



Research article

Non-linear effect of different humidity types on scrub typhus occurrence in endemic provinces, Thailand

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ABSTRACT

Background: Reported monthly scrub typhus (ST) cases in Thailand has an increase in the number of cases during 2009–2014. Humidity is a crucial climatic factor for the survival of chiggers, which is the disease vectors. The present study was to determine the role of humidity in ST occurrence in Thailand and its delayed effect.**Methods:** We obtained the climate data from the Department of Meteorology, the disease data from Ministry of Public Health. Negative binomial regression combined with a distributed lag non-linear model (NB-DLNM) was employed to determine the non-linear effects of different types of humidity on the disease. This model controlled overdispersion and confounder, including seasonality, minimum temperature, and cumulative total rainwater.**Results:** The occurrence of the disease in the 6-year period showed the number of cases gradually increased summer season (Mid-February – Mid-May) and then reached a plateau during the rainy season (Mid-May – Mid-October) and then steep fall after the cold season (Mid-October – Mid-February). The high level (at 70% of minimum relative humidity (RH_{min}) was associated with a 33% (RR 1.33, 95% CI 1.13–1.57) significant increase in the number of the disease; a high level (at 14 g/m³) of minimum absolute humidity (AH_{min}) was associated with a 30% (RR 1.30, 95% CI 1.14–1.48); a high level (at 1.4 g/kg) of minimum specific humidity (SH_{min}) was associated with a 28% (RR 1.28, 95% CI 1.04–1.57). The significant effects of these types of humidity occurred within the past month.**Conclusion:** Humidity played a significant role in enhancing ST cases in Thailand, particularly at a high level and usually occurred within the past month. NB-DLNM had good controlled for the overdispersion and provided the precise estimated relative risk of non-linear associations. Results from this study contributed the evidence to support the Ministry of Public Health on warning system which might be useful for public health intervention and preparation in Thailand.

1. Introduction

Scrub typhus (ST) is the most prevalent rickettsial and zoonotic disease in Australia (Odorico et al., 1998; McBride et al., 1999), China (Li et al., 2014; Yang et al., 2014; Wu et al., 2016; Sun et al., 2017; Wei et al., 2017), India (Razak et al., 2010), Japan (Seto et al., 2016), Korea (Kwak et al., 2015; Jeung et al., 2016), Taiwan (Lee et al., 2006; Kuo et al., 2011), and Thailand (Lerdthusnee et al., 2008; Suputtamongkol et al., 2009; Rodkvamtook et al., 2013). In endemic countries, people aged 30–59 years are at the highest risk of acquiring the disease throughout the year. There is no difference in the disease incidence

between sexes (Xu et al., 2017). Epidemiologic evidence showed that approximately one billion people living in an endemic area were at a risk of infection (Xu et al., 2017). According to the National Surveillance System, the median of monthly reported ST cases in Thailand during 2003–2014 was approximately 6,000 cases. Remarkably, the median of cases in each year during 2009–2014 sharply increased to >5,000 cases and peaked in 2013 with more than 10,000 reported cases (Bureau of Epidemiology Thai Ministry of Public Health, 2015). The number of cases during 2003–2008 showed a low incidence of the disease, contributing to misdiagnosis and underreported disease at the initiation of tracking with the ST-reporting system, as mentioned in a review of ST

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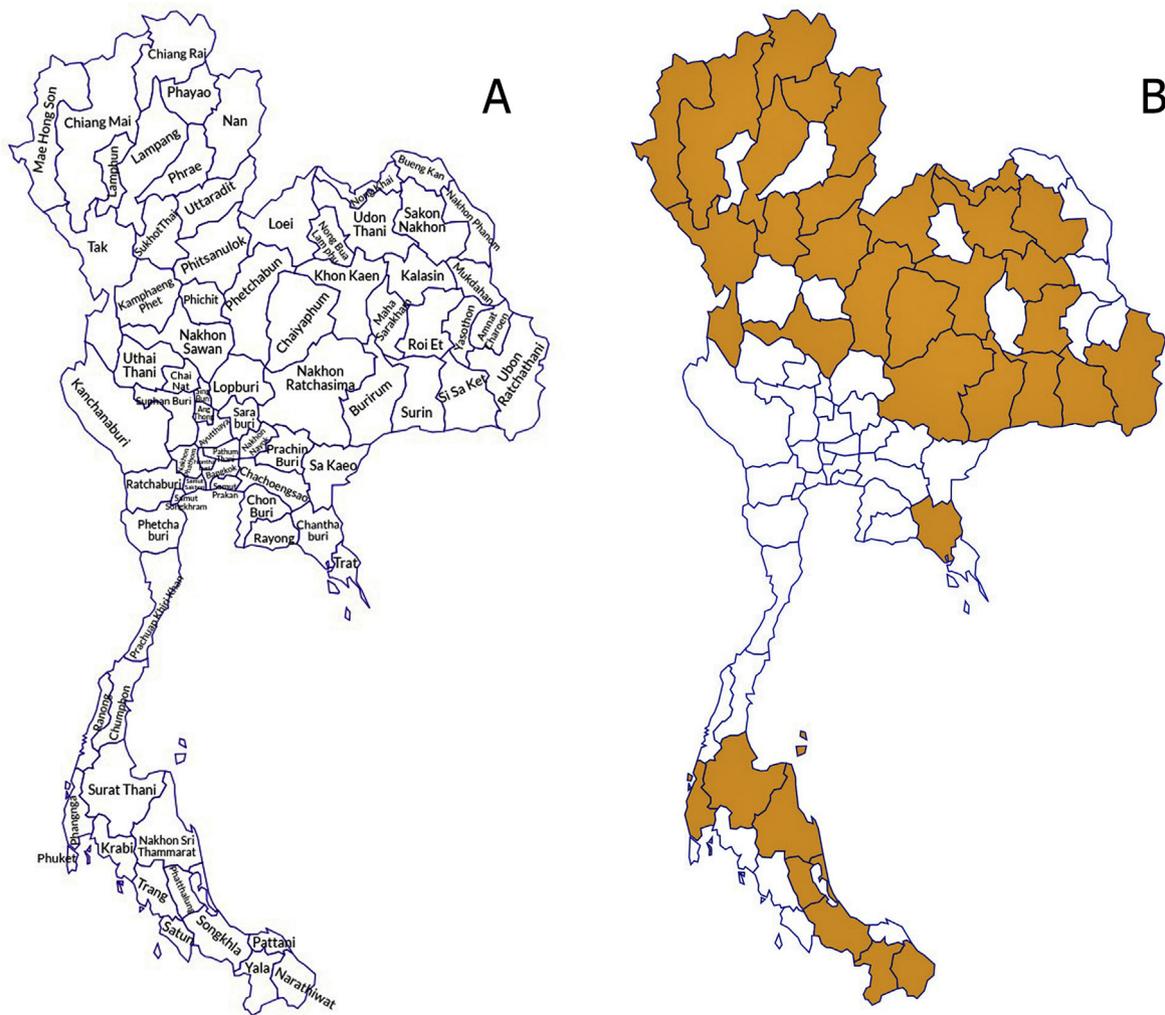


Figure 1. A Map of Thailand and provinces: B; Study sites of scrub typhus 33 provinces, which have average reported case count ≥ 36.0 cases/month during a 6-year period (2009–2014).

by Luce-Fedrow et al. (2018). High incidence of the disease occurs during the period between the end of the rainy season (July–October) and the beginning of the cold season (November–December). Most individuals with ST reside in the northern part of the country, followed by

north-eastern and southern Thailand. The high number of cases in the northern region are owing to high occupational exposure and favourable environmental conditions (Bureau of Epidemiology Thai Ministry of Public Health, 2015).

	sctprov	Tmean	Tmin	TotalRain	RHmean	RHmin	pmean	AHmean	AHmin	SHmean
sctprov	1.00									
Tmean	-0.07	1.00								
Tmin	0.02	0.72	1.00							
TotalRain	0.16	0.29	0.61	1.00						
RHmean	0.22	-0.08	0.33	0.76	1.00					
RHmin	0.18	0.05	0.48	0.80	0.93	1.00				
pmean	-0.12	-0.67	-0.74	-0.65	-0.32	-0.41	1.00			
AHmean	0.08	0.54	0.73	0.78	0.73	0.77	-0.70	1.00		
AHmin	0.12	0.32	0.75	0.84	0.80	0.92	-0.60	0.86	1.00	
SHmean	0.16	0.24	0.56	0.84	0.93	0.92	-0.56	0.92	0.90	1.00
SHmin	0.15	0.20	0.64	0.84	0.87	0.97	-0.53	0.83	0.98	0.93

Figure 2. Spearman's correlations (ρ) among climatic variables in Scrub typhus (sctprov) 2009–2014; If $\rho \leq 0.4$ is weak correlation, if $0.4 < \rho < 0.8$ is moderate correlation, and if $\rho \geq 0.8$ is strong correlation (Shi and Conrad, 2009). Degree of a color indicates the strength of ρ . Blue is the positive correlation with statistical significance (p -values < 0.05); Red is the negative correlation with statistical significance; White is the correlation with non-significance. Tmean is the monthly mean of temperature. Tmin is the monthly mean of minimum temperature. TotalRain is cumulative total rainwater. RHmean is the monthly mean of relative humidity. RHmin is the monthly mean of minimum relative humidity. pmean is the monthly mean of local pressure. AHmean is the monthly mean of absolute humidity. AHmin is the monthly mean of minimum absolute humidity. SHmean is the monthly mean of specific humidity. SHmin is the monthly mean of minimum specific humidity.

