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The impact of climate variability on dengue fever risk in central java, Indonesia

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ABSTRACT

Background: Dengue fever is a growing concern for public health under future climate variability. This study aims to investigate the dengue fever from 35 cities/counties linked with historical observation and anomaly of weather variables from 4 weather stations in Indonesia.
Method: We collected monthly surveillance data of dengue fever in central java, temperature and precipitation from Tegal, Semarang, Tunggul wulung and Sleman weather stations, and flood event from 2009 to 2019. The distributed non-linear model was adopted to evaluate the effect of extremes weather variables and anomalies on the dengue risks. The extreme thresholds were defined at 5th and 99th percentile. Random-effects *meta*-analysis was applied to estimate weather station-specific pooled relative risk (RR) and 95% confidence intervals (CI) for the studied areas.
Result: Dengue prevalence rates were higher in the rainy season (Nov–March) compared to dry season (Apr–Oct). Extreme high temperature was positively associated with dengue fever in Semarang with RR of 4.92 (95 % CI: 1.01, 24.0). Extreme low precipitation was positively associated with dengue fever in Tegal with RR of 9.60 (95 % CI: 2.65, 34.6). The risk of dengue fever in western part of Central Java, especially in the Tunggul wulung, was positively associated with extreme high anomaly of precipitation [RR = 4.05 (95 % CI: 1.86, 13.7). Meanwhile, extreme low anomaly of precipitation was positively associated with the risk of dengue fever with RR of 2.75 (95 % CI: 1.75, 4.32) in Semarang.
Conclusion: These findings highlight the importance of considering weather variability in addressing the risks associated with dengue fever in Central Java, Indonesia.

Introduction

Dengue fever is the most widespread and rapidly increasing vector-borne disease globally and has caused a serious public health problem (World Health Organization, 2020). The incidence of dengue fever has risen dramatically in recent decades. Over the last two decades, the number of dengue cases reported to WHO has increased by 8-fold, from 505,430 cases in 2000 to over 2.4 million in 2010 and over 5.2 million in 2019 (World Health Organization, 2021). The prior study estimated that 70 % of the actual dengue fever global burden was found in Asia (Bhatt et al., 2013). The rapid spread of dengue fever has been attributed to climate change, globalization, and a lack of effective mosquito control (Gubler, 2011). There is also a possibility that ongoing climate change, frequent international travel, or unplanned urbanization may contribute to the changing geographical distribution and increasing burden of dengue epidemics in recent years (Ebi and Nealon, 2016; Messina et al., 2014).

Dengue viruses are transmitted by two species of *Aedes* female

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Fig. 1. The area coverage by weather stations located in Central Java, Indonesia.

mosquitoes, mainly *Aedes aegypti* and, to a lesser extent, *Aedes albopictus* (Kraemer et al., 2015). It has four distinct serotypes (DENV-1 to 4), and patients infected by the dengue virus have a wide range of non-specific clinical manifestations, including high fever, maculopapular rash, and pain in five distinct areas: severe frontal headache, *retro*-orbital pain, bone pain, myalgia, arthralgia (Chang et al., 2018; Guzmán and Kourí, 2002). Another severe clinical dengue fever level can occur with bleeding tendency, thrombocytopenia, and plasma leakage, as seen in dengue hemorrhagic fever and dengue shock syndrome (Wang et al., 2020). Some diseases, such as influenza, enteric fever, leptospirosis, typhus fever, and malaria, have similar manifestations; thus, distinguishing dengue fever from other dengue-like diseases is important for early diagnosis and treatment.

With projected climate changes, there is a noticeable increase in global surface temperature, accompanied by a high risk of both floods and rising sea levels in Indonesia (IPCC, 2022). Climatic change and variability are known as the key driver of vector abundance and the dynamics of dengue fever transmission (Nosrat et al., 2021). Numerous studies conducted in tropical regions have revealed that dengue fever transmission takes place within an optimal temperature range of 25–30 °C (Monintja et al., 2021; Lahondère and Lazzari, 2012). Temperature can affect the mosquito biological process such as reproduction, biting rate, development rate, etc. Additionally, rainfall emerges as the foremost influencing factor in vector development and dynamics (Bai et al., 2013; Naish et al., 2014). Abundant rainfall negatively correlated with dengue incidence because it flushed away the mosquito eggs; however, rainfall can provide suitable environment for mosquito to breeding (Méndez-Lázaro et al., 2014; de Melo et al., 2012).

Furthermore, wind speed and sunshine duration might be weather factors that influence the risk of dengue fever (Masrani et al., 2021; Pham et al., 2011). Previous studies have shown that low wind speed increased dengue incidences compared to high wind speed (Masrani et al., 2021). A longer duration of sunlight will lead to higher temperature, which increases the transmission rate of dengue fever in various ways (Lai, 2018).

The latest IPCC (AR6) report estimated that vector-borne diseases is likely to have longer epidemics seasons and wider distribution in Asia in the future, which may jeopardizing the health and welfare of 2.25 billion people due to dengue fever (IPCC, 2022). Indonesia, a tropical island country, long-term experience epidemics and endemics of mosquito-borne disease transmission like malaria and dengue fever. It is necessary to strengthen the community resilience against climate hazards. With regards to dengue fever, such adaptation measures require appropriate knowledge of the underlying association between the dengue fever and climate variability. Hence, this study aims to investigate the effects of extremes and anomalies of weather variables, including temperature, precipitation, wind speed, sunshine hours, and flood event, on dengue fever risk using time-series population-based 11 years (2009–2019) surveillance data of dengue fever in Central Java, Indonesia.

