

Meteorological Factors Associated with the Incidence of Hand, Foot, And Mouth Disease; Meliodosis; Leptospirosis; and Mushroom Poisoning in Chiang Mai Province, Thailand

Chatsiri Chatphuti, M.N.S.(Nursing Administration)*

Vadhana Jayathavaj, Ph.D.(Applied Mathematics)**

Puttiphong Jaroonsiriphan, Ph.D.(Electrical & Computer Engineering)***

* Department of Community Health Nursing, Faculty of Nursing, North Bangkok University

** Department of Thai Traditional Medicine, Faculty of Allied Health Sciences, Pathumthani
University

*** Department of New Energy Engineering, Faculty of Engineering and Technology,
Shinawatra University, Thailand

Corresponding author: Vadhana Jayathavaj, Email: vadhana.j@ptu.ac.th

Date received:	2025 Jun 28
Date revised:	2026 Apr 18
Date accepted:	2026 May 7

Abstract

Meteorological factors have an impact on the incidence and spread of diseases in Thailand, including Hand, Foot, and Mouth Disease (HFMD), Leptospirosis, Meliodosis, and mushroom poisoning. This correlational study aimed to quantify the relationship between meteorological factors and the number of infectious disease cases in Chiang Mai province. Meteorological data were obtained from the Northern Meteorological Center, while reported cases of HFMD, Meliodosis, Leptospirosis, and mushroom poisoning were sourced from the Bureau of Epidemiology, Department of Disease Control. There were 90 months covering the period from January 2017 to June 2024. The statistical analysis was the descriptive statistics, the Shapiro–Wilk test, Pearson’s correlation, and the generalized linear model, analyzed by the jamovi statistical analysis software with the GAMLj – General Analyses Linear Models. The results showed that the best-fit models were the Quasi-Poisson model for HFMD ($R^2 = 0.198$, sunshine hours: IRR = 0.786, $p < 0.05$), leptospirosis ($R^2 = 0.198$, relative humidity: IRR = 1.060, $p < 0.05$), and the negative binomial model for mushroom poisoning ($R^2 = 0.438$, relative humidity: IRR = 1.073, $p < 0.05$; atmospheric pressure: IRR = 0.780, $p < 0.05$). Meteorological factors were associated with HFMD, leptospirosis, and mushroom poisoning in Chiang Mai, but no model was identified for meliodosis. The primary limitation is the use of monthly data, which may not capture time-lagged or daily dynamics.

Keywords: meteorological factors; association; infectious diseases

Introduction

Meteorological factors significantly influence disease incidence in Thailand, including hand, foot, and mouth disease (HFMD), leptospirosis, melioidosis, and mushroom poisoning. HFMD, a viral illness common in children, can affect individuals of any age. Key preventive measures include handwashing, surface disinfection, and avoiding contact with infected persons⁽¹⁾. Studies across Asia reveal consistent associations between meteorological conditions, air pollution, and HFMD risk. In Zhejiang Province (2013–2021), temperature, humidity, and precipitation positively interacted with air pollutants, while wind speed showed a negative effect. Heavy rainfall increased HFMD risk linked to PM₁₀, SO₂, and CO₂⁽²⁾. Similar patterns were observed in Malaysia⁽³⁾ and Yangzhou, China (2017–2022), where temperature, pressure, humidity, rainfall, and sunshine duration significantly influenced HFMD risk⁽⁴⁾. In Chengdu (2014–2020), high humidity, heavy rain, and extreme pollutant levels (PM₁₀, O₃, SO₂, CO) were associated with increased HFMD cases⁽⁵⁾. A meta-analysis of 11 studies confirmed that a 1°C rise in temperature and a 1% increase in humidity correlated with higher HFMD incidence (temperature: IRR 1.05; 95%CI 1.02–1.08; humidity: IRR 1.01; 95%CI 1.00–1.02)⁽⁶⁾. HFMD remains widespread in Asia, notably in Singapore, where its growing burden affects both economy and society⁽⁷⁾.

