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Climate factors and the East Asian summer monsoon may drive large outbreaks of dengue in China

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1 **Climate factors and the East Asian summer monsoon may drive large** 2 **outbreaks of dengue in China**

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Abstract

Objective To investigate the relationship between climate variables, East Asian summer monsoon (EASM) and large outbreaks of dengue in China.

Methods We constructed ecological niche models (ENMs) to analyse the influence of climate factors on dengue occurrence and predict dengue outbreak areas in China. Furthermore, we formulated a generalised additive model (GAM) to quantify the impact of the EASM on dengue occurrence in mainland China from 1980 to 2016.

Results Mean Temperature of Coldest Quarter had a 62.6% contribution to dengue outbreaks. Southern China including Guangdong, Guangxi, Fujian and Yunnan provinces are more vulnerable to dengue emergence and resurgence. In addition, we found population density had a 68.7% contribution to dengue widely distribution in China using ENMs. Statistical analysis indicated a dome-shaped association between EASM and dengue outbreak using GAM, with the greatest impact in the South-East of China. Besides, there was a positive nonlinear association between monthly average temperature and dengue occurrence.

Conclusion We demonstrated the influence of climate factors and East Asian summer monsoon on dengue outbreaks, providing a framework for future studies on the association between climate change and vector-borne diseases.

Key words: Dengue, EASM, Climate variables, ecological niche model, generalised additive model

Introduction

Dengue is the most rapidly spreading mosquito-borne viral disease in the

world(Jentes, Lash et al. 2016) and has significant economic, political, and social impact(Kyle and Harris 2008, Wilder-Smith, Gubler et al. 2017, Wilder-Smith, Ooi et al. 2019). The epidemiological triangle of dengue includes the host, pathogen(including 4 antigenically-distinct serotypes), and environment, with mosquito vectors(including *Aedes aegypti* and *Ae. albopictus*) playing an important role in the interaction between environment, host, and agents(Naish, Dale et al. 2014). An estimated of 500,000 people worldwide are hospitalised with severe dengue each year, and the incidence of severe dengue has increased 30-fold with geographic expansion to new countries in the last 50 years(World Health Organization. 2009). From 1949 to 1977, there was no record of dengue epidemics in mainland China. However, due to the geographic spread of imported dengue cases from southeast Asian countries, there was a dengue outbreak in Guangdong Province in 1978(Luo, Liang et al. 2012). Since then, dengue outbreaks have occurred sequentially in Hainan, Guangxi, Fujian, and Zhejiang provinces, with the two most severe dengue outbreaks in Hainan Province in 1980 and 1986. Dengue has gradually faded out from Hainan since 1991 but remains active in South China(Sang, Yin et al. 2014). Despite the rapid increase of dengue incidence has and several large epidemics, long-term and large-scale quantitative modelling studies spanning over China is limited.

Climate variation, among other factors(Chen, Zhao et al. 2019), determines both the spatial distribution(Bhatt, Gething et al. 2013, Phanitchat, Zhao et al. 2019) and temporal dynamics of dengue(Xu, Fu et al. 2014, Liyanage, Tissera et al. 2016, Xu, Stige et al. 2017). Climate variation has the potential to promote dengue transmission

via alterations in the prevalence of vectors(Liu-Helmersson, Stenlund et al. 2014) and changes in human behaviour. Thus, human population exposure to dengue will increase as temperate weather zones become more receptive to dengue and other vector-borne diseases(Hales, de Wet et al. 2002, Sutherst 2004). Dengue outbreaks across the globe have been associated with climate change(Barclay 2008, Williams, Mincham et al. 2014, Lowe, Stewartibarra et al. 2017, de Oliveira-Junior, Gois et al. 2019). Although many studies have examined the association between the risk of dengue epidemics and climate variability, the complex effects of climatic factors on dengue are uncertain. To improve control and prevention of dengue at the national level, studies that explore spatial and temporal relationships between climatic factors and dengue outbreaks are still required, particularly in China and other developing countries.

Monsoons are the main determinant of climatic variability over much of Asia and affect the most densely populated region on Earth. The East Asian Summer Monsoon (EASM) is driven by moisture and temperature gradients between the Pacific Ocean and the Asian continent(Li, Park et al. 2018). The regions influenced by EASM include eastern China and the South China Sea, Korea, Japan, and the adjacent marginal seas (Yihui and Chan 2005). This is a distinctive component of the Asian climate system and previous studies have discussed the impact of the EASM on regional climates, such as the Mei-yu front, which brings intense seasonal rainfall to China(Wang, Wu et al. 2008). Dengue outbreaks have largely coincided with the post-monsoon period of anomalous rainfall(Chakravarti and Kumaria 2005), and the

dengue vector is more abundant in the post-monsoon season(Baruah and Dutta 2013). A study(Hayes and Gubler 1992) found there was a lag of 9 weeks between the peak of rainfall during monsoon and peak of the Dengue incidences in Ahmedabad city in western India. However, there is no large-scale models have been developed to investigate the link between monsoon strength and dengue occurrence.