Materials and methods

Study area

This study focused on monthly and four regions analysis for dengue fever in Central Java, Indonesia. Central Java is located at 7.1510° S, 110.1403° E. It has an area of 32,800.69 km^2, with 34,718,204 people in 2019 making Central Java the third most populous province in Indonesia. This study first evaluated the city-specific dengue fever risk associated with extremes and anomalies of weather variables, and further the pooled relative risks were estimated by region of the weather stations. The city/counties covered in each region of the weather stations (Tegal, Semarang, Tunggul wulung, and Sleman) is shown in Fig. 1 and Supplementary Table 1.

Data sources

A laboratory-confirmed dengue fever cases admitted to the city/county hospitals must be reported to the City Health Office within 24 h of diagnosis. The Provincial Health Office (PHO) summarizes all cases weekly and reports to the Indonesian Ministry of Health on a monthly basis. Dengue cases were regarded as positive based on the following criteria: (1) anti-dengue virus IgM in acute or convalescent serum samples; (2) a 4-fold increase in specific IgG antibody titers between the acute and the convalescent samples; (3) isolation of dengue virus; (4) detection of dengue antigen or RNA in serum (MoHRo, 2005). We successfully retrieved monthly surveillance of laboratory-confirmed dengue fever cases (indigenous and imported cases) admitted to the hospitals from the Central Java PHO for 35 cities/counties in Central Java from January 2009 to December 2019.

Meteorology, Climatology, and Geophysical Agency (Indonesian: Badan Meteorologi, Klimatologi, dan Geofisika, abbreviated: BMKG) provided daily weather data of average temperature (°C), cumulative precipitation (mm), wind speed (m/s) and sunshine hours (hour) for the same period. We aggregated the daily weather data into monthly average weather data from 4 observatories, namely Tegal, Semarang, Tunggul wulung and Sleman weather stations. For Central Java, weather data were obtained from 3 stations in Semarang, Tegal, and Cilacap, and one station located in Sleman, Yogyakarta. The locations of four weather stations are illustrated in Fig. 1. Detailed station information and quality assurance criteria are available on the portal (https://dataonline.bmkg.go.id/).

Further, to calculate the monthly anomalies of weather variables, this study used the 30-years records of monthly weather data from 1990 to 2019 to calculate the baseline. In this case, because of the limitation of data availability, Sleman weather station used 16 years of recorded monthly weather data (2004 to 2019) to calculate the baseline. World Meteorological Organization (WMO) suggested that above ten years of data provided a predictive skill similar to that from a standard 30-year period (World Meteorological Organization, 2017) [125]. This study's climate anomaly varied by city, month, and year. The formula used for climate anomalies calculation is mentioned below:

$$Climate\ anomalies\ value\ for\ month\ 'm'\ and\ year\ 'y' = X - \bar{X} \tag{1}$$

where X is an actual observation of climate variables (average temperature, cumulative precipitation, wind speed, and sunshine hours) for month 'm' and year 'y'. $\bar{X}$ is the mean of 30 year or 15 year meteorological variables for month 'm'.

Indonesian National Board for Disaster Management (Indonesia: Badan Nasional Penanggulangan Bencana abbreviated: BNPB) web page (https://dibi.bnpb.go.id/) provides monthly flood events in Central Java. Data were obtained at city level from 2009 to 2019. According to the Indonesian National Board for Disaster Management, a flood event is an event or condition where an area or land is submerged due to an increased volume of water (Law on Disaster Management, 24, 2007).

Data analysis

Prevalence rate analysis

The prevalence rate is the number of people with a particular disease in a population at a certain time, expressed as a percentage per 100,000 people (Health USDo, 2011):

$$Prevalence rate = \frac{\text{number of all existing cases at the time (or period)}}{\text{the average number of people in the same period}} \times 100,000 \tag{2}$$

This study calculated the prevalence rates by month and region to observe the seasonal (rainy season: from November to March; dry season: from April to October) and spatial difference in prevalence rate from January 2009 to December 2019.

Non-linear association between monthly climatic variability and dengue fever risks

This study investigated the temporal association between dengue fever cases and meteorological factors using a two-stage analytical method. In the first stage, we adopted distributed lag non-linear model (DLNM) proposed by Gasparrini et al. (Gasparrini et al., 2010). Generally, DLNM is used to assess the relationship between meteorological factors and infectious disease in an epidemiological study (Xiang et al., 2017; Limper et al., 2016). In this study, quasi-Poisson was developed, which was specified as:

$$Log[E(Y)]\ BS(T, lag) + BS(PP, lag) + ns(ws, df = 3) + ns(sh, df = 3) + ns(time, df) + Floodevent + log(population) \tag{3}$$

Where Y is the monthly city-specific number of laboratory-confirmed dengue fever cases, T is the monthly measurement or anomaly of average temperature, and PP is the monthly measurement and anomaly of cumulative precipitation in the specific city. This study evaluated the lag non-linear associations between weather variability and dengue fever risks using the basis spline (BS) function with 3 degrees of freedom (*df*) for monthly average temperature and cumulative precipitation, the effects were assessed for lag 0 to 2 months. Based on prior studies using a monthly time scale, lag in weather variables would not be set for more than two months (Xiang et al., 2017; Ramadona et al., 2016; Colón-González et al., 2013). In addition, the model controlled the monthly average wind speed (ws) and sunshine hour (sh) and both were set as the natural cubic spline with *df* equal to 3 (Xu et al., 2019). While there are other available options of spline, our study adopted natural cubic splines in our model setting. By using ns as a splines, model constructs a fixed locations for the knots throughout the data range and it has less number of degree of freedom (Yan et al., 2019; Yang et al., 2012). Additionally, we included flood event variable in our model. We computed binary variables to indicate a city is experiencing flood during the specific month. This model also considered time as a natural cubic spline to control the seasonal and long-time trend components by changing the degree of freedom from 4 and 7 *df*/year for temporal adjustment (Cheong et al., 2013). A variable or a set of variable representing time (t) had been widely used in statistical regression models in environmental health or epidemiology field to control for seasonality and long-term trend (Kim et al., 2021; Andhikaputra et al., 2023). In addition, natural cubic spline (ns) with degrees of freedom (df) per year are commonly used and its performance has been tested by simulation studies (Kim et al., 2021; Peng et al., 2006; Perrakis et al., 2014). The model selection is based on the lowest Akaike's information criterion generated by the model (Supplementary Table 2) (Ramadona et al., 2016).