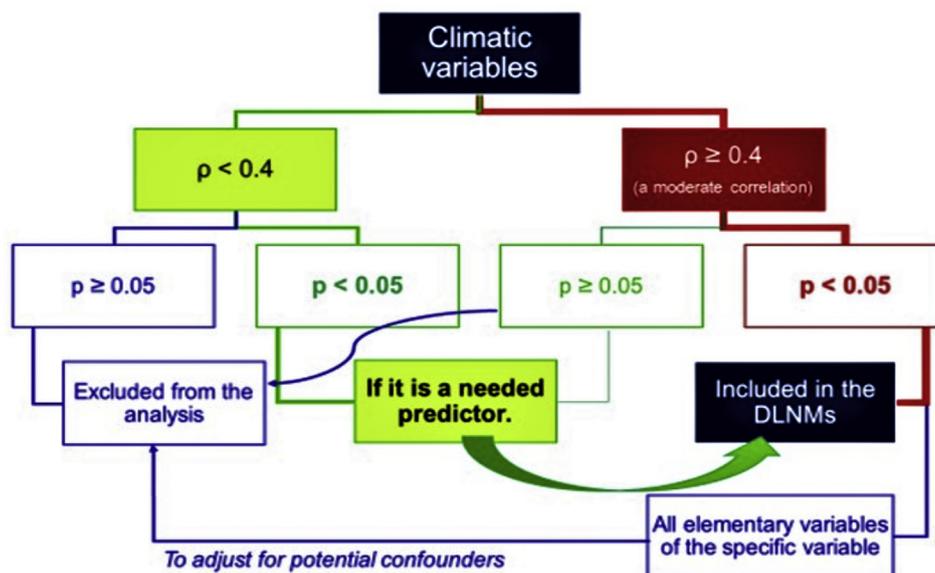


Figure 3. Selection of climatic variables based on their Spearman's rho to include in a model.

Table 1. Choice of lag period, basis variables, and their basis lags.

Selected predictor	Variable basis with df and degree	The basis for lag with df and degree
1. Tmin	ns with 5 df	ns with 4 df
2. TotalRain	bs with 5 df and degree 3	Poly with 5 df and degree 3
3. RHmin	ns with 5 df	ns with 4 df
4. AHmin	ns with 5 df	ns with 4 df
5. SHmin	ns with 5 df	ns with 4 df

The disease is caused by intracellular zoonotic bacteria *Orientia tsutsugamushi* and is transmitted by various species of the infected larva of Trombiculidae mites (chiggers) (Lerdthusnee et al., 2003; Yang et al., 2014; Walker, 2016b; Xu et al., 2017). The chiggers are parasitic, consuming skin cells or host lymph fluid (Lerdthusnee et al., 2008). The disease distribution is clearly determined by the distribution of the *Lep-totrombidium* mite and a population density of reservoirs, contributing to the difference of disease incidence in a country. The chigger acquires infection transovarially or from animal reservoirs such as birds, rodents, and mammals (Walker, 2016a). The life-cycle of chiggers can be 2–3 months, particularly in the laboratory (Sasa, 1960; Santibáñez et al., 2015; Sun et al., 2017). In general, the outdoor activities of humans can directly expose a cluster of chiggers on the blade of grass tips for attaching to humans when they walk through a grassy area (Santibáñez et al., 2015). The disease results from the bites of infected chiggers

carrying the causative organism in their salivary glands. Approximately 6–21 days after chigger bite, a patient develops an eschar at the site of the bite. Signs and symptoms include high fever, intense generalized headache, myalgia, injected conjunctivae, maculopapular rash, generalized lymph node enlargements and liver and spleen enlargement (Xu et al., 2017). These signs and symptoms are characterized by foci and disseminated vasculitis that may result in many severe complications until multi-organ failure (Rajapakse et al., 2012).

The chigger is highly climate dependent because it is an ectothermic insect (Kwak et al., 2015). Its activity and fertilization are mainly influenced by temperature and humidity (Yang et al., 2014; Kwak et al., 2015; Jeung et al., 2016; Seto et al., 2016). Mainly, humidity is a critical factor in the development, disease transmission, and the survival of chiggers. Therefore, relative humidity (RH) is the most common variable used to describe the disease-weather associations (Davis et al., 2016). Although the RH directly reflects surface moisture, it has not responded to rising temperatures (Willett et al., 2007; Valsson and Bharat, 2011). Moreover, the outdoor RH is not accurate indicator of indoor RH (Nguyen et al., 2014), and it does not reflect the environmental condition of chiggers' breeding sites in nature. As a result, the water vapor mass-based predictors such as absolute humidity (AH) and specific humidity (SH) (Davis et al., 2016) should be used instead of RH to determine their effects on ST under rising global temperature. AH is the mass of water in a unit volume of air, and it has a linear relationship with RH (Nguyen et al., 2014; Davis et al., 2016). It is a good indicator of both outdoor and indoor humidity (Nguyen et al., 2014). Furthermore, the indoor AH is strongly correlated to the outdoor AH all year round, and it has a very close correlation with

Table 2. Summary of statistics for ST cases and climatic predictors in endemic Thai provinces, 2009–2014.

Selected Variables	Median	Minimum	Maximum	Mean	Standard deviation	Variance
ST*	9.0	0.0	272.0	19.5	28.6	816.2
Tmin	23.5	0.0	27.9	22.3	3.3	11.1
TotalRain*	1144.3	0.0	29330.3	2652.5	3849.3	14817075.0
pmean	1009.1	1002.7	1016.9	1009.0	2.8	7.9
RHmin*	57.0	25.0	80.0	55.3	10.9	119.8
AHmin*	12.2	2.7	17.8	11.2	3.4	11.3
SHmin	1.2	0.4	1.6	1.1	0.3	0.1

* Their variances are higher than their means, indicating overdispersion in the dataset; therefore, the Negative binomial regressions should be considered to account for the overdispersion.

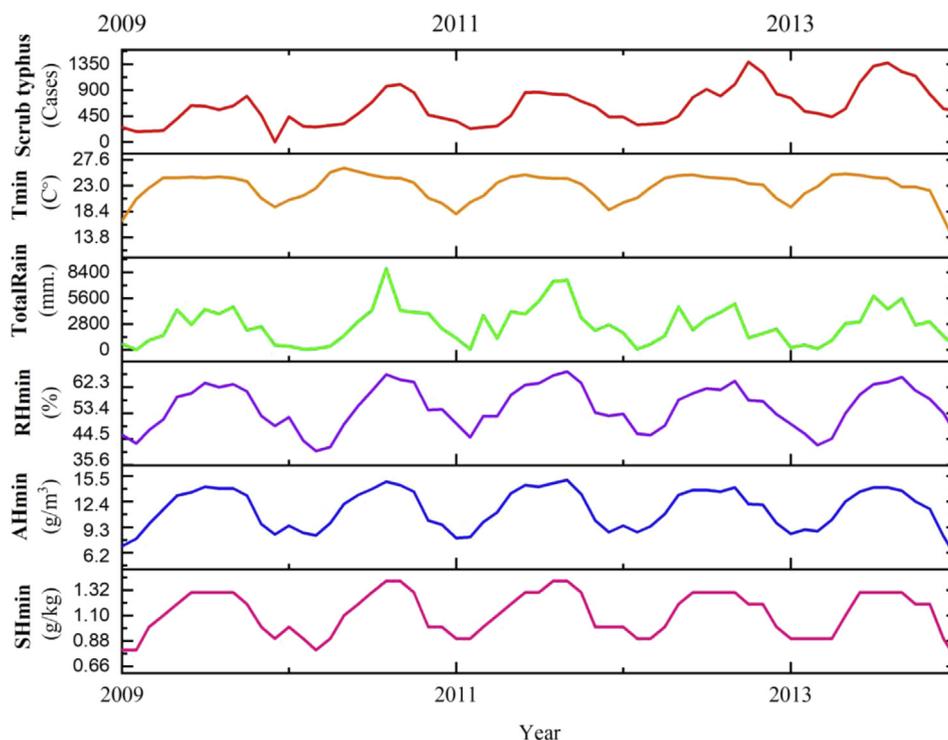


Figure 4. Time series of total reported ST cases in each month and the average monthly minimum of climatic variables in all endemic provinces, during 2009–2014.

Table 3. Model selections for ST in different humidity scenarios.

Scenario	Selected model
RH	Tmin + RHmin + climate type*
AH	AHmin + climate type*
SH	SHmin + TotalRain**

* A climate type is defined as a triple classification of climate type such as a semi-arid, semi-humid, and humid. However, the effects of climate types were not included in the study.

** It is referred to the monthly cumulative total rainwater in given year.

outdoor temperature (Nguyen et al., 2014), therefore AH is most likely to be reflected the indoor-like condition of chiggers' breeding sites rather than RH. SH is the mass of water vapor per unit mass of air, and it directly reflects the amount of the air moisture that influences surface conditions (Sahin and Cigizoglu, 2013). It also directly results from global temperature rising and may determine the geographical distribution, intensity, and pattern of precipitation and the distribution of vector-borne diseases. Its activity and fertilisation are mainly influenced by temperature and humidity such as ST (Willett et al., 2007).

Several published reports showed that temperature and precipitation were positively correlated to many notified ST cases (Fan et al., 2014; Kwak et al., 2015; Seto et al., 2016; Wei et al., 2017), but available evidence on the impact of humidity on the incidence of ST cases is scarce (Sun et al., 2017; Wei et al., 2017). Furthermore, the effects of AH and SH on the incidence of ST have not been studied, although some scientific evidence showed how humidity impacted distribution and abundance of chiggers (Sun et al., 2017; Wei et al., 2017). A better understanding of the current temporal relationship between different types of humidity and the ST occurrence is essential for public health in Thailand to mitigate the impact of the disease on the community. The ST-humidity associations need to be investigated, primarily focusing on separate analyses for different types of humidity predictors. The current study aimed to retrospectively estimate the association between different monthly types of humidity each month and reported ST cases at the provincial level in Thailand. Different three humidity scenarios were proposed.