Melioidosis is a life-threatening infectious disease caused by *Burkholderia pseudomallei*, commonly found in soil and water in tropical and subtropical regions. Transmission occurs via contact with contaminated soil or water, inhalation of dust, or ingestion of tainted water⁽⁸⁾. A retrospective study of 90 patients in north-

ern Hainan (2010–2020) found a strong positive correlation between monthly precipitation and melioidosis incidence, with most cases occurring during the rainy season⁽⁹⁾. Another 10-year analysis (2009–2018) showed that while rainfall and case numbers peaked between July and September, their correlation was not statistically significant. However, both maximum and minimum temperatures were significantly associated with disease incidence⁽¹⁰⁾.

Leptospirosis is a bacterial infection with symptoms ranging from mild to life-threatening. It spreads through contact with water, soil, or bodily fluids contaminated by infected animals, posing higher risks to those in poor sanitation or with animal exposure⁽¹¹⁾. Meteorological factors play a complex role in leptospirosis dynamics. In Salvador, Brazil (1996–2010), a dynamic model revealed increased cases during periods of excessive rainfall, cooler temperatures, and high humidity⁽¹²⁾. Environmental moisture also enhances leptospira growth and survival^(13,14). In Fiji (2006–2017), a Bayesian time series analysis found that cumulative rainfall over six weeks (lagged by one week) was strongly associated with increased cases. Additionally, La Niña conditions (negative Niño 3.4 index lagged by four weeks) were linked to a reduced risk⁽¹⁵⁾.

Mushroom poisoning ranges from mild gastrointestinal symptoms to severe, potentially fatal organ failure, depending on the species and toxins involved. Notably, *Amanita phalloides* (death cap) produces amatoxins that can cause lethal liver damage. Symptom onset varies—some toxins act within hours, while others take days, with delayed symptoms often indicating greater danger⁽¹⁶⁾. A 2023 study in Guizhou Province analyzed mushroom poisoning cases and their

relationship with meteorological factors using descriptive statistics, Spearman correlation, and a generalized additive model. Most cases occurred among individuals aged 20–59, primarily presenting with gastrointestinal symptoms. Incidence peaked between June and October, especially in the northeast region. All meteorological factors showed statistically significant positive correlations with poisoning cases ($p < 0.05$)⁽¹⁷⁾.

The climate of Chiang Mai Province is distinctly divided into three seasons: summer, (from mid-February to mid-May), rainy season (from mid-May to mid-October), and winter (from mid-October to mid-February). The average annual temperature is 26.2°C, with an average minimum temperature of 21.3°C and an average maximum temperature of 32.25°C. The province receives an average annual rainfall of 1,100.0 mm, spread over 116 rainy days. August is the wettest month, with an average monthly rainfall of 223.2 mm and 21 rainy days⁽¹⁸⁾. The climate of Chiang Mai is conducive to the occurrence of Hand, Foot, and Mouth Disease (HFMD), leptospirosis, melioidosis, and mushroom poisoning. Therefore, it is essential to study the relationship between climatic factors and the incidence of these diseases.

Studies on meteorological factors and HFMD have been conducted in China^(2,4), Malaysia⁽³⁾, and Singapore⁽⁷⁾. Melioidosis has been studied in China⁽⁹⁾ and Thailand⁽¹⁰⁾. Leptospirosis research has been carried out in Brazil⁽¹²⁾, Fiji⁽¹⁵⁾, and India⁽¹⁴⁾. Mushroom poisoning has been examined in China⁽¹⁷⁾. However, no previous study has quantified these associations specifically for Chiang Mai Province. Understanding the relationship between climatic factors and infectious diseases is vital for effective public health planning

and response in Thailand. By closely monitoring weather patterns and implementing preventive measures, the impact of these diseases can be significantly mitigated⁽¹⁷⁾. A comprehensive analysis of HFMD, melioidosis, leptospirosis, and mushroom poisoning requires accurate climate and disease data. In 2024, the Northern Meteorological Center provided monthly data on rainfall, temperature, humidity, and air pressure for Mueang District, Chiang Mai. Additionally, the Bureau of Epidemiology maintains provincial records of monthly disease incidence, including these four diseases⁽¹⁸⁾.