Ecological niche models (ENM), or species distribution modelling, habitat modelling, and climate envelope-modelling(Miller 2010), have been used to estimate the influencing of climate variation on dengue(K, J et al. 2018) and predict the distribution of dengue vectors(Peterson, Martinez-Campos et al. 2005, Arboleda, Jaramillo et al. 2009, Carvalho, Rangel et al. 2017) and other infectious diseases(Neerinckx, Peterson et al. 2010). In addition, Generalised additive model (GAM) has previously proven useful to elucidate the nonlinear statistical relationship between human incidence and climate conditions(Xiao, Liu et al. 2018). The purpose of this study was to investigate large-scale spatial-temporal dynamics of dengue in China and to explore the link between global climate change and dengue outbreaks. Firstly, we used ENM to analysis the influence of climate variables on dengue outbreaks and estimate dengue outbreak regions, to better understand the distribution of dengue across China. Then, we explored the effects of the regional climate variable EASM on dengue incidence in mainland China from 1980 to 2016 using GAM. Our results will provide scientific evidence for early warning and facilitate improved control and prevention of dengue in identified outbreak regions.

Methods

Ethical approval for the study came from Chinese Center for Disease Control and Prevention Ethics Committee (No.201214).

Dengue data

Human dengue data from 1978 to 2004 was collected from historical records at county level. We digitalised the historical records and matched geographic coordinates. Dengue data from 2005 to 2017 was obtained from the China National Notifiable Disease Surveillance System. We categorised the annual dengue prevalence data into 3 groups, (1) less than 10 dengue fever cases (minor outbreak), (2) 10 to 100 cases (medium outbreak), and (3) greater than 100 cases (major outbreaks). We hoped to distinguish the high-risk areas and found the distribution pattern according to the artificial classification method and there were not classified references. We categorised the intensity of dengue fever outbreaks rather than using raw case counts, because locally-infected human dengue cases cannot be identified from exported cases by using historical data and many locations have a small number of dengue cases (Fig. 1).

EASM index

The EASM index (EASMI) is defined as an area-averaged seasonally (June-July-August; JJA) dynamical normalised seasonality (DNS) at 850 hPa within the East Asian monsoon domain (10°-40°N, 110°-140°E) (Li and Zeng 2002, Li, Wu et al. 2010). Time series data were collected from the relevant website (<http://ljp.gcess.cn/dct/page/65577>). There is an apparent negative correlation between

the EASM index and summer (JJA) rainfall in the middle and lower regions of the Yangtze River in China, indicating that drought years over the valley are associated with a strong EASM and flood years with a weak EASM.

Meteorological variables

The raster data of local meteorological variables by surface horizontal resolution was $0.5^{\circ} \times 0.5^{\circ}$ for GAM, including monthly average temperature and total precipitation from 1980 to 2016 that were obtained from the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn>). The monthly cases of dengue in each county were matched with local meteorological factors according to point coordinates of the dengue cases at county level using R (version 3.3.3).

Spatial gridded climate data

The spatial gridded climate data for the ecological niche model (ENM) included Mean Temperature($^{\circ}\text{C}$) of the Warmest Quarter, Mean Temperature($^{\circ}\text{C}$) of the Coldest Quarter, Precipitation(mm) of the Wettest Quarter, and Precipitation(mm) of the Warmest Quarter by $10\text{ km} \times 10\text{ km}$, which were downloaded from the current section dataset of the WorldClim website (<http://worldclim.org/version2>). Population density data were collected from the history database of the global environment programme (<http://themasites.pbl.nl/tridion/en/themasites/hyde/basicdrivingfactors/population/index-2.html>) and the population density with $10\text{ km} \times 10\text{ km}$ in the year 2000 was used in the model.