2. Methods

This study was a 6-year retrospective study and included the two essential datasets of reported ST cases and local climate. We obtained the number of reported monthly ST case from 33 endemic of 77 Thai provinces from the Thai Bureau of Epidemiology (Thai-BOE), Department of Disease Control and Prevention, Ministry of Public Health. Common meteorological variables were collected from the Thai Meteorological Department (TMD). The study also included two additional types of humidity, minimum absolute humidity (AHmin) and minimum specific humidity (SHmin), which were computed. All climatic predictors were used to investigate their effects on the occurrence of ST in the country, using a distributed lag non-linear model combined with negative binomial regression. The proposed study explained the ST-climate associations in different types of humidity.

2.1. Study location

Thailand is in a tropical area in Southeast Asia between latitude 5° 37' North to 20° 27' North and longitude 97° 22' East to 105° 37' East. The total land surface is 513,115 square kilometers, and approximately 30% of the entire surface is mountainous topography with 8% of the total surface considered rolling topography. The country shares a northern border with Myanmar and Laos, an eastern border with Laos, Cambodia and the Gulf of Thailand, a southern border with Malaysia and the western border with Myanmar and the Andaman Sea (Khedari et al., 2002; Climatological Group, Meteorological Development Bureau, 2012). The current study included only 33 (42.9%) of 77 provinces from all parts of the country, focusing on areas where the disease was endemic with a median of average reported cases ≥ 36.0 cases/month through the study period (Figure 1). The study provinces included 13 northeastern, 11 northern, seven southern, one middle, and one eastern province. The average of monthly minimum temperature (Tmin) ranged from 0 °C to 27.9 °C, and the median of monthly rainfall (RF), number of days with rain (RD), and RH was 96.1 mm, 12 days and 57.0%, respectively.

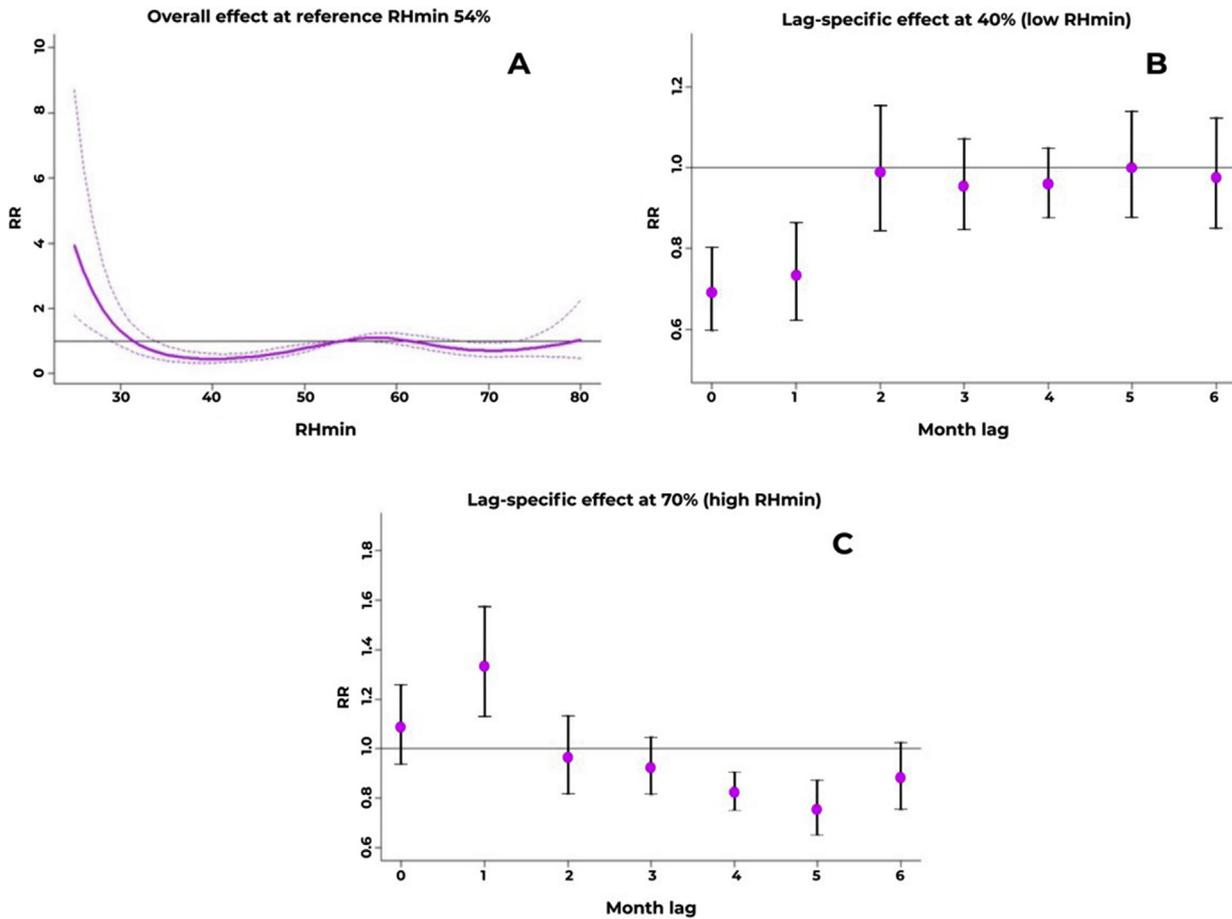


Figure 5. Overall (A) and lag-specific at 40% (B) and 70% (C) effects of RHmin above the threshold (54.0%) on the incidence of ST in Thailand, 2009–2014.

2.2. Scrub typhus (ST) case counts

According to the Thai passive surveillance system, Thai-BOE provided monthly ST case counts in each endemic province were available from January 2009 to December 2014. A case of the disease was defined as a patient who had ST's clinical features and 1) the complete blood count showed low white cell count with normal platelet count or 2) there was an epidemiological linkage to other patients who had a specific laboratory result on at least one measure. The testing measures included 1) a 4-fold or significant rise in serum IgG antibody titers between acute and convalescent sera or specific IgG antibody titer >1:1,280 for single serum using Hemagglutination Inhibition (HI), 2) specific IgM antibody using ELISA, and 3) The detection of *O. tsutsugamushi* from blood by the polymerase chain reaction or isolation the organisms from clinical specimens by a culture. The system collected only incident cases of clinically diagnosed ST in both hospitalized patients and outpatients from all government hospitals all over the country, including some private hospitals as well as private clinics. In this study, the 33 provincial ST data were included, according to a match for the 33 provincial climatic datasets in the same provinces. There were no missing values in the monthly ST dataset.

2.3. Local weather data

Monthly climatic data in the studied provinces included Tmin (°C), mean local pressure (pmean; Pascal) and RHmin (%). Moreover, monthly average RF (mm) and total numbers of RD (days) also were involved. The cumulative total rainwater (TotalRain) was computed by the multiplication of monthly RF and RD to avoid collinearity among the rain-related predictors. Selection of a representative weather station in each endemic province was based on these criteria: (1) the station with completed

climatic data in each province was included first and (2) in the case of a province with one or more stations, the municipality district station's climatic data was the first choice. Therefore, the climatic data has represented the character of local weather conditions throughout that province. Besides, we applied the mean imputation to complete missing values in the dataset by completing with the average of particular climatic variables in the same month for the entire year.

We also simultaneously computed the monthly AHmin (g/m³) and SHmin (g/kg) for each station to represent the characteristic of local humidity conditions throughout the studied province. The AHmin was a function of the Tmin and RHmin. We used a minimum measurement of temperature and RH instead of a mean of that, which was original AH formula to create a new statistical dengue modeling in Singapore (Xu et al., 2014). The approximated equations estimated by the following Eqs. (1), (2), and (3) below:

$$AH = \frac{1000 * (6.11 * 10^{T_1} * 100)}{[(T_C + 273.16) * 461.5]} \tag{1}$$

T_C referred to the monthly Tmin (°C), and T_d was the dew point temperature and was estimated from the equation below. It was a function of dry bulb temperature and RHmin:

$$T_1 = (7.5 * T_d) / (237.7 + T_d) \tag{2}$$

$$T_d = [(-430.22) + 237.7 * \ln(E)] / (-\ln(E) + 19.08) \tag{3}$$

where E = (RH * E_s)/100,

$$E_s = 6.11 * 10^{T_2}, \text{ and} \\ T_2 = (7.5 * T_C) / (237.7 + T_C)$$

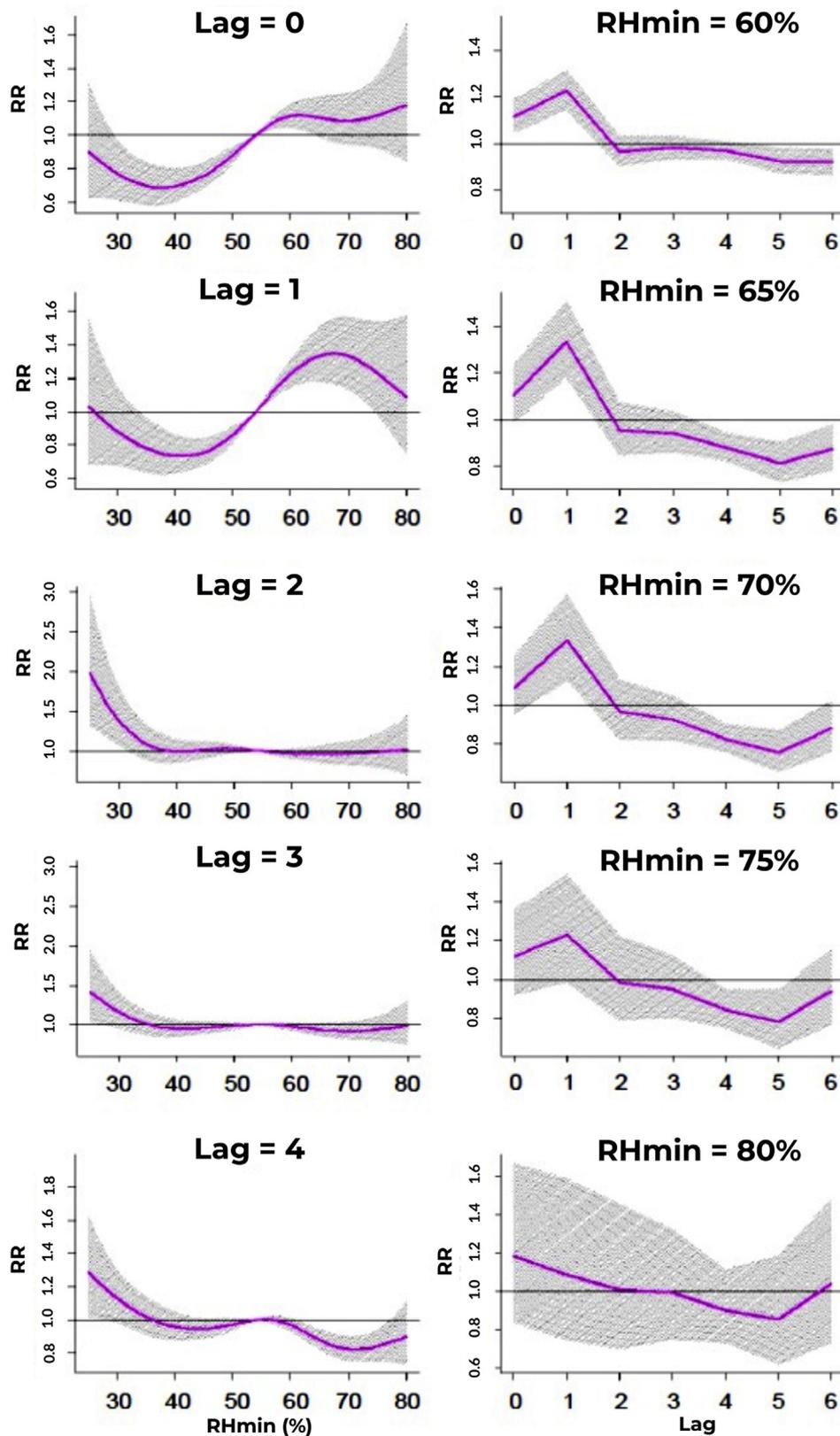


Figure 6. The lag-specific effect at different values of the RHmin (Right) and the RHmin-specific effects at different lags (Left) on the incidence of ST cases in Thailand during 2009–2014, with reference at 54%. The graphs also show 95% CI.

RH was defined as the monthly RHmin (%). Therefore, monthly AHmin was calculated as the average of monthly minimum measurement of climatic predictors over each month, based on exploratory data analysis and review literature. Gill et al. have provided the original SH for-

mula (Gill 1982), but we adapted Gill's formula by calculating SHmin from monthly Tmin, RHmin, and pmean instead of the mean SH. The following Eq. (4) was here below:

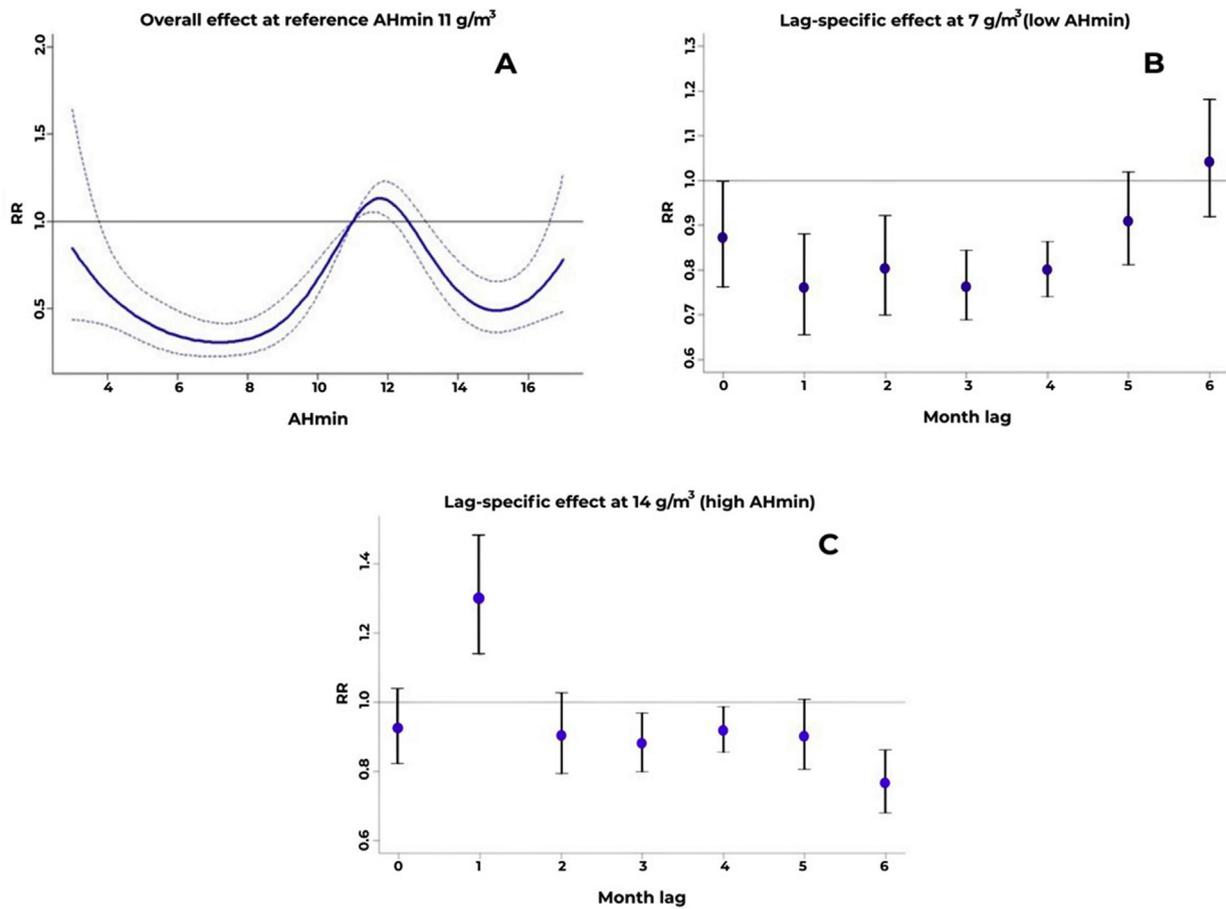


Figure 7. Overall (A) and lag-specific at 7 (B) and 14 g/m³ (C) effects of an AHmin above the threshold (11 g/m³) on the incidence of ST in Thailand, 2009–2014.

$$SH = \frac{0.622e_a}{P_a - 0.378e_a} \quad (4)$$

e_a was defined as the vapor pressure of the air (Pascal), and was approximated from the Eq. (5) below, based on T_{min} and RH_{min} :

$$e_a^o = RH^* 10^{\frac{(0.7859 + 0.03477 * T_a)}{(1.0 + 0.004212 * T_a)^2}} \quad (5)$$

T_a referred to the monthly T_{min} (°C), and RH referred to the monthly RH_{min} (%). P_a was the monthly p_{mean} (Pascal). Monthly SH_{min} was calculated as the average of the monthly minimum measurement, like AH_{min} .

2.4. Statistical analysis

Exploratory data analysis (EDA) was performed to assess the distribution and normality of all variables in the study, including summary basic statistic description, Anderson-Darling test for normality testing, and correlation assessment. We applied Spearman's correlation as presented in Figures 2 and 3 to evaluate collinearity among climatic predictors in the study owing to non-normal distribution. According to correlation analysis, we used a minimum measurement of climatic predictors for generating a further model. In case of different types of humidity, we found that there was a very high correlation ($\rho > 0.9$) among various types of humidity; therefore, different three humidity scenarios were done to avoiding collinearity, and to prevent the distortion of the association between the disease outcomes and predictors, thereby estimating the effect of different humidity on the disease case counts.

The negative binomial (NB) regression model was performed to select a model for advanced analyses. We excluded both p_{mean} and

TotalRain from the analysis because of non-statistical significance in the NB regression. Also, the p_{mean} was a crucial component of SH; the indirect effect of p_{mean} was already shown through the SH. Therefore, the p_{mean} was excluded from all further models to prevent over-estimation. For the TotalRain, it was excluded from the further model with a climate type, excepted for SH scenario. Although the TotalRain was a statistically insignificant variable in the previous NB regression, it was a fixed predictor in the SH scenario only to evaluate the effect of SH_{min} on the disease. The final NB regression model in each humidity scenario was chosen, according to their Akaike's Information Criteria (AIC). The selected models were used in an advanced statistical model.