This study aimed to (1) analyze the correlation between meteorological factors and the incidence of hand, foot, and mouth disease (HFMD), melioidosis, leptospirosis, and mushroom poisoning, and (2) determine the incidence rate ratio for each disease in relation to climatic factors in Chiang Mai province.

Methods

This quantitative research was a correlational study conducted in Chiang Mai province.

Data Collection

The monthly data for Chiang Mai province from January 2017 to June 2024, a total of 90 months are as follows; The Monthly average daily value of the 6 meteorological factors were presented as follows; pressure (hPa), temperature (°C), relative humidity (%), rainfall (mm), sunshine (h), and Evaporation (mm) collected from the Northern Meteorological Center, the Mueang district, Chiang Mai province⁽¹⁸⁾. The reported cases of HFMD, melioidosis, leptospirosis, and mushroom poisoning were sourced from the database of the Digital Disease Surveillance, R506, the Bureau of Epidemiology, Department of Disease

Control, Ministry of Public Health⁽¹⁹⁾.

Descriptive Statistics and Correlation Analysis

Descriptive statistics included mean, median, standard deviation (SD), variance, minimum, and maximum values. Normality was assessed using the Shapiro–Wilk test⁽²⁰⁾. Pearson’s correlation measured the strength and direction of relationships between variables: values near 1 indicate perfect correlation; 0.50–1 strong, 0.30–0.49 moderate, ≤ 0.29 weak, and values near 0 suggest no correlation. Since the variables were not normally distributed, Spearman’s rho, a non-parametric correlation test, was employed as an alternative to Pearson’s correlation⁽²¹⁾.

Generalized Linear Model

Poisson regression is suitable for count-based time series data with equidispersion. For overdispersed data, quasi-Poisson or negative binomial regression is preferred; the latter also accommodates underdispersion^(22,23,24). These generalized linear models use a log-link function, with the response variable representing counts over time or space.

For the random component, we assume that the response y has a Poisson distribution. That is, $y_i \sim \text{poisson}(\mu_i)$ for $i=1,2,\dots,n$ where the expected count of y_i is $E[Y_i]=\mu_i$. The link function is usually the (natural) log, but sometimes the identity function may be employed. The systematic component consists of a linear combination of explanatory variables x . This is analogous to that of logistic regression. Thus, in the case of a single explanatory, the model is written

$$\text{Ln}(y)=\alpha+\beta x$$

This is equivalent to:

$$Y = e^{\alpha+\beta x} = e^{\alpha}e^{\beta x}$$

Interpretations of these parameters are similar to those for logistic regression. e^{α} is the effect on the

mean of y when $x=0$., and e^{β} is the incidence rate ratio (IRR), representing the multiplicative effect on the mean number of events for each 1-unit increase in x .

If $\beta=0$, then $e^{\beta}=1$, and the expected count, $\mu=E[y]=e^{\alpha}$, and y and x are not related.

If $\beta>0$, then $e^{\beta}>1$ and $\mu=E[y]$ the expected count is e^{β} times larger than when $x=0$.

If $\beta<0$, then $e^{\beta}<1$ and $\mu=E[y]$ the expected count is e^{β} times smaller than when $x=0$.

For multiple variables, the model is

$$\text{Ln } y = a + b_1 x_1 + b_2 x_2 + \dots + b_n x_n$$

or

$$y = e^{(a + b_1 x_1 + b_2 x_2 + \dots + b_n x_n)} = e^a e^{b_1 x_1} e^{b_2 x_2} \dots e^{b_n x_n}$$

when y is the dependent variable,

$x_1, x_2, \dots, x_n$ are the independent variables,

e^a is the average of y , when $x_1, x_2, \dots, x_n$ are equal to 0.

$b_1, b_2, \dots, b_n$ are the coefficients of the independent variables x_i for $i=1,2,\dots,n$

The jamovi statistical analysis software was used together with the GAMLj – General Analyses Linear Models in jamovi module for data analysis^(25,26). The significant p -value < 0.05 .