Ecological niche models

We built 3 ENMs to predict the probability of dengue occurrence with (1) the counties with at least 1 dengue case, (2) the counties with more than 10 dengue cases, and (3) the counties with more than 100 dengue cases across the whole study period from 1978 to 2017 (Fig. 1). The purpose of building 3 separate models was to divide the predictive map into 3 categories of low, medium, and high dengue outbreak risk. As only county level dengue presence data were available, but predictive variables were available at 10×10 km, the “point sampling” approach was used to model the data. This approach has been previously used to predict the climatically suitable area (CSA) at fine resolutions from coarse-scale malaria vectors presence records (e.g., county level presence records) in China (Ren, Wang et al. 2016). A random location within each county was assigned using the point sampling approach. Predictive variables were then extracted at that point location and assigned to the dengue presence data for modelling with ENM. In order to incorporate the uncertainty caused by the random assignment of dengue presence location within each county, we repeated the point assignment process 100 times and calculated the mean prediction value at each pixel.

Training data included 75% of the dengue cases, and the remaining 25% were used for testing each model. The model was set to regularisation multiplier 2 and each model was repeated 10 times according the subsample method. Using the above calculation, we obtained 100 results for 3 models and calculated the average for every model. The ENM was built using the software R (version 3.3.3) and Maxent (version 3.3.3e), with the maximum entropy approach. The receiver operating characteristic

(ROC) curve evaluated the model prediction effect, in which the area under the curve (AUC) is a measured value. AUC follows: 0.50–0.60, insufficient; 0.60–0.70, poor; 0.70–0.80, average; 0.80–0.90, good; and 0.90–1.00, excellent (Li, Ren et al. 2017, Ma and Sun 2018).

Generalised additive model

The GAM with a Gaussian distribution family (Hastie and Tibshirani 1990) (link function was identity) was used to detect the effect of monthly temperature, precipitation, and monsoon intensity (EASMI) on dengue prevalence. The ‘mgcv’ package (version 1.8-12) of R (version 3.3.3) was used for these analyses (R 2009). To analyse the association between climate factors and space-time dynamics of dengue intensity, we used the model formula given by:

$$D_{i,j} = a_{i,j} + b_i + c(Lon_j, Lat_j) + d(D_{i-1,j}) + e(T_{i,j}) + f(P_{i,j}) + g(M_i) + \varepsilon_{i,j}$$

Here, $D_{i,j}$ is the log transformed dengue prevalence in the county j and in the month i . Parameter $a_{i,j}$ is the overall intercept, b_i is a smooth (natural cubic spline function with the maximally 3 degrees of freedom) function of month. $c(Lon_j, Lat_j)$ is a 2D smooth function modelling the spatial effects (thin plate spline), $d(D_{i-1,j})$ is the linear function of log transformed dengue prevalence at the same location the previous month (added 1 to avoid taking the logarithm of zeros), $e(T_{i,j})$ and $f(P_{i,j})$ are the smooth function (natural cubic spline function with the maximum 2 degrees of freedom) of average temperature and total precipitation in the dengue prevalence county j in the month i . $g(M_i)$ is a smooth function (natural cubic spline function with the maximum 2 degrees of freedom) of the EASMI in the month i . $\varepsilon_{i,j}$ are

uncorrelated random errors of zero mean and finite variance. Note that the term $d(D_{i-1,j})$ was included to account for serial correlation. We selected the model by using the generalised cross validation value(GCV)(Stige, Ottersen et al. 2006) and Akaike information criterion (AIC)(Cox 1981) and ecological effect.

Results

Dengue cases have been reported in many areas of China since 1978 (Fig. 1). However, large outbreaks, i.e., more than 10 cases each year, concentrated in provinces along the south coastline in China, including Yunnan, Guangxi, Hainan, Guangdong, Fujian, and Zhejiang, as well as other provinces, such as Henan (Fig. 1). Dengue are predicted to occur over a large area of China (Fig. 2A). Of note, medium-risk areas with the potential to have more than 10 cases per year were predicted to restrict in South China, mostly in Yunnan, Guangxi, Guangdong, and Hainan Provinces (Fig. 2B). The high-risk area of dengue outbreaks with more than 100 cases was only found in Guangdong and Guangxi provinces and Taiwan (Fig. 2C).

The AUC for the model predicting all counties with an occurrence of dengue (Model 1), dengue outbreaks with at least 10 cases (Model 2), and dengue outbreaks including more than 100 cases (Model 3) was 0.867 ± 0.003 , 0.954 ± 0.005 , and 0.974 ± 0.004 , respectively. Moreover, population density had 68.7%, 28.8%, and 21.6% contribution to dengue outbreaks in three models, respectively. The mean temperature of the coldest quarter had 12.0%, 53.1%, and 62.9% contribution, and

precipitation of the wettest month had 13.0%, 12.9%, and 6.2% contribution, respectively (Table 1). These results suggest that population density and mean temperature of the coldest quarter were the most important environmental factors influencing the geographical distribution of dengue.