This study implemented the NB regression combined with a distributed lag non-linear model (NB-DLNM), which was not a Quasi-Poisson regression as in the original DLNM. However, the NB-DLNM could still describe a non-linear and delayed effect of meteorological predictors, and the disease case counts simultaneously and need two primary functions, including cross-basis and cross-predict functions, like the original DLNM. Therefore, the two cross-basis matrices were built for all predictors and included them in the model formula of the NB regression function. The variable basis and basis for lag in each selected predictors were assigned based on review of literature. The degree of freedom (df) for all variable basis and lag basis were mainly founded on the results of EDA. As shown in Table 1, the natural cubic spline (ns) basis with various degrees was implemented for all selected predictors, except for the TotalRain. The B-spline was a basis function with 5 df and degree 3 for the TotalRain, while polynomial function with 5 df and degree 3 was applied as a basis for its lag. We controlled seasonality and the long-term trend by the ns function of calendar time in the models (Gasparrinia et al.,

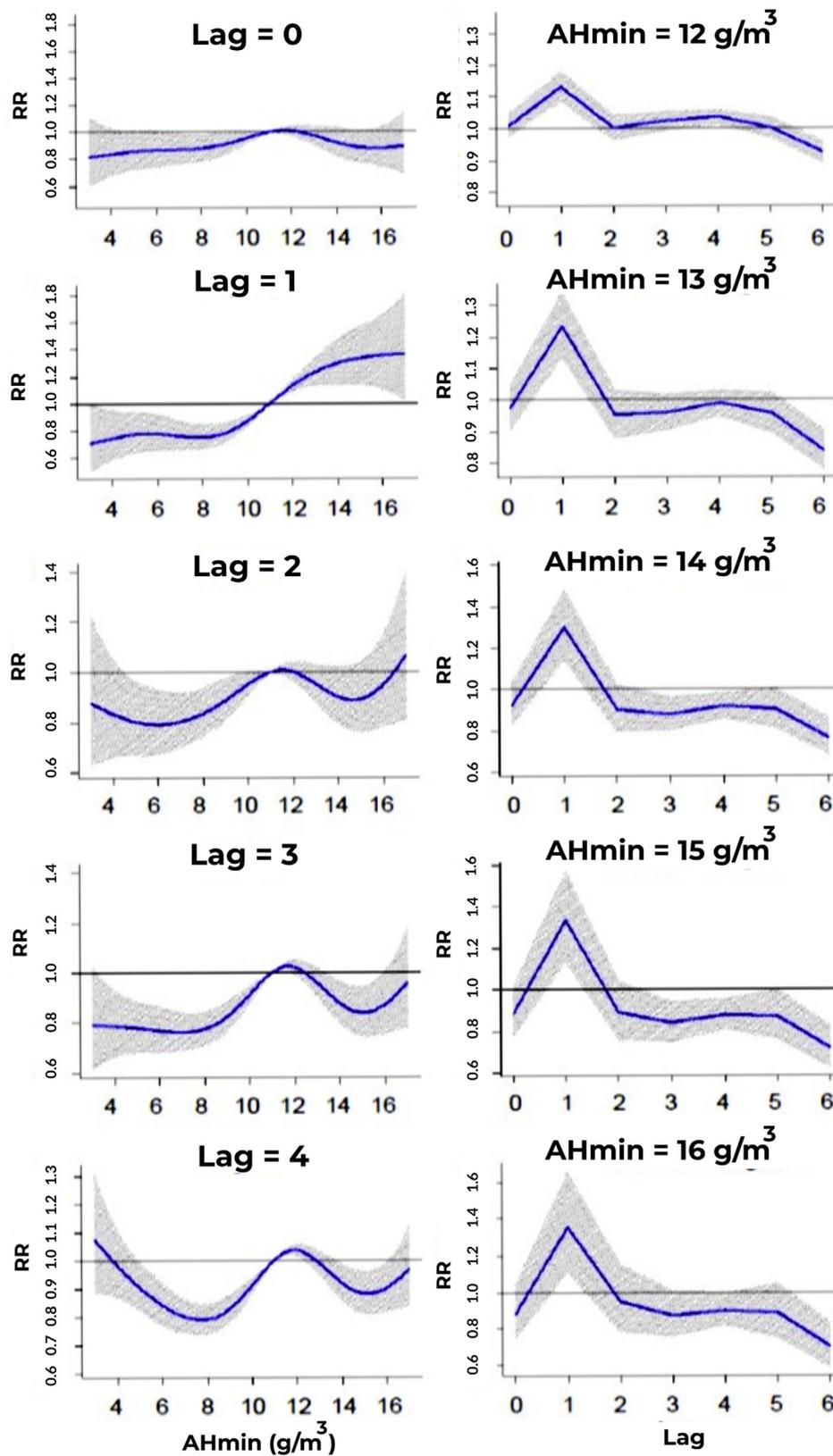


Figure 8. The lag-specific effect at different values of the AHmin (Right) and the AHmin-specific effects at different lags (Left) on the incidence of ST cases in Thailand during 2009–2014, with reference at 11 g/m³. The graphs also show 95% CI.

2010). In addition, the monthly lag period in this study was assigned for six months that provides the maximum reasonable period of time for the pathogenesis of the disease, contributing to improve the precision of the NB-DLNM.

The relative risk (RR) curve was shown with 95% confident intervals (CIs), adjusting for various confounders. To interpret the RR curve, the percentage change with 95% CI in the ST case counts for each

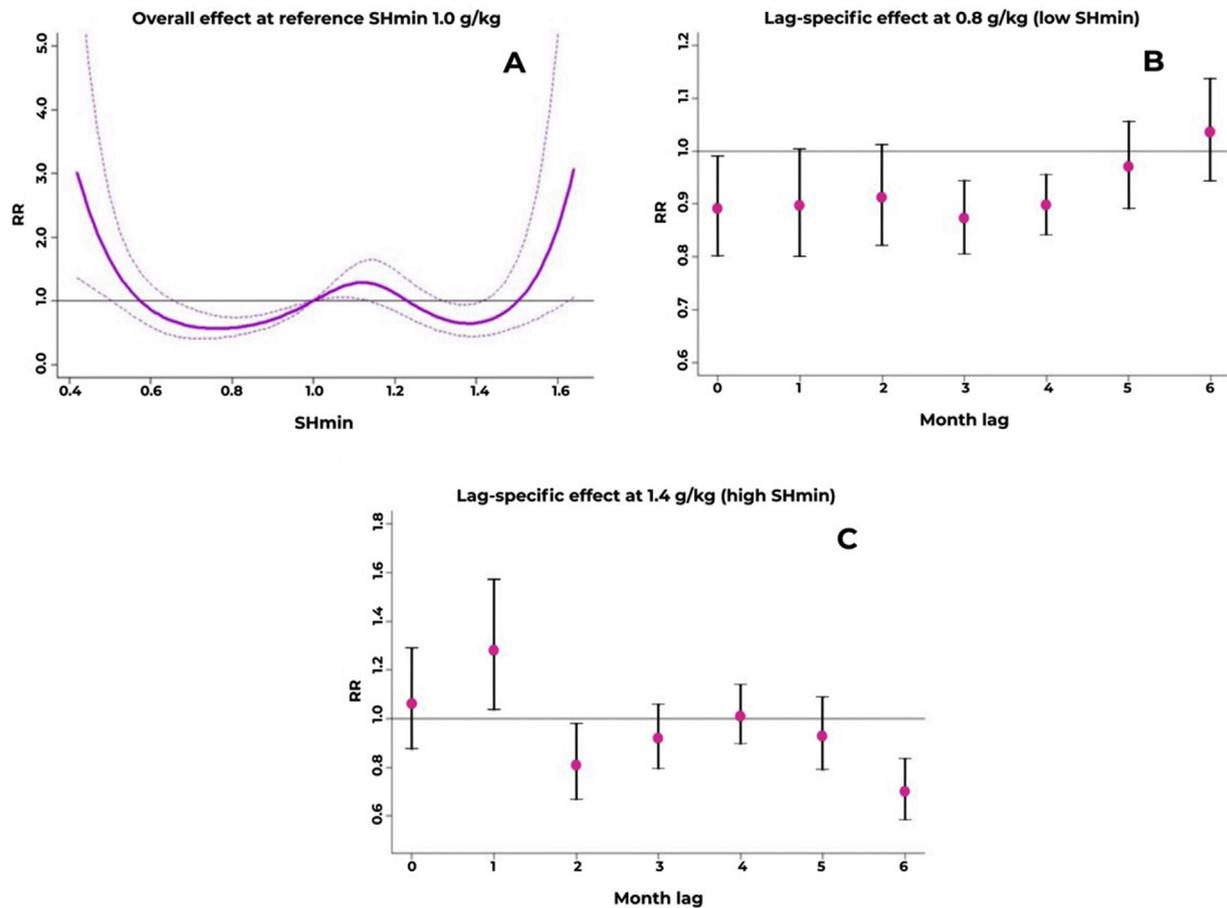


Figure 9. Overall (A) and lag-specific at 0.8 (B) and 1.4 g/kg (C) effects of a SHmin above the threshold (1.0 g/kg) on the incidence of ST in Thailand, 2009–2014.

meteorological factor was calculated, including different climate types. The percentage change was estimated by the following Eq. (6):

$$\text{Percentage change} = (\text{RR} - 1) * 100\% \tag{6}$$

Moreover, a slice plotting of a specific predictor and its lag were depicted, and the RR with 95% CI also was indicated to determine a specific level of predictor and its lag.