In the second stage, *meta*-analysis was fitted with a random-effects model to pool the relative risk of city-specific exposure–response associations and 95 % confidence interval for dengue fever in each region of the weather station from the results of the first stage analysis. The risk estimates for extremes of monthly average temperature and cumulative precipitation and their anomalies were reported at both 5th and 99th. The risk of extreme low and high is reported at 5th and 99th percentile of the monthly average temperature/cumulative precipitation and their anomalies, respectively. Instead of defining symmetrical percentile for the extremes cut, this study used 5th percentile to assess the risk of extreme low temperature and 99th for extreme high temperature. Those numbers were chosen because Indonesia has tropical climate condition, the 1st percentile is considered too low in Indonesia and the frequency of it will be decreasing in the future due to the climate change. Moreover, we believe that global temperatures are likely to continue rising in the future, so we preferred to report the risks at 99th instead of 95th

Table 1
Total cases and prevalence rate of dengue fever (per 100,000 people) by month in Central Java, 2009 to 2019.

Region	Sum of cases	Prevalence rate (per 100,000 people)											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tegal	15,907	17.5	18.1	16.1	18.6	14.7	12.3	9.93	7.68	6.11	8.31	7.41	9.14
Semarang	64,464	163	139	116	102	74.7	53.1	56.1	43.3	41.6	52.4	58.8	72.1
Tunggul wulung	14,476	32.2	37.9	34.1	39.1	32.5	24.7	23.5	16.1	11.4	9.84	8.51	14.9
Sleman	32,778	35.3	32.4	33.4	38.3	31.6	28.1	26.7	18.5	14.1	13.4	11.8	16.8
Total	127,625	248	227	200	198	153	118	116	85.5	73.3	83.9	86.5	113

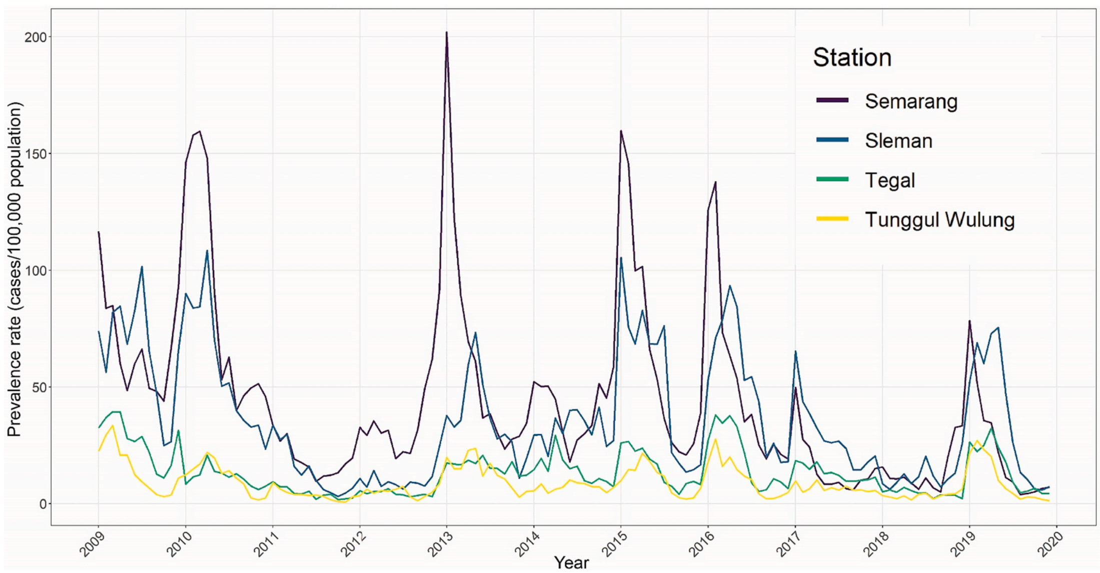

Fig. 2. Monthly dengue fever cases in Central Java by regions from 2009 to 2019.