The relationship between dengue incidence and EASMI is shown in Fig. 3. We separately estimated the effects of climatic factors on dengue transmission in China (Fig. S1) and the southern coastal area of China (Fig. S2), including Fujian, Guangxi, Guangdong, and Yunnan provinces. The results of the selected models are shown in Table S1. Seasonality in dengue was captured by including the calendar month in the model ($F_{3.0, 20.7} = 146.34, p < 0.01$, Fig. S1A). The GAM revealed a positive nonlinear association between monthly average temperature for lag time 0 month and dengue incidence in China ($F_{1.9, 20.7} = 7.45, p < 0.01$, Fig. 4A). Monthly total precipitation for lag time 1 month had positive nonlinear effects on dengue incidence ($F_{1.6, 20.7} = 5.79, p < 0.01$, Fig. 4B). The EASM exhibited a dome-shaped association with dengue incidence ($F_{2.0, 20.7} = 83.73, p < 0.01$, Fig. 4C). Furthermore, the analysis applied to southern China showed similar relationships between climate factors and dengue outbreak in the whole of China (Fig. S2).

Discussion

It is notoriously difficult for risk mapping and predictions for dengue and there were different methods to predict the risk areas of dengue using different variables (Louis, Phalkey et al. 2014, Chen, Zhao et al. 2019). In the study, we used

ENM to explore the influencing of climate variables on dengue and determine the geographical distribution of dengue, which revealed a wide distribution of dengue prevalence in China. However, medium and high-risk areas (occurrence >10) were confined to southern coastal areas(Li and Zeng 2002) . We found a similar climate-dengue association between China and the southern coastal region, suggesting the dominate role of southern coastal region in shaping the entire dengue dynamics. Accordingly, target interventions should be implemented in this region. Additionally, both strength of EASM and local temperature and precipitation impacted dengue outbreak intensity.

The impact of monsoon on dengue outbreaks may through a monsoon-weather-mosquito-dengue mechanism. Specifically, monsoon will regulate local weather conditions which may further manifest the density of local vectors and hence dengue outbreak risks. The moisture transport plays a crucial role in moisture supply for precipitation in East Asia after the beginning of the Asian summer monsoon, thus leading to a dramatic change in climate regimes in East Asia(Yihui and Chan 2005). A study in southern India, another monsoon zone, showed that the House and Breteau Indices, indices of vector density, were relatively higher during the northeast monsoon, whereas the Container Index was higher during southwest monsoon(Mariappan, Srinivasan et al. 2008). Our study showed that the EASM exhibited a dome-shaped association with dengue outbreaks in the whole of China and in the south of China, and we speculate that the EASM may be a key contributing factor of climate change and outbreaks of dengue fever in China. Summers in the

southern coastal regions of China, located in a subtropical monsoon climate region, are hot and rainy. There is also a long rainy season before summer that lasts, on average, from June 12th to July 8th, called “Meiyu”, which is influenced by the EASM(Chen and Chang 1980). A previous study showed that the monsoon was the main determinant of environmental conditions over much of Asia(Zahn 2003). In middle and lower reaches of the Yangtze River in China, a study showed a negative correlation between EASM and summer rainfall, indicating that drought years were associated with a strong EASM and flood years were associated with a weak EASM(Yihui and Chan 2005, Li, Park et al. 2018). The monsoon signals were reflected in the temperature and Meiyu precipitation variations in China(Hao, Sun et al. 2015). A dengue epidemic occurred in Pakistan throughout the year but had a peak incidence in the post monsoon period(Khan, Kisat et al. 2010), indicating that the monsoon may play an important role in disease transmission. Our results, showing that monsoon strength is associated with dengue prevalence in southern coastal China, may help provide a better understanding of the effects of monsoon and climate change on dengue transmission in the country, providing important insights for dengue control and prevention in China.