Sensitivity analyses were performed by different month lags in each humidity scenario, considering a smaller AIC implied a better goodness-of-fit. All statistical analysis related to the NB regression and DLNM was performed with R software version 3.2.2 using the package MASS version 7.3–45 and dlnm version 2.3.2, respectively.

2.5. Ethical consideration

This study was approved by the ethical committee of the Faculty of Tropical Medicine, Mahidol University. Written informed consent was not required in this study because we used aggregated data instead of individual data.

3. Results

3.1. Overview

A total of 46,226 ST cases was reported from 33 endemic provinces. Interestingly, 56.5% of all cases occurred in northern Thailand, followed by northeastern (30.1%) and southern (11.8%) Thailand. The occurrence of the disease in the country during the 6-year period showed the number of cases gradually increased in April (summer season) and then reached a

plateau from July to October (rainy season). There was a steep fall after October (cold season) until the end of the year.

As shown in Table 2, the median of the monthly average temperature was 23.5 °C for Tmin. Monthly cumulative rainwater was 1,144.3 mm with very high variance, like the case counts of the disease, RHmin, and AHmin. Median monthly average local pressure was 1,009.1 Pa. For the median of monthly average humidity, it was 57.0% for RHmin; 12.2 g/m³ for AHmin and 1.2 g/kg for SHmin, respectively. Figure 4 shows the time series of monthly ST cases and some selected meteorological predictors over the study period, characterized by seasonal patterns.

The final models of different humidity scenarios are shown in Table 3. The selected models included specific predictors, depending on the results of the standard NB regression, as well as scientific reasons related to such meteorological variables. The effects of various types of humidity on the disease are described next.

3.2. Effect of relative humidity (RH)

The overall effect of RHmin at the threshold (54%) of the occurrence of ST showed the W-shaped non-linear association, leading to the very low (<30%), low (34%–53%), and high (68%–72 %) range of percentages of RHmin (Figure 5A). The first level of RHmin expressively increased the disease by two times or more, while the last two levels significantly decreased the incidence of the disease by 5%–34% and a 27%–29%, respectively. The estimated single-month lag effects of the lowest point of low percentage at 40% showed a 1% increase in the low RHmin was associated with a 31% (RR 0.69, 95% CI 0.60–0.80) and 27% (RR 0.73, 95% CI 0.62–0.86) significant decrease in the number of cases of ST in the same month and in the past month, respectively (Figure 5B).

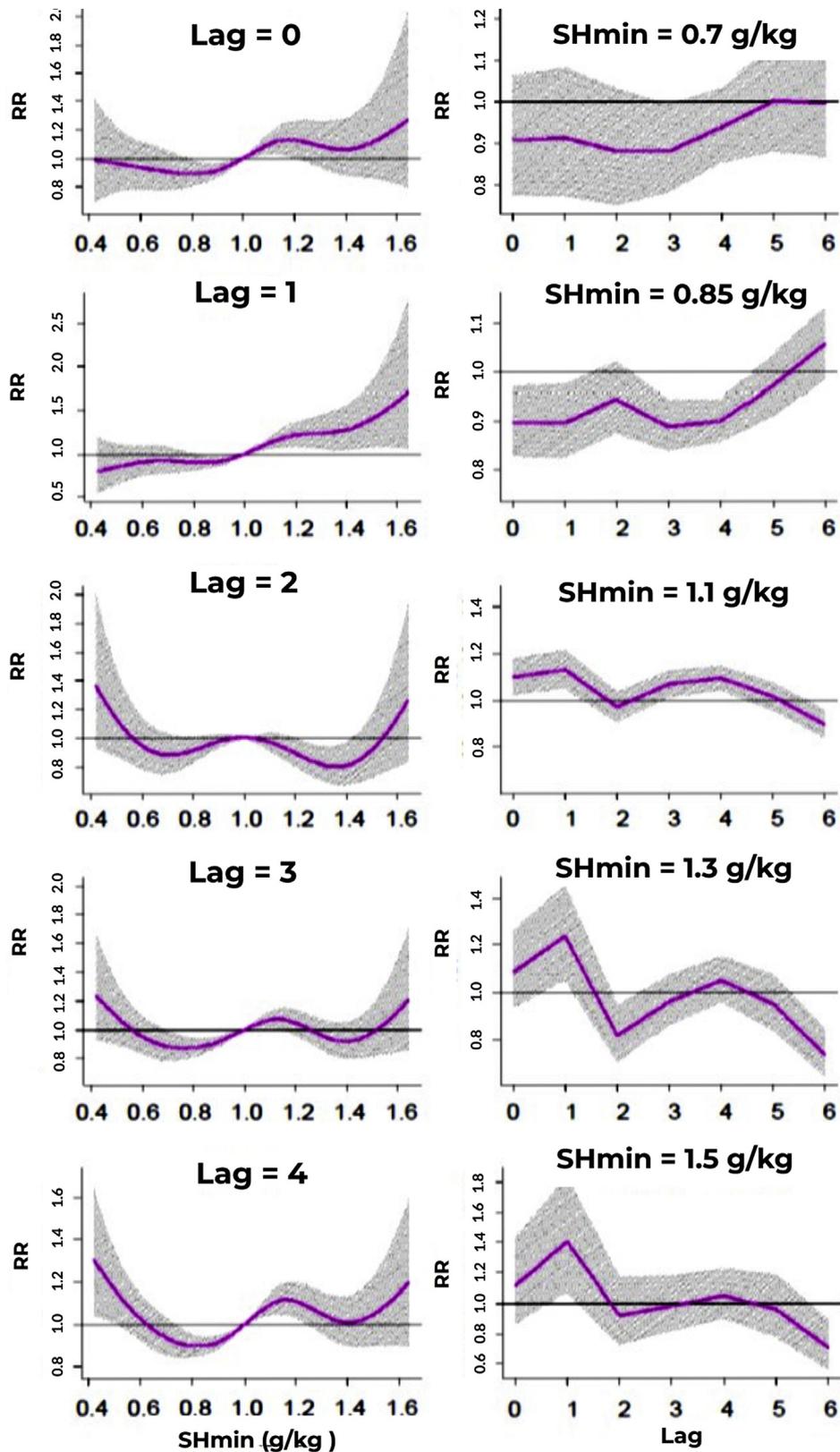


Figure 10. The lag-specific effect at different values of the SHmin (Right) and the SHmin-specific effects at different lags (Left) on the incidence of ST cases in Thailand during 2009–2014, with reference at 1.0 g/kg. The graphs also show 95% CI.

The lowest point of high percentage at 70% demonstrated that a 1% increase in the high RHmin was associated with a 33% (RR 1.33, 95% CI 1.13–1.57) significant increase in the incidence the disease within the past month (Figure 5C). For the lag-specific effect, different levels of

RHmin indicated that the RR would increase within a month when RHmin was rising, particularly in 60%–70% range (Figure 6 Right Column). The RHmin-specific effects at different lags showed that the number of ST cases in the country would significantly decrease within a