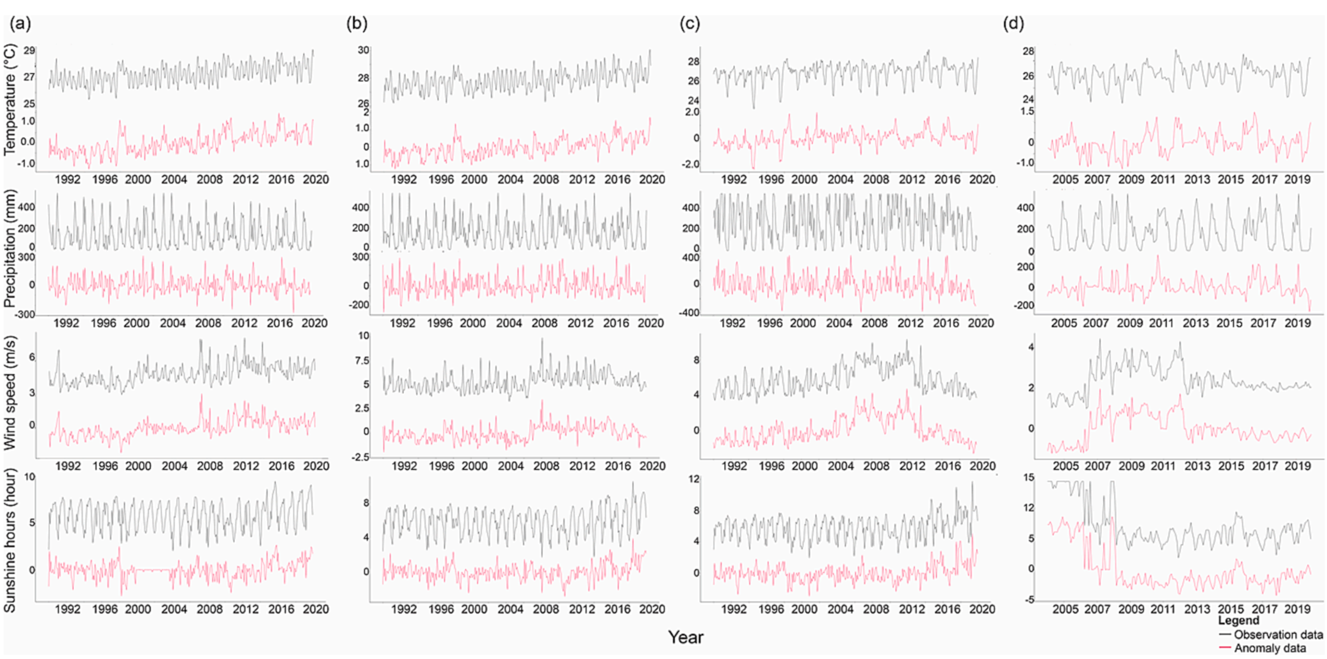

Fig. 3. The monthly average temperature (°C), cumulative precipitation (mm), wind speed (m/s) and sunshine hours (hour) in the Tegal weather station (a), Semarang weather station (b), Tunggul wulung weather station (c) from 1990 to 2019 and the Sleman weather station (d) from 2004 to 2019.

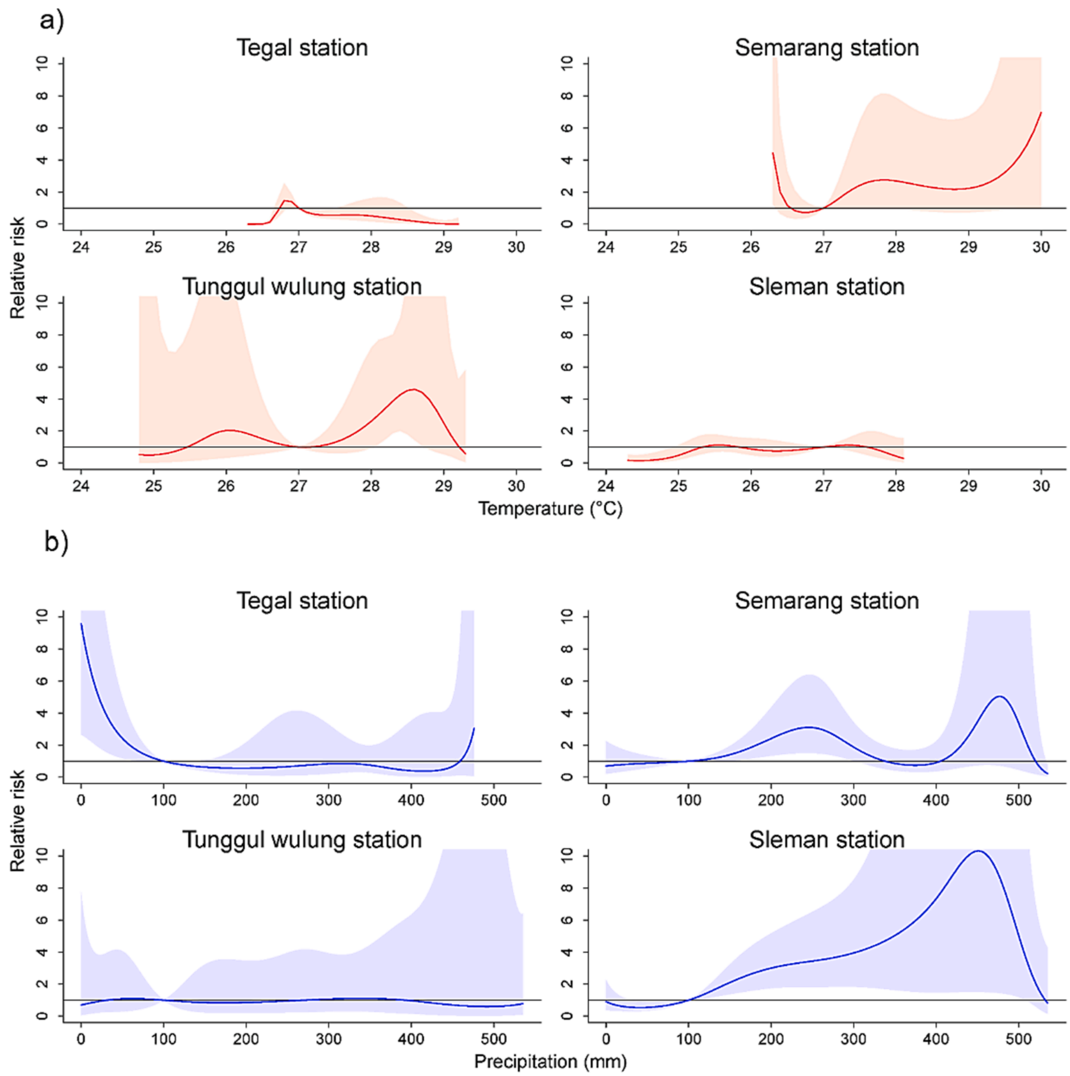

Fig. 4. Relative risk (95% confidence interval) of region-specific dengue fever associated with monthly (a) average temperature and (b) cumulative precipitation in Central Java from 2009 to 2019.

percentile.