Our study indicated that Mean Temperature of Coldest Quarter played an important role in dengue outbreak in ENM. Besides, there was a positive nonlinear association between monthly average temperature and dengue occurrence, which was consistent with previous studies(Xiao, Liu et al. 2018). Chakravarti(Chakravarti and Kumaria 2005) highlighted rainfall, temperature, and relative humidity as major

climatic factors, which could alone or collectively be responsible for an outbreak, based on the analysis of dengue data in India in 2003. Temperature variation may affect the efficiency of mosquito vectors in spreading dengue virus; as the temperature increases, the extrinsic dengue virus incubation period in *Ae. albopictus* gradually shortens, resulting in infection rates showing a tendency to initially increase followed by a decrease (Colón González, Fezzi et al. 2013). Relationships between the cumulative incidence of dengue fever and climatic factors were explored in Taiwan, which revealed that the number of months with an average temperature higher than 18 °C per year was associated with increasing risk of dengue fever incidence at a township level, and every 1 °C increase in the monthly average temperature accounted for a 1.95 times increase in dengue fever transmission in the total population. In some regions, temperature had a negative effect on dengue outbreaks, as extremely hot temperatures may also increase the rate of mosquito mortality and thus decrease dengue risk (Gomes, Nobre et al. 2012, Naish, Dale et al. 2014). The contrasting results of temperature effect on dengue may be due to spatial heterogeneity, as Malaysia is in the tropical region.

In addition, our results also revealed that monthly total precipitation had a positive nonlinear effect on dengue incidence. Many studies (Naish, Dale et al. 2014, Xiao, Liu et al. 2018) found that precipitation significantly influences dengue incidence and that relationships are highly nonlinear. For example, a study in Mexico (Colón-González, Fezzi et al. 2013) found an increasing effect of monthly accumulated precipitation up to about 550 mm, beyond which the effect declined. A

10-millimetre rise in precipitation led to a consistent 6% increase in dengue cases in the following month from 2001 to 2009 in the city Rio de Janeiro, Brazil(Gomes, Nobre et al. 2012). Precipitation is thought to have nonlinear effects on dengue risk, as heavy rainfall may flush eggs, larvae, and pupae away from containers in the short term, but residual water can create breeding habitats in the longer term.

Other factors may also influence dengue outbreak risk. Amongst them, population density was the major contributing factor for the spatial distribution of dengue cases in China. Previous studies revealed that dengue was ubiquitous throughout the tropics, with local spatial variations in risk influenced by rainfall, temperature, and the degree of urbanisation(Bhatt, Gething et al. 2013). Global dengue risk maps had shown that very few rural areas in Europe were suitable for dengue at present, but several major cities appeared to be at some degree of risk, probably due to a combination of thermal conditions and high human population density(Rogers, Suk et al. 2014). Using a dataset from 2007 to 2010, monthly average precipitation was found to be associated with the distribution of dengue in Colombia(Restrepo, Baker et al. 2014). Connectivity between large and warm cities was one of the most important factors determining the spatial diffusion of dengue across Brazil(Barcellos and Lowe 2014), and social economic factors, such as the practice of water storage at home, low frequency of garbage collection, and lack of basic sanitation were also closely linked to dengue outbreaks(Cordeiro, Donalisio et al. 2011).

In brief, the prevalence and spread of dengue is a complex and multi-factors

process. The ever-increasing global commerce and travel facilitate the spread of dengue. Dengue in China not only poses health threat for local people, but also indicates a risk of disseminating it to other related countries. A study(Quam, Sessions et al. 2016) found the sequence of dengue virus from an outbreak in 2014 in Japan similar to that in China, which suggested that the dengue virus was likely to be imported from China. With the change of global climate, dengue is spreading in the world (Jentes, Lash et al. 2016) and all countries need to work together to prevent dengue fever occurrence. This study provides a convincing evidence on the linking between climate and dengue, considering both short-term climate factors and long-term climate influence such as EASM. In addition, the findings identified high risk areas, which is beneficial for local government to issue early warning of dengue outbreak. More health resources can be allocated to the high-risk areas with high population density to prevent dengue outbreak. Besides, mosquito control should be prioritized, particularly before adverse weather conditions. The limitations of this study should be acknowledged. Firstly, there was a lack of analysis of vector density due to data unavailability. Secondly, there might have been under-reporting or missing values of dengue cases in rural areas of China, especially in the 1970s and early 1980s. Moreover, the underlying mechanisms of the spatial heterogeneity of the EASM and the association with large dengue outbreaks are still unclear. Further, the role of monsoon as a driver of dengue outbreaks should be validated in other parts of the world. The strength and inter-annual variability of the monsoon on other metrological variables, such as wind strength, and the seasonality of local climate factors require

further research.

Conclusions

Our study predicted the risk areas of dengue outbreaks and demonstrated that temperature and monsoon are important environmental factors influencing the timing and intensity of dengue outbreaks, particularly in South China, the region of the country most sensitive to the EASM. Thus, our findings provide a framework for uncovering the linkage between climate change and vector-borne diseases, which could be applied to other parts of the world.