Ethical Consideration

The reported cases of the four communicable diseases were obtained as secondary data from a government agency and made publicly accessible in the form of monthly totals, with no identifiable links to individual case reports⁽²⁷⁾. This study was classified as “non-human research” and, therefore, exempt from requiring ethical approval for research involving human subjects, in accordance with Mahidol University’s official announcement⁽²⁸⁾.

The Pathumthani University Institutional Review Board (IRB) has issued a certificate letter for non-human Subject Research Reference No.: PTU-EC/NHS/2567-001. Dated: 18 April 2025.

Results

Descriptive statistics and normality test

The 90-month data period had descriptive statistics presented in Table 1. For the reported cases of the 4 diseases, the variances were greater than their means (indicating overdispersion). Additionally, the distribution of variables was found to be non-normal. The 6 meteorological factors analyzed included pressure, temperature, relative humidity, rainfall, sunshine hours, and evaporation.

The descriptive statistics and normality test results for the monthly reported cases of four diseases in Chiang Mai Province from January 2017 to June 2024 (n=90). Hand, Foot, and Mouth Disease (HFMD) had the highest mean (115.00 cases) and the greatest variability (SD=154.00, Variance=23,813.00), with cases ranging from 1 to 666 per month. In contrast, melioidosis had a very low mean (0.72 cases)

and a median of 0, indicating that most months reported no cases, with a maximum of only 8 cases. leptospirosis (mean=2.90, SD=3.38) and mushroom poisoning (mean=2.48, SD=3.92) showed moderate case numbers. For all four diseases, the mean was substantially larger than the median, and the variance exceeded the mean, indicating positive skewness and overdispersion in the data. Furthermore, the Shapiro-Wilk test yielded $p < 0.001$ for all diseases, confirming that none of the disease datasets followed a normal distribution. These findings justified the authors' use of non-parametric correlation tests (Spearman's rho) and overdispersion-tolerant models (Quasi-Poisson and negative binomial) rather than standard Poisson or Pearson's correlation.

The descriptive statistics and normality test results for six meteorological factors in Chiang Mai Province from January 2017 to June 2024 (n=90) were shown in Table 2. The Shapiro-Wilk test yielded p-values below 0.05 for all variables—pressure ($p < 0.001$), temperature ($p = 0.025$), relative humidity ($p < 0.001$), rainfall ($p < 0.001$), sunshine ($p < 0.001$), and evaporation ($p < 0.001$) — indicating that none of the

Table 1 Descriptive statistics and Shapiro-Wilk test of monthly incidents of the four infectious diseases (n=90)

Statistics	The reported cases			
	HFMD	Melioidosis	Leptospirosis	Mushroom Poisoning
Mean	115.00	0.72	2.90	2.48
Median	54.50	0.00	2.00	1.00
Standard deviation	154.00	1.40	3.38	3.92
Variance	23813.00	1.96	11.40	15.40
Minimum	1.00	0.00	0.00	0.00
Maximum	666.00	8.00	15.00	18.00
Shapiro-Wilk W	0.727	0.544	0.800	0.686
Shapiro-Wilk p-value	< 0.001*	< 0.001*	< 0.001*	< 0.001*

Table 2 Descriptive statistics and Shapiro–Wilk test of meteorological factors (n=90)

Statistics	Pressure (hPa)	Temperature (° C)	Relative humidity (%)	Rainfall (mm)	Sunshine (hour)	Evaporation (mm)
Mean	1009.00	27.30	68.30	3.22	7.32	4.02
Median	1009.00	27.70	70.80	2.14	8.08	3.80
Standard deviation	3.45	2.32	9.34	3.54	2.14	0.98
Variance	11.90	5.38	87.30	12.50	4.57	0.96
Minimum	1004.00	22.30	44.60	0.00	2.73	2.49
Maximum	1016.00	32.50	81.80	15.10	10.20	6.26
Shapiro–Wilk W	0.932	0.968	0.928	0.837	0.919	0.937
Shapiro–Wilk p-value	<0.001*	0.025*	<0.001*	<0.001*	<0.001*	<0.001*