All analyses were conducted using the *mgcv, dlnm,* and *mvmeta* packages in R (version 3.3.3).

Results

Characteristics of dengue fever and climatic factors

The descriptive statistics of the number of dengue fever cases from 2009 to 2019 is presented in Table 1. The total number of dengue fever cases was 127,625 cases in Central Java, with the highest case number in the Semarang region (n = 64,464 cases). The trends of monthly dengue fever cases are shown in Fig. 2. Transmission of dengue fever usually starts in December and reaches its peak in January and February. **Supplementary** Fig. 1 A illustrates the prevalence rates of dengue fever per 100,000 populations during 2009–2019 by city. We found that Semarang City, Magelang City, and Jepara County were the top three areas with the highest prevalence rates during the study period. The study also observed a strong seasonal pattern with a high monthly average prevalence rate occurring from November to March (**Supplementary** Fig. 1 **B**).

Fig. 3 shows the trends for monthly climate parameters and anomalies in each weather station of Central Java. The average temperature rose gradually during the study period, and the cumulative precipitation decreased at the end of the study period. On the other hand, the wind speed trend fluctuated, especially in the Tunggul wulung and Sleman weather stations. In line with temperature, sunshine hours were also found elevated each year.

Supplementary Table 3 lists statistics for monthly observed and anomaly of weather variables from 2009 to 2019 in each weather station of Central Java. The observed monthly average temperature varied from 26.2 °C (Sleman weather station) to 28.2 °C (Semarang weather station) while the warmest anomaly of monthly average temperature was observed in Tegal station with 0.43 °C and the lowest was shown in Sleman station with 0.11 °C during 2009–2019. The observed monthly cumulative precipitation ranged from 139 to 254 mm and the monthly anomaly of cumulative precipitation ranged from −5.77 to 6.75 mm. In terms of wind speed, the observed monthly average wind speed ranged from 2.49 to 6.03 m/s and its anomaly ranged from 0.07 to 0.55 m/s. In terms of sunshine hours, the observed monthly average sunshine hours ranged from 5.59 to 6.19 h and the anomaly ranged from −1.62 to 0.41 h in the study period.

The descriptive statistics of the number of flood events from 2009 to 2019 is presented in Supplementary Table 4 and the trend can be seen in Supplementary Figure 2. The total number of flood events was 1,175 in Central Java, with the highest number in the Semarang region (n = 438).

Table 2
Region-specific relative risk (95% confidence interval) of dengue fever cases associated with the observed weather and anomalies at 5th and 99th percentiles relative to the reference value from 2009 to 2019.

Variables \Region	Tegal	Semarang	Tunggul wulung	Sleman
Observed				
Extreme low temperature	1.46 (0.84, 2.56)	1.56 (0.91, 2.67)	0.62 (0.05, 6.99)	0.17 (0.04, 0.59)
Extreme high temperature	0.02 (0.01, 0.24)	**4.92 (1.01, 24.0)**	1.71 (0.41, 7.18)	0.74 (0.29, 1.90)
Extreme low precipitation	**9.60 (2.65, 34.6)**	0.70 (0.21, 2.25)	0.70 (0.06, 7.23)	0.90 (0.36, 2.25)
Extreme high precipitation	1.01 (0.11, 8.70)	0.22 (0.06, 0.76)	0.78 (0.09, 6.40)	0.81 (0.16, 4.26)
Anomaly				
Extreme low temperature	0.84 (0.41, 1.72)	1.07 (0.37, 3.06)	0.60 (0.19, 3.33)	0.40 (0.14, 1.10)
Extreme high temperature	3.77 (0.18, 76.2)	2.26 (0.27, 18.9)	0.28 (0.01, 7.03)	0.81 (0.29, 2.23)
Extreme low precipitation	0.72 (0.37, 1.40)	**2.75 (1.75, 4.32)**	1.33 (0.42, 4.20)	**2.23 (1.51, 3.28)**
Extreme high precipitation	3.84 (0.37, 39.1)	1.06 (0.74, 1.51)	**4.05 (1.86, 13.7)**	1.06 (0.47, 2.39)

It was found that Tegal City, Batang County, and Wonosobo County are the top three areas with the highest beta estimates of flood events (Supplementary Table 5).

The association between dengue fever cases and observation and weather anomalies

Fig. 4 demonstrates the pooled relative risk of dengue fever associated with monthly average temperature and cumulative precipitation by region of weather station. We observed the temperature with the lowest risk of dengue fever was around 27 °C in study regions. A significant risk of dengue fever was observed as the average temperature was above 28.3 °C in the region of Tunggul wulung weather station. Nevertheless, the risk declined as the temperature increased. The risk of dengue fever was significantly associated with extreme high average temperature in the region of Semarang weather station with RR of 4.92 (95 % CI: 1.01, 24.01) (Table 2).

The results of observed extreme temperatures for the pooled analyses were similar with the city-specific analyses. Supplementary Figs. 3-4 show that the cities in the Semarang and Tunggul wulung weather station region were more vulnerable to dengue fever infection at higher temperature.