		Temperature (°C)																																											
RH (%)		15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	RH (%)		15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
30	3.84	4.08	4.33	4.60	4.88	5.18	5.49	5.81	6.15	6.51	6.89	7.29	7.70	8.14	8.60	9.07	9.58	10.10	10.65	11.22	11.82	66	8.45	8.98	9.54	10.12	10.74	11.39	12.07	12.78	13.54	14.33	15.16	16.03	16.95	17.90	18.91	19.96	21.06	22.22	23.43	24.69	26.01		
31	3.97	4.22	4.48	4.75	5.04	5.35	5.67	6.01	6.36	6.73	7.12	7.53	7.96	8.41	8.88	9.38	9.89	10.44	11.00	11.60	12.22	67	8.58	9.12	9.68	10.27	10.90	11.58	12.25	12.98	13.74	14.55	15.39	16.27	17.20	18.18	19.20	20.26	21.38	22.56	23.78	25.07	26.41		
32	4.10	4.35	4.62	4.91	5.21	5.52	5.85	6.20	6.56	6.95	7.35	7.77	8.22	8.68	9.17	9.68	10.21	10.77	11.36	11.97	12.61	68	8.71	9.25	9.82	10.43	11.06	11.73	12.43	13.17	13.95	14.76	15.62	16.52	17.46	18.45	19.48	20.57	21.70	22.89	24.14	25.44	26.80		
33	4.23	4.49	4.77	5.06	5.37	5.69	6.03	6.39	6.77	7.16	7.58	8.02	8.47	8.95	9.45	9.98	10.53	11.11	11.71	12.33	13.01	69	8.84	9.39	9.97	10.58	11.23	11.90	12.62	13.37	14.15	14.98	15.85	16.76	17.72	18.72	19.77	20.87	22.02	23.23	24.49	25.81	27.20		
34	4.35	4.63	4.91	5.21	5.53	5.87	6.22	6.59	6.97	7.38	7.81	8.26	8.73	9.22	9.74	10.28	10.85	11.45	12.07	12.72	13.40	70	8.96	9.52	10.11	10.73	11.39	12.08	12.80	13.56	14.36	15.20	16.08	17.00	17.97	18.99	20.06	21.17	22.34	23.57	24.85	26.19	27.59		
35	4.48	4.76	5.06	5.37	5.69	6.04	6.40	6.78	7.18	7.60	8.04	8.50	8.98	9.49	10.03	10.58	11.17	11.78	12.42	13.09	13.80	71	9.08	9.66	10.26	10.89	11.55	12.25	12.98	13.75	14.58	15.41	16.31	17.25	18.23	19.26	20.34	21.47	22.66	23.90	25.20	26.56	27.98		
36	4.61	4.90	5.20	5.52	5.86	6.21	6.58	6.97	7.38	7.82	8.27	8.74	9.24	9.77	10.31	10.89	11.49	12.12	12.78	13.47	14.19	72	9.22	9.80	10.40	11.04	11.71	12.42	13.16	13.95	14.77	15.63	16.54	17.49	18.49	19.53	20.63	21.78	22.98	24.24	25.56	26.94	28.38		
37	4.74	5.03	5.35	5.67	6.02	6.38	6.77	7.17	7.59	8.03	8.50	8.99	9.50	10.04	10.60	11.19	11.81	12.46	13.13	13.84	14.58	73	9.35	9.93	10.55	11.19	11.88	12.59	13.35	14.14	14.97	15.85	16.77	17.73	18.74	19.80	20.91	22.08	23.30	24.58	25.91	27.31	28.77		
38	4.87	5.17	5.49	5.83	6.18	6.56	6.95	7.36	7.79	8.25	8.73	9.23	9.76	10.31	10.89	11.49	12.13	12.79	13.49	14.22	14.98	74	9.48	10.07	10.69	11.35	12.04	12.77	13.53	14.33	15.18	16.07	17.00	17.97	19.00	20.07	21.20	22.38	23.62	24.91	26.27	27.68	29.17		
39	4.99	5.31	5.63	5.98	6.34	6.73	7.13	7.55	8.00	8.47	8.96	9.47	10.01	10.58	11.17	11.80	12.45	13.13	13.84	14.59	15.37	75	9.60	10.20	10.84	11.50	12.20	12.94	13.71	14.53	15.38	16.28	17.23	18.22	19.26	20.35	21.49	22.68	23.94	25.25	26.62	28.06	29.56		
40	5.12	5.44	5.78	6.13	6.51	6.90	7.31	7.75	8.20	8.68	9.19	9.72	10.27	10.85	11.46	12.10	12.77	13.47	14.20	14.97	15.77	76	9.73	10.34	10.98	11.65	12.36	13.11	13.90	14.72	15.58	16.50	17.46	18.46	19.51	20.62	21.77	22.99	24.26	25.59	26.98	28.43	29.95		
41	5.25	5.58	5.92	6.29	6.67	7.07	7.50	7.94	8.41	8.90	9.42	9.96	10.53	11.12	11.75	12.43	13.09	13.80	14.55	15.34	16.16	77	9.88	10.48	11.12	11.81	12.53	13.28	14.08	14.92	15.79	16.72	17.69	18.70	19.77	20.89	22.06	23.29	24.58	25.92	27.33	28.81	30.35		
42	5.38	5.71	6.07	6.44	6.83	7.25	7.68	8.14	8.62	9.12	9.65	10.20	10.78	11.39	12.03	12.70	13.41	14.14	14.91	15.71	16.55	78	9.99	10.61	11.27	11.96	12.69	13.46	14.26	15.11	16.00	16.93	17.92	18.95	20.03	21.16	22.35	23.59	24.89	26.26	27.69	29.18	30.74		
43	5.51	5.85	6.21	6.59	7.00	7.42	7.86	8.33	8.82	9.34	9.88	10.44	11.04	11.67	12.32	13.01	13.72	14.48	15.26	16.08	16.95	79	10.12	10.75	11.41	12.11	12.85	13.63	14.44	15.30	16.20	17.15	18.15	19.19	20.28	21.43	22.63	23.89	25.21	26.60	28.04	29.56	31.14		
44	5.63	5.98	6.36	6.75	7.16	7.59	8.05	8.52	9.03	9.55	10.11	10.69	11.30	11.94	12.61	13.31	14.04	14.81	15.62	16.46	17.34	80	10.24	10.88	11.56	12.27	13.01	13.80	14.63	15.50	16.41	17.37	18.37	19.43	20.54	21.70	22.92	24.20	25.53	26.93	28.40	29.93	31.53		
45	5.76	6.12	6.50	6.90	7.32	7.76	8.23	8.72	9.23	9.77	10.34	10.93	11.55	12.21	12.88	13.61	14.36	15.15	15.97	16.84	17.74	81	10.37	11.02	11.70	12.42	13.18	13.97	14.81	15.68	16.61	17.58	18.60	19.67	20.80	21.97	23.21	24.50	25.85	27.27	28.75	30.30	31.93		
46	5.89	6.26	6.65	7.05	7.48	7.94	8.41	8.91	9.44	9.98	10.57	11.17	11.81	12.48	13.18	13.91	14.68	15.49	16.33	17.21	18.13	82	10.50	11.16	11.85	12.57	13.34	14.15	14.99	15.88	16.82	17.80	18.83	19.92	21.05	22.24	23.49	24.80	26.17	27.61	29.11	30.68	32.32		
47	6.02	6.39	6.79	7.21	7.65	8.11	8.59	9.10	9.64	10.20	10.80	11.42	12.07	12.75	13.47	14.22	15.00	15.82	16.68	17.58	18.53	83	10.63	11.29	11.99	12.73	13.50	14.32	15.18	16.08	17.02	18.02	19.06	20.16	21.31	22.52	23.78	25.10	26.49	27.94	29.46	31.05	32.71		
48	6.15	6.53	6.94	7.38	7.81	8.28	8.78	9.30	9.85	10.42	11.03	11.68	12.32	13.02	13.75	14.52	15.32	16.16	17.04	17.96	18.92	84	10.76	11.43	12.14	12.88	13.67	14.49	15.36	16.27	17.23	18.24	19.29	20.40	21.57	22.79	24.07	25.41	26.81	28.28	29.82	31.43	33.11		
49	6.28	6.67	7.08	7.51	7.97	8.45	8.96	9.49	10.05	10.64	11.25	11.90	12.58	13.29	14.04	14.82	15.64	16.50	17.39	18.33	19.31	85	10.89	11.56	12.28	13.03	13.83	14.68	15.54	16.46	17.43	18.45	19.52	20.65	21.82	23.06	24.38	25.71	27.13	28.62	30.17	31.80	33.50		
50	6.40	6.80	7.22	7.67	8.13	8.63	9.14	9.68	10.26	10.86	11.48	12.14	12.84	13.56	14.33	15.12	15.96	16.83	17.75	18.71	19.71	86	11.01	11.70	12.43	13.19	13.99	14.84	15.72	16.66	17.64	18.67	19.75	20.89	22.08	23.33	24.64	26.01	27.45	28.95	30.53	32.17	33.90		
51	6.53	6.94	7.37	7.82	8.30	8.80	9.33	9.88	10.46	11.07	11.71	12.39	13.09	13.84	14.61	15.43	16.28	17.17	18.10	19.08	20.10	87	11.14	11.84	12.57	13.34	14.15	15.01	15.91	16.85	17.85	18.89	19.98	21.13	22.34	23.60	24.93	26.31	27.77	29.29	30.88	32.55	34.29		
52	6.66	7.07	7.51	7.97	8.46	8.97	9.51	10.07	10.67	11.29	11.94	12.63	13.35	14.11	14.90	15.73	16.60	17.51	18.46	19.45	20.50	88	11.27	11.97	12.71	13.49	14.32	15.18	16.09	17.05	18.05	19.10	20.21	21.37	22.59	23.87	25.21	26.62	28.09	29.63	31.24	32.92	34.68		
53	6.79	7.21	7.66	8.13	8.62	9.14	9.69	10.27	10.87	11.51	12.17	12.87	13.61	14.38	15.18	16.03	16.92	17.84	18.81	19.83	20.89	89	11.40	12.11	12.88	13.65	14.46	15.35	16.27	17.24	18.28	19.32	20.44	21.62	22.85	24.14	25.50	26.92	28.41	29.96	31.59	33.30	35.08		
54	6.92	7.35	7.80	8.28	8.79	9.32	9.87	10.46	11.08	11.72	12.40	13.12	13.86	14.65	15.47	16.33	17.24	18.18	19.17	20.20	21.28	90	11.55	12.24	13.00	13.80	14.64	15.53	16.46	17.43	18.46	19.54	20.67	21.86	23.11	24.41	25.78	27.22	28.72	30.30	31.95	33.67	35.47		
55	7.04	7.48	7.95	8.43	8.95	9.48	10.06	10.65	11.28	11.94	12.63	13.36	14.12	14.92	15.76	16.64	17.55	18.52	19.52	20.56	21.68	91	11.65	12.38	13.15	13.95	14.80	15.70	16.64	17.63	18.67	19.76	20.91	22.10	23.36	24.69	26.07	27.52	29.04	30.64	32.30	34.04	35.87		
56	7.17	7.62	8.09	8.59	9.11	9.66	10.24	10.85	11.49	12.16	12.86	13.60	14.38	15.19	16.04	16.94	17.87	18.85	19.88	20.95	22.07	92	11.78	12.52	13.29	14.11	14.97	15.87	16.82	17.82	18.87	19.97	21.13	22.35	23.62	24.96	26.36	27.83	29.36	30.97	32.66	34.42	36.26		
57	7.30	7.76	8.24	8.74	9.27	9.83	10.42	11.04	11.69	12.38	13.09	13.85	14.63	15.46	16.33	17.24	18.19	19.19	20.23																										

RHmin at < 30% could increase the disease occurrence by two times or more, while RHmin at >30% caused a decrease of ST cases by approximate 5%–34%. However, when considering the lag-specific effect, a high level of RHmin (at 70%) could increase in the number of cases about 33% within the past month. In term of AH, the overall effect showed the number of ST cases was increased by 12% when AHmin was at 12 g/m³; however, the low (5–8 g/m³) and high (14–16 g/m³) levels of AHmin were associated with 60%–70% and 35%–40% decrease in ST case counts, respectively. Like the lag-specific effect in RH, a high level of AHmin (at 14 g/m³) was associated with a 30% increase in ST case counts within the past month. For SH, the overall effect demonstrated that the disease cases were increased by 27% when SHmin was at 1.1 g/kg; however, the low (0.7–0.9 g/kg) and high (1.4 g/kg) levels of SHmin were associated with 29%–43% and 35% decrease in the disease cases, respectively. For the lag-specific effect in SH, a high level of SHmin (at 1.4 g/kg) was associated with a 28% increase in ST case counts within the past month.