Competing interests

The authors declare that no competing interests exist.

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Authors contributions:

Keke Liu, Xiang Hou, Lei Xu, Qiyong Liu designed the study, performed data analysis, and wrote the study. Zhoupeng Ren, Jimin Sun, Yiguan Wang, Ruiyun Li, Chutian Zhang, Shaowei Sang, Yuan Gao, and Jing Li performed the study analysis. Xiaobo Liu, Xiuping Song, Jun Wang, HaixiaWu, Liang Lu, Wenwu Yao, and

Jianping Li contributed to the data collection. All authors assisted in writing the manuscript.

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- 551 □

Table 1. Contribution rate of different factors to dengue in China

Variables	Contribution (%)				
	PD	MTCQ	MTWQ	PWM	PWQ
Model 1	68.7	12.0	5.7	13.0	0.6
Model 2	28.8	53.1	4.3	12.9	0.9
Model 3	21.6	62.9	2.9	6.2	6.4

552 PD: Population density. MTCQ: Mean Temperature of Coldest Quarter. MTWQ:

553 Mean Temperature of Warmest Quarter. PWM: Precipitation of Wettest Month. PWQ:

554 Precipitation of Warmest Quarter.

555

Fig. legends

Fig. 1. The distribution of dengue annual cumulative cases in mainland China from 1978 to 2017. Blue points indicate counties that have had 1-10 dengue cases since 1978. Yellow points indicate the counties that have had 11-100 dengue cases. Red points indicate counties that have had more than 101 dengue cases.

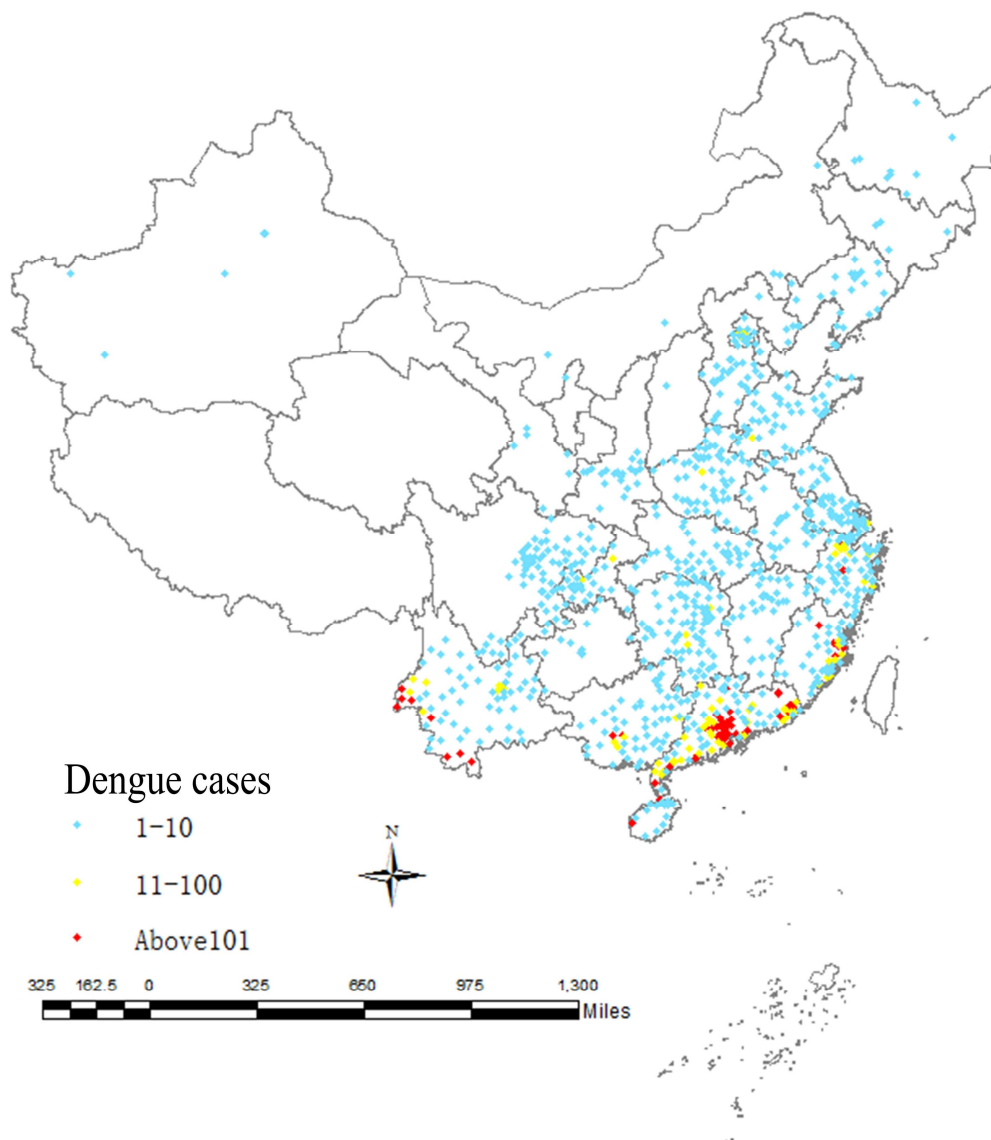
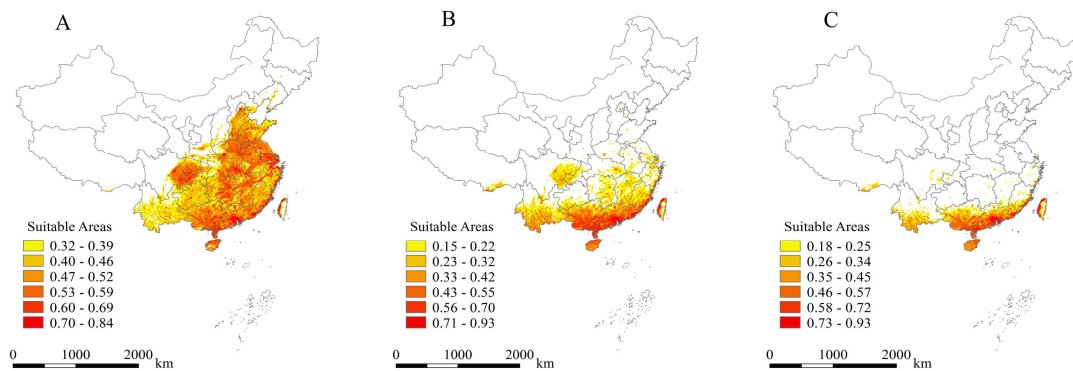