On the other hand, for associations between monthly cumulative

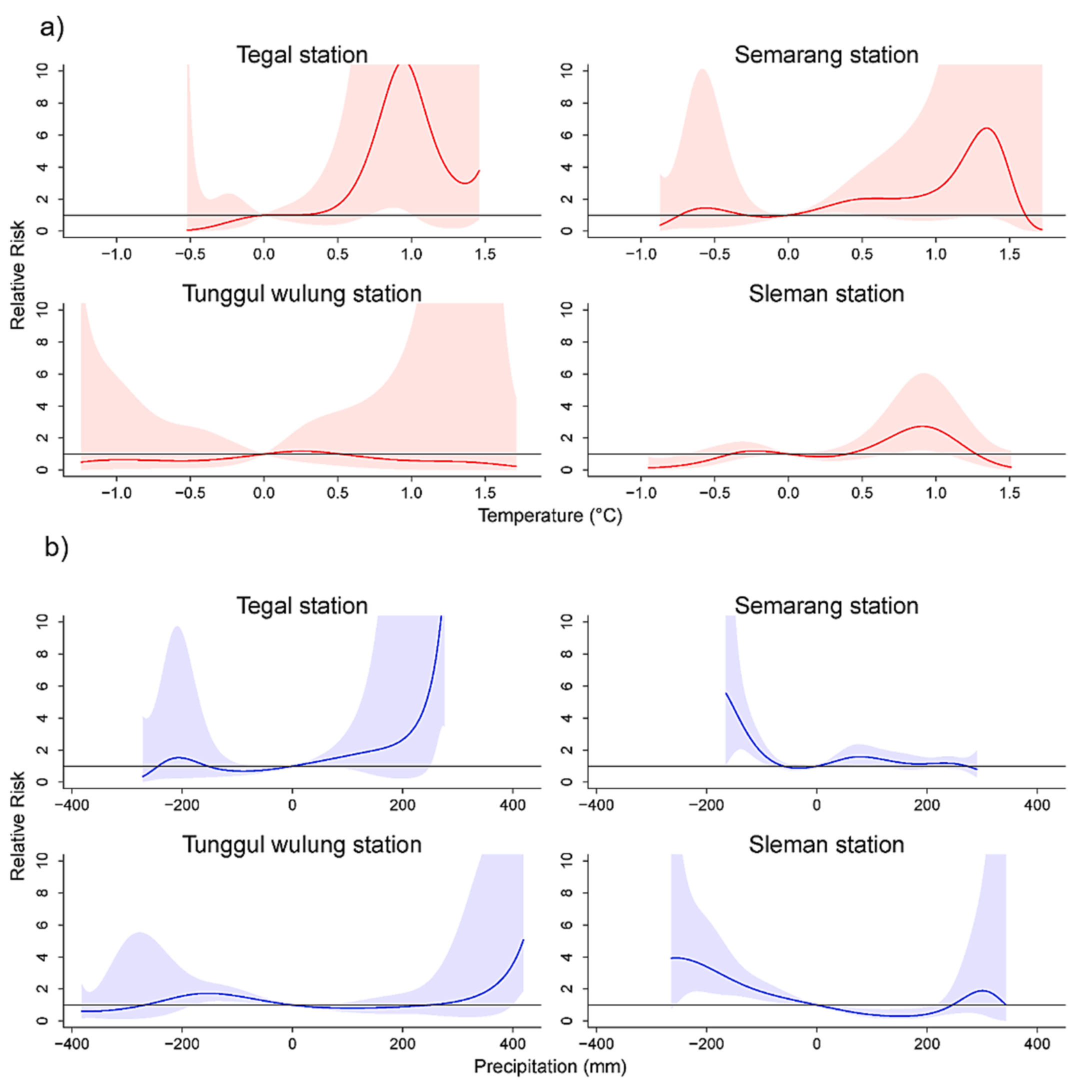

Fig. 5. Relative risk (95% confidence interval) of region-specific dengue fever associated with anomalies of monthly (a) average temperature and (b) cumulative precipitation in Central Java from 2009 to 2019.

precipitation and dengue fever risk, the reference value for all studied regions was set at 100 mm. Fig. 4**b** displays a significant risk association of dengue fever with monthly cumulative precipitation above 130 mm in the region of Semarang weather station, and above 100 mm in the region of Sleman weather station. However, the risk was decreased as the precipitation reached the 99th percentile. The effect of extreme low cumulative precipitation was only found in the Tegal weather station region with RR of 9.60 (95 % CI: 2.65, 34.6) (Table 2). The relative risk of city-specific dengue fever associated with the observed cumulative precipitation in 35 cities of Central Java can be seen in Supplementary Fig. 5-6.

Fig. 5 displays the pooled relative risk of dengue fever associated with anomalies of monthly average temperature and cumulative precipitation by region of the weather station. The reference values were set at 0 °C for anomaly of average temperature and 0 mm for anomaly of cumulative precipitation to represent the present condition. We found a significant association with an anomaly of average temperature at 0.74 °C in the region of Tegal weather station and at 0.65 °C in the region of Sleman weather station. However, we did not observe a significant risks at both extreme low and high anomaly of average temperature in four regions. In terms of anomaly of monthly cumulative precipitation, significant associations between extreme high anomaly of cumulative precipitation and the risk of dengue fever was identified in regions of Tunggul wulung weather station, with RR of 4.05 (95 % CI: 1.86, 13.7) (Table 2). In addition, the positive associations between extreme low anomaly of cumulative precipitation and increase risk of dengue fever were captured in Semarang and Sleman weather station regions, with RR of 2.75 (95 % CI: 1.75, 4.32) and 2.23 (95 % CI: 1.51, 3.28), respectively (Table 2). The results capture the relative risk of city-specific dengue fever and anomalies of temperature (Supplementary Figs. 7–8) and cumulative precipitation (Supplementary Figs. 9–10) were similar with the pooled analyses.

