review and editing. JR: Supervision, resources, methodology, visualization, writing—review and editing. REP: Supervision, writing—review and editing. OVS: Resources, supervision. MSR: Writing—review and editing. MM: Funding acquisition, project administration, data curation, writing – review. CP: Funding acquisition, project administration. PP: Data curation, SA: Data curation. TP: Data curation. NS: Data curation. UH: Funding acquisition, project administration, conceptualization, supervision, methodology, visualization, writing—review and editing.

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**Data availability** The data used in this study are available from the corresponding author, the Norwegian Agency for Shared Services in Education and Research (Sikt). Access to the data sets must be requested from Sikt using a Data Access form at this link: <https://sikt.no/en/tjenester/finn-data/guide-ordering-data-sikt> and referring to project ID NSD0000.

## Declarations

**Conflict of interest** The contributing authors declare no competing interests exist that could have influenced the reported work in this paper.

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