RH can influence the occurrence of the ST, because it determines the distribution and prevalence of chiggers that are reservoirs of the disease. Another point is that water vapor in the air is a vital source of water for chiggers to survive (Li et al., 2014). The current study shows that low RHmin (at 40%) can diminish the number of disease cases, while the high RHmin (at 70%) can increase the disease case counts. This corresponds to the natural life cycle of chiggers that a high population density of chigger larvae can be found in high RH, and the chiggers can easily live in areas with high RH above 50% (Clopton and Gold, 1993; Rubio and Simonetti, 2009). However, if RH is less than 50%, the chiggers will gradually die (Rubio and Simonetti, 2009).

Approximately 31% of ST case counts were decreased, when there was 40% of RHmin within the past month. This is greater than the study in mainland China by Wu et al., which have reported that only an 11% decrease in the number of ST cases was attributed to every 1% increase in monthly RH (Wu et al., 2016). This discrepancy may result from a different statistical method. Wu et al. study implemented a Poisson regression without accounting for month lag and overdispersion in his dataset, while the current study has applied the NB-DLNs to adjust for several points.

Conversely, 70% of RHmin could increase the ST occurrence in the country by a 33% within the past month. This is consistent with two studies in southern China and one study in northern China. First, Wei et al. showed that a 1% increase in monthly RH contributed to an 8.5% increase in the number of ST cases with a four-month lag (Wei et al., 2017). Second, Sun et al. reported that only a 4% increase in the incident cases was attributed to a 10% increase in monthly RHmean at two-month lags (Sun et al., 2017). Finally, Yang et al. reported that every 1% increase in monthly RHmean at two-month lags would result in a steady rise by 12.6% of ST cases in northern China (Yang et al., 2014). However, the first study has used the original DLNM to assess the ST-RH associations, and only four districts in the same province were included in the study. Therefore, the small number of study sites is most likely to show a low percentage of increased ST cases in southern China. Similarly, the last two studies were conducted in only one province in each study that could result in a small percentage of increased ST cases. Moreover, they have used a different statistical method of NB regression and a different measurement of RH such as RHmean that contributed to a different percentage of RH from the current study.

According to the literature review, the study of the RH-ST associations was minimal. Several reasons include 1) unavailable humidity dataset in some countries, 2) restriction of the endemic area of the disease, 3) exclusion of a humidity variable from the analysis, owing the statistically insignificant variable, 4) being not giving RH enough attention when compared to temperature and 5) an inappropriate humidity predictor in global warming condition. However, the current study first confirms the role of surface humidity such as RH in the change of numbers of ST cases in Thailand, corresponding to the life cycle of the disease's reservoirs.

AH, which is a vapor concentration, is a newly studied predictor for many infectious diseases under global temperature rising (Shaman and

Kohn, 2009; Shoji et al., 2011). AH linearly correlates to the RH and changes over time, depending on temperature (Nguyen et al., 2014). Moreover, it inversely corresponds to temperature, like RH (Davis et al., 2016). Indoor AH showed a robust correlation to the outdoor temperature, and the outdoor AH was the only data available for human weather exposure (Nguyen et al., 2014). In addition, AH was the outdoor measure least prone to measurement error (Nguyen et al., 2014). Therefore, it should be applied instead of RH to determine the effect of humidity on any infectious diseases. SH directly reflects the amount of the air moisture that influences surface conditions (Sahin, 2012), and it directly depends on temperature and rainfall (Willett et al., 2007). Global mean surface SH is rising in several regions, along with global temperature rising (Willett et al., 2007); therefore, the SH is a good predictor to reflect the effect of global warming on the infectious diseases.

To our knowledge, the study of ST-AH associations is also minimal, like RH. We found a study on the AH-dengue associations that was only that has conducted in Singapore (Xu et al., 2014). The proposed study first determined the relationship between ST and AH and demonstrated an adverse effect of AHmin on ST occurrence in both low and high levels. Interestingly, an appropriate time lag for AH ranges from the same month to three-month lags, particularly in the high levels of AHmin. ST case counts trend to a drop in the number of cases over month lags. Based on the literature review, we found several studies to report the effect of AH on some infectious diseases such as human influenza (Shaman et al., 2011; Shoji et al., 2011; te Beest, 2013; Jaakkola et al., 2014); avian influenza (Murray and Morse, 2011); and hepatitis A (Wang et al., 2015). In terms of SH, there was an adverse effect of SH on ST occurrence in our study. Most SH levels showed no association with the disease, and an appropriate month lag could not be determined in the disease owing to statistical insignificance. Likewise, there is no previous study about the SH-ST relationships, according to the literature review. However, the effects of SH on the occurrence of infectious disease were also found in human influenza (Tamerius et al., 2013; Soebiyanto et al., 2014, 2015; Emukule et al., 2016) and respiratory syncytial virus infection (Kamigaki et al., 2016). It is observed that several studies on the effects of AH and SH on infectious diseases usually focus on viral diseases; some evidence clearly showed the role of humidity in the survival of viruses clearly, particularly in influenza (Shaman and Kohn, 2009) and hand-foot-mouth disease (Xu et al., 2015; Qi et al., 2018). Interestingly, our study demonstrated the role of AH and SH in the number of ST case counts in a tropical country, and it may be the first study of a non-viral disease to determine the association between various types of humidity and ST.

A strength of this study is that the model selection was performed, based on the NB regression, leading to the use of NB-DLNM. This method changed the link function of a non-linear model from Quasi-Poisson regression to NB regression for first estimating the ST-weather associations in Thailand firstly. Consequently, there is a good control for overdispersion, giving a smaller AIC and exact RR estimations. This is an appropriate rationale to implement the NB-DLNM for our datasets. Second, the effect of month lag is focused so that the estimates of the ST-humidity relationships are consistent with the natural history of the disease. For example, the life cycle of ST is 2–3 months (Sun et al., 2017), and the intrinsic incubation period ranges from one to three weeks (Rajapakse et al., 2012); therefore, the RR estimates of the lags are needed to determine the delayed effect of climatic predictors on the disease during at least the previous 3 months. Third, alternative humidity predictors can significantly reflect outdoor humidity condition and global warming rather than RH, and their effects on the disease are initially confirmed. They should be implemented instead of RH in further research. Finally, the use of the AH and SH can contribute to reducing the number of the predictors in the model that cause non-sophisticated models and partially avoids collinearity among the predictors.

Some limitations can be found. First, although the period of study indicates the period of high ST incidence in the country, under-reporting is still a common problem for the passive surveillance data, leading to the underestimation of ST-weather associations. Second, the disease is a

zoonotic disease in rural and forest areas, but almost climatic data in each endemic province was collected from the municipality district station, which is an urban area. This contributes to underrepresenting a real local weather-permitting condition in the disease vector habitats. Third, although a spatial interpolation of the climatic data may provide much precise information than the selection of one station to represent each province, the method may introduce a bias prediction with high spatial variance. However, it depends on an interpolation technique (Xu et al., 2013). Fourth, the spatial and temporal scales may have an impact on the results. For example, both datasets are monthly data that they could also be a limitation to perceive finer fluctuations of the disease incidence. For instance, although the study might not be possible at the district scale, the humidity can also be very variable at the provincial scale. Fifth, the ST occurrence depends on the host-vector interactions, including other non-climatic predictors such as population density, chigger intensity, and a population density of mammal reservoirs. These non-climatic predictors including human population density, land-use and vegetation, and socioeconomic status (i.e., educational levels, income, and occupation) were not included in the study owing to the lack of data sources. However, a study with DLNMs in Southern China demonstrated that common climatic predictors only promoted the disease to certain levels, depending on specific predictors (Wei et al., 2017). Finally, overfitting a model may occur in the study, resulting from low overdispersion of each model in each humidity scenario. This could cause a reduction of generalizability outside the original dataset and misleading the RR estimates. However, each NB-DLNM includes a few predictors, and each predictor has an important observation; thus, it is expected that overfitting in the study is less likely to occur with less chance for misleading RR estimates.

5. Conclusion

The present study first demonstrated the active role of different types of humidity in the number of ST cases in a tropical country. The W-shaped non-linear association was found for all humidity types. Almost overall effects of humidity on the disease trend to diminish many cases, but the lag-specific effect of all types of humidity revealed that ST case counts could be enhanced within the past month when all types of humidity met high levels. Although RH provides the highest estimate of RR to increase the disease case counts (more than AH and SH), the implementation of AH and SH is useful for the modeler to reduce the number of predictors in a specific model. Interestingly, AH is a good indicator of both indoor and outdoor climatic parameters; hence, it should be collected routinely by provincial weather stations. Furthermore, we also developed the AH index to estimate the risk of acquiring ST infection, which is the specific RR in given temperature and RH, in the country, based on the results of our study as shown in the supplement document (Figure 11).

Declarations

Author contribution statement

B. Bhopdhornangkul: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

A. Cooper Meeyai: Conceived and designed the experiments; Analyzed and interpreted the data.

W. Wongwit, Yanin Limpanont, S. Iamsirithaworn, Y. laosiritaworn: Conceived and designed the experiments.

K. Tantrakarnapa: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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