Discussion

This study is the first population-based study intended to identify the temporal association between the risk of dengue fever and extremes and anomaly for weather variability in Central Java, Indonesia. We evaluated the effect of climate change on vector-borne disease (dengue fever) by adopting both anomalies and direct measurements of weather variables as the exposure metric in our study. Previous study indicates that anomalies on weather variables can reflect changes in the historical context of climate and fill-out the scientific gap in how long-term changes climate impact the disease burden (Andhikaputra et al., 2023).

Our study found that exposure to extreme high temperature and extreme low precipitation of direct measurement would increase the risk of dengue fever in Semarang and Tegal station regions, respectively. Furthermore, anomaly of extreme precipitation was elevated the risk of dengue in almost all study area, except for Tegal station region. On the other hand, our study did not capture a significant effect of anomaly of extreme temperature on the risk of dengue fever in Central Java, Indonesia. A previous study mentioned that anomaly metrics cannot be compared directly with the direct measurements variables because anomaly is a generalized variable that considers the human adaptation over that particular historical period (Liu et al., 2022).

The observed extreme high average temperature may elevate the risk of dengue fever in the Semarang weather station region. The average temperature in Semarang weather station region was relatively higher than in other regions. Semarang weather station covers an area on the northeast coast of Central Java with ports and industrial areas. The average temperature near ports and industrial areas was higher than in other areas (Asariotis et al., 2018). Previous studies observed that extreme temperature positively affects dengue fever risk (Cheng et al., 2020; Ferreira, 2014). Extreme temperature in the summer months drives people to store the water in open containers in their homes, providing ideal breeding sites for *Aedes* mosquitoes (Beebe et al., 2009). A study in Thailand found that larva development was negatively affected by extreme high or low temperature (Campbell et al., 2013). The physiological process of mosquitoes would be slower at temperature higher than 35 °C, the optimum average temperature for mosquito growth is 25–30 °C (Monintja et al., 2021; Lahondère and Lazzari, 2012). However, this study defined the extreme temperature as 27.8–29.7 °C (99th percentile) on a monthly scale that is in line with the optimal temperature threshold for *Aedes* mosquitoes (Mordecai et al., 2017).

There was no effect at extreme low and high anomaly of average temperature on the dengue fever risk in the overall study area. Nevertheless, the risk of dengue fever has been associated with warmer climates. In warmer conditions, the mosquitoes' gonotrophic cycle can be accelerated and make female *Ae. aegypti* are more aggressive by increasing the biting rate and potentially transmitting viral practices to susceptible hosts (Teurlai et al., 2015; Focks et al., 2000; Scott et al., 2000). On the contrary, the low temperature might accelerate the dengue virus transmission by *Aedes aegypti* (Carrington et al., 2013). The mosquitoes with longer life-span in lower temperature would be expected to increase vector capacity and thus enhance virus transmission potential (Chang et al., 2007).

This study found extreme low monthly cumulative precipitation from the direct measurement variable increased the dengue fever risk in the region of Tegal weather station. The region of Tegal weather station is located in the northwest parts of Central Java which is a lowland and coastal area. A prior study in Brazil indicated that coastal areas are likely to face more drought and heatwaves (Rodrigues, 2020). Previous study also found that extreme drought increased the risk of dengue with different delays (Lowe et al., 2021). Extremely low precipitation can increase ambient temperature, water usage, air-coolers, and water storage that may serve as a breeding site (Hii et al., 2009).

Extreme low and high anomalies of cumulative precipitation were associated with dengue fever risk. According to a study in Hong Kong, the relative risk of dengue fever was higher when rainfall intensity before summer was lower than before (Yuan et al., 2020). A prior study also found that anomalously hot and dry conditions can lead to increased water storage around households and subsequent increases in populations of container-breeding mosquitoes like *Ae. aegypti* may transmit dengue virus (Anyamba et al., 2014). On the other hand, anomalously wet conditions could trigger the large-scale emergence of mosquito-borne disease and enhance the production and sustainment of vegetation that is the habitat of mosquitoes (Anyamba et al., 2012). This study also found that the higher prevalence rate occurs in rainy seasons. Several epidemiological studies have perceived a strong association between high precipitation and dengue fever risk (Xu et al., 2019; Kakarla et al., 2019). Another study in Indonesia found that dengue fever was a seasonal disease that mostly occurred in the rainy season when the precipitation is higher (Nuraini et al., 2021). During periods of high precipitation, rural areas inclined to be better able to absorb excess rainwater than urban areas and their artificial water catchments (Nosrat et al., 2021; Wasko and Sharma, 2017), potentially preventing a flood and instead of providing more stable water pools for mosquito breeding. Heavy rainfall observed with a higher transmission risk of dengue fever for up to 2 months (Kakarla et al., 2019; Fuller et al., 2017).

This study observed dengue fever risk would be elevated with extreme high anomaly of cumulative precipitation in the western parts of Central Java (regions of Tunggul wulung stations), meanwhile, the extreme low anomaly of cumulative precipitation increased the dengue fever risk in the eastern parts of Central Java (Fig. 5). The cumulative precipitation in the Sleman weather station region was relatively lower than the Tunggul wulung weather station region. Likewise, despite as a province with the highest rainfall in the Java Island (Avia, 2019), prior study proved that the eastern part of Central Java tends to have lower rainfall compare to the western part (Avia, 2019). In addition, the near future prediction from 2009 to 2028 of rainfall distribution pattern in Central Java was reported that almost half of Central Java Province will

Practical implications

Climate change has been projected to increase the frequency and intensify the extreme weather events in the foreseeable future (IPCC, 2022), which may exacerbate the risk of infectious diseases in the Asia. While studies have proven climate variables (temperature and precipitation) with the increment burden of dengue fever, there is a scarce information available regarding how long term changes in climate situation affect disease burden. Thus, this study tried to include weather anomaly as exposure metrics in the analysis to quantify the effect of long term anomalies in temperatures and precipitation on dengue fever, which are more relevant in terms of climate change. To the best of our knowledge, this is the first study to untangle the temporal association between extremes and weather anomalies on vector-borne disease in Central Java, Indonesia using 11 years (2009–2019) of surveillance data.