Fig. 2. A. The predicted dengue risk regions based on all locations with at least 1 case.

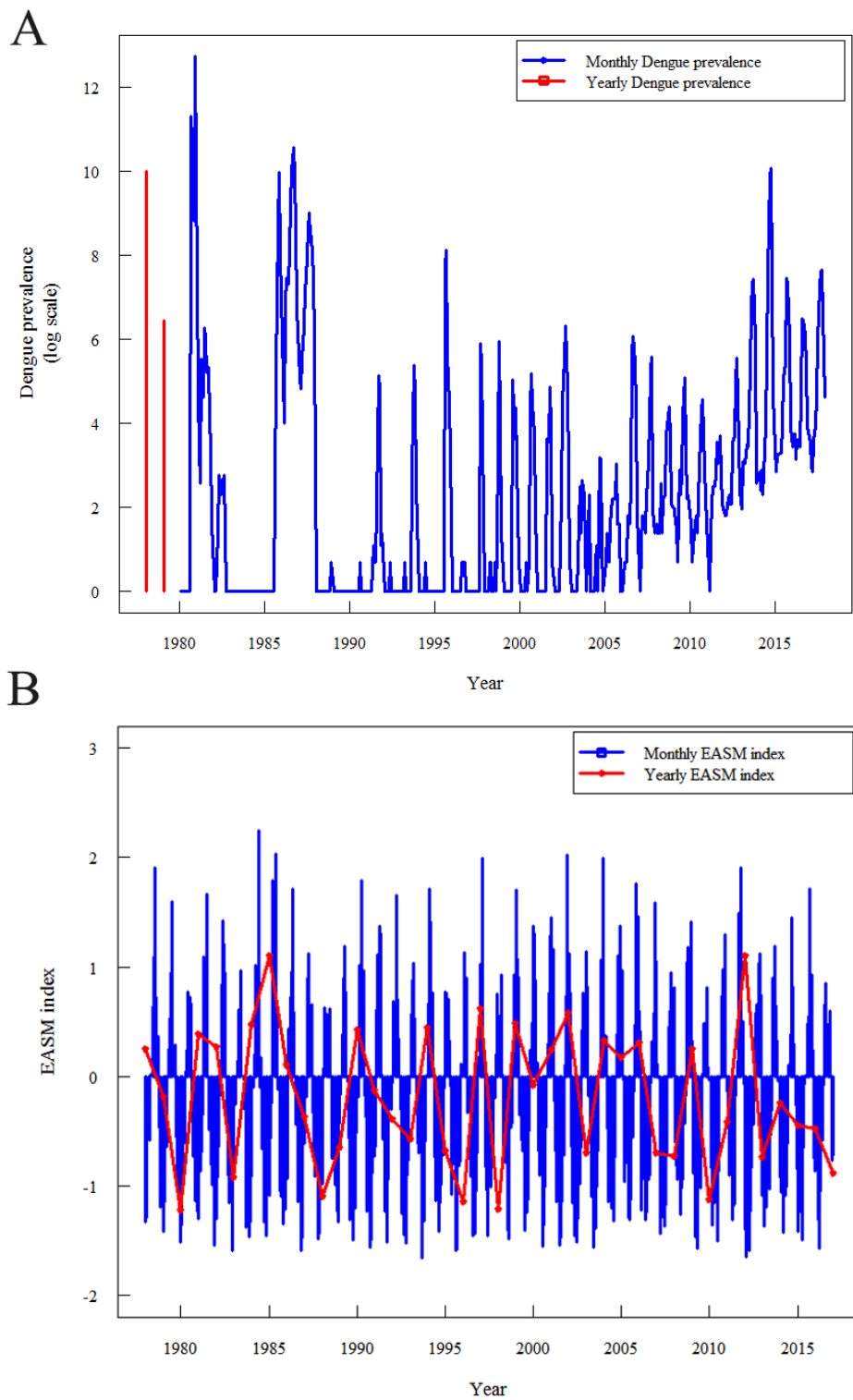
B. The predicted medium risk region based on locations that had more than 10 cases.