Our analysis reveals that dengue fever has seasonal pattern in Indonesia with highly monthly prevalence rate starts from November to March. We captured there was steady increment of monthly average temperature over the years, while, precipitation had decline trend in the past few years. The non-linear lagged regression model showed there was significant association between both extreme low and high of observation and anomaly climate factors and dengue fever, the risks varied between regions in Central Java, Indonesia. The distinction in specific climate-hazards on dengue fever highlight the urgency of integrating differences in public health preparedness measures to enhance community resilience toward the effect of climate change. The policymakers are suggested to take this knowledge for strengthening the preventive strategies to curb the dengue fever burden, which may include developing climate-based dengue fever early warning systems and community-based adaptation, may be worth considering for the future actions.

experience a decrease in high rainfall, and can cause drought (Nurrohman et al., 2021). Thus, based on climate projections and the present epidemiological findings, we would expect the greater challenge of control for dengue fever risk in Central Java in near future.

In addition, this study found that several city/county has positive beta estimates of flood event, top three areas with the highest beta estimates are Tegal City, Batang County, and Wonosobo County (Supplementary Table 5). Likewise, a review study reported that flooding has strong association with increased incidence of vector-borne diseases, including malaria, dengue, and other diseases (Coalson et al., 2021). On the contrary, study from island-wide country of Singapore indicated that rainfall-induced flushing event is statistically associated with the decreased risk of dengue outbreak (Benedum et al., 2018). Therefore, further study should be initiated in the future to untangle the nebulous association between flood event and dengue fever risk.

The various climate variables analyzed in this study reveal distinct patterns in the association between climate and dengue fever. For instance, utilizing observed precipitation data is likely to capture seasonal trends in dengue fever transmission. Conversely, anomalies in data highlight variations in the intensity of extreme precipitation events (Dimitrova et al., 2022). Given the ongoing climate change, it is anticipated that the frequency and intensity of such extremes will rise, leading to disruptions in both human and ecological systems. These disruptions can impact vector survival, transmission routes, human behavior, and immune responses. The findings indicate a heightened risk during the dry season in the western regions of Central Java and increased risks during rainy seasons in the eastern regions.

There are a lot of studies in Indonesia that have reported the risk of dengue fever. Yet, limited studies are available to study the anomaly of weather variability on dengue fever risk (Nosrat et al., 2021). Understanding how extreme climate events impact infectious disease transmission is essential as climate change accelerates and intensifies (Nosrat et al., 2021). A strength of the study is the estimation of monthly observation and weather anomalies to explain dengue fever risk. There is a possibility that the study's findings can be applied to other dengue-endemic areas similar to Central Java, Indonesia, and its findings regarding temperature- and precipitation-related risks can be applied to other regions with similar climates, demographics and socio-economics conditions. Future studies comparing the available weather data with the gridded weather data will strengthen give novel and robust epidemiological evidence linking dengue fever and these novel climate exposure metrics. Moreover, a study focus on the effects of flood on the dengue fever risks would be very helpful in the future for the government or policy makers in building the community's resilience in the future.

However, this study had few limitations. First, there is paucity in the meteorological data, since there are only four nearby stations located around the study area, thus we decided to divide the province in to four regions to match the spatial resolutions of the weather stations. Second, we did not incorporate socio-demographics details as confounding, as this individual-level information was not available. Additionally, the study only considered hospitalization at the public hospital, so the actual amount of dengue fever incidence is likely underestimated.

This study gives evidence that may have an important role in improving regional public policies to control dengue fever risk. The temporal association between the risk of dengue fever and extremes and anomaly for weather variability can be used as a reference for the regional health sector to develop an early warning based on the weather variation. Community-based adaptation can be designed and implemented, and the information and knowledge should be educated on the general public to enhance the community capacity and reduce the impacts of dengue fever in extreme weather events.

Conclusions

Dengue fever in Central Java was influenced by extremes and anomalies of weather variables. The extreme high average temperature was associated with the risk of dengue fever in the Semarang weather station region. Dengue fever risk was also associated with extreme low cumulative precipitation in the Tegal weather station region. Moreover, dengue fever risk was also associated with extreme low and high anomalies of precipitation. Dengue fever risks in regions of Tunggul wulung weather stations were increased with the extreme high anomaly of cumulative precipitation. Meanwhile, the extreme low anomaly of cumulative precipitation elevated the risk of dengue fever in Semarang and Sleman weather station regions. Compiling with future climate forecasts, this study suggests local authorities should design and implement preventive strategies and actions to control the increasing dengue fever risk in Central Java.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Data not available due to [ethical/legal/commercial] restrictions.

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CRediT authorship contribution statement

Bima Sakti Satria Wibawa: Conceptualization, Formal analysis, Writing – original draft. **Yu-Chun Wang:** Conceptualization, Writing – original draft, Formal analysis, Writing – review & editing. **Gerry Andhikaputra:** Formal analysis, Writing – review & editing. **Yu-Kai Lin:** Conceptualization. **Lin-Han Chiang Hsieh:** Conceptualization. **Kun-Hsien Tsai:** Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2023.100433.

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