C. The predicted high-risk region based on locations that had greater than 100 dengue cases. The ecological Niche Model (ENM) was used for all predictions. The numbers and colours indicate the different risk level of dengue suitability areas in the map.

Comparing the 3 level predictions, we found that although most high population density regions in China are threatened by dengue, the coastal region has the most exposure to high risk and big outbreaks of dengue infection.



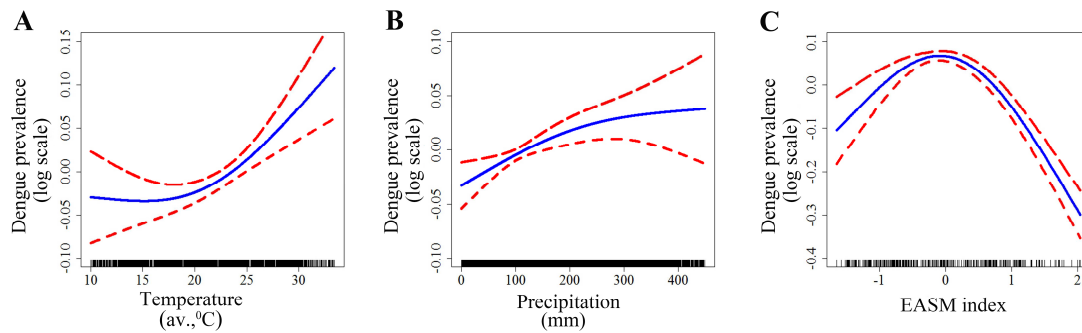
573 **Fig. 3.** Time series of the East Asian summer monsoon (EASM) index and dengue
574 prevalence in China. **A.** The blue line indicates the log-transformed monthly dengue
575 prevalence (log scale) from 1980-2017 and the red bar shows yearly dengue
576 prevalence in 1978-1979 (monthly dengue data is unavailable from 1978 to 1979). **B.**
577 The blue line shows the time series of the monthly EASM index from 1978-2017 and
578 the red line indicates the annual average EASM index (only from July to August every
579 year).



580

581

Fig. 4. Partial effects on dengue prevalence (log scale) based on the monthly data from 1980 to 2016 using the generalised additive model (GAM). **A.** The effect of the monthly average temperature ($^{\circ}\text{C}$) in the current month (time lag=0). **B.** The effect of the previous monthly total precipitation (mm) (time lag=1). **C.** The effect of the East Asian summer monsoon (EASM) index in the current month (time lag=0). Blue lines indicate the estimated mean value and the red dashed lines indicate the 95% confidence intervals.



Highlights

- Mean Temperature of Coldest Quarter had an 62.6% contribution on dengue outbreaks.
- The south of China areas including Guangdong, Guangxi, Fujian and Yunnan provinces were more vulnerable to a high risk of dengue infection.
- Statistical analysis indicated a dome-shaped association between EASM and dengue outbreak in China, with the greatest impact around the southeast of China.

There is no conflict in our study.

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