Remarks: * p<0.05

meteorological factors followed a normal distribution, which justified the authors' use of Spearman's rho (a non-parametric correlation test) for the initial analysis. Regarding variability, rainfall showed a high standard deviation (3.54) relative to its mean (3.22), with values ranging from 0.00 to 15.10 mm, demonstrating that rainfall in Chiang Mai is highly inconsistent from month to month, characterized by many dry months interspersed with a few very wet months—a pattern often associated with disease transmission, particularly for leptospirosis. Additionally, when considering Table 1 in conjunction, the enormous range of HFMD cases (1 to 666 per month) compared to its mean (115) confirms that HFMD is a significant and episodic public health concern in Chiang Mai, with occasional large outbreaks that are important to predict.

The Spearman's rho correlation coefficients

The Spearman's rho correlation coefficients between the two of the six meteorological factors were shown in Table 3. The strongest correlations were observed between relative humidity and sunshine

(p<0.001), indicating that months with higher humidity tended to have significantly fewer sunshine hours, and between temperature and evaporation (p<0.001), showing that higher temperatures were strongly associated with increased evaporation. Rainfall was moderately to strongly correlated with several factors, including a negative correlation with sunshine (p<0.001) and a positive correlation with relative humidity (p<0.001). Pressure showed moderate negative correlations with temperature (p<0.001) and rainfall (p<0.001). Most correlations were statistically significant at p<0.05, except for the relationships between temperature and relative humidity (p=0.087), temperature and sunshine (p=0.442), and rainfall and evaporation (p=0.674). These strong inter-correlations among meteorological factors highlight the complexity of isolating individual weather effects on disease transmission.

The Spearman's rho correlation coefficients between the four infectious diseases and the meteorological factors were shown in Table 4. Mushroom poisoning showed the strongest and most consistent

Table 3 Spearman's rho correlations of the meteorological factors

	Pressure		Temperature		Relative humidity		Rainfall		Sunshine	
	r	p-value	r	p-value	r	p-value	r	p-value	r	p-value
Temperature	-0.754	<0.001*	—							
Relative humidity	-0.287	0.006*	-0.181	0.087	—					
Rainfall	-0.584	<0.001*	0.321	0.002*	0.726	<0.001*	—			
Sunshine	0.539	<0.001*	-0.083	0.442	-0.862	<0.001*	-0.747	<0.001*	—	
Evaporation	-0.462	<0.001*	0.836	<0.001*	-0.545	<0.001*	0.045	0.674	0.316	0.003*

associations, with significant correlations for pressure ($p<0.001$), sunshine ($p<0.001$), relative humidity ($p<0.001$), and rainfall ($p<0.001$), indicating that cases increased with higher humidity and rainfall but decreased with higher pressure and more sunshine. Leptospirosis was significantly correlated with relative humidity ($p<0.001$), rainfall ($p=0.012$), and sunshine ($p=0.014$), suggesting that moist, rainy conditions were associated with more cases. HFMD showed weak but significant negative correlations with pressure ($p=0.004$) and sunshine ($p=0.041$), as well as a weak positive correlation with mushroom poisoning ($p=0.005$).

In contrast, melioidosis showed no statistically

significant correlations with any meteorological factor (all $p > 0.05$), which aligns with the authors' later finding that no fitted model could be identified for this disease. These correlation patterns provided the foundation for building the generalized linear models presented in the results section.

The Generalized Linear Model

The best-fitted generalized linear model, the backward stepwise regression, was applied to each of the four diseases using the selected meteorological factors. The analysis revealed that only HFMD, Leptospirosis, and mushroom poisoning cases showed significant associations with relative humidity as shown in Table 5.

Table 4 Spearman's rho correlations of the four diseases and the meteorological factors

	HFMD		Melioidosis		Leptospirosis		Mushroom poisoning	
	r	p-value	r	p-value	r	p-value	r	p-value
Melioidosis	-0.050	0.637	—					
Leptospirosis	-0.184	0.082	0.188	0.075	—			
Mushroom poisoning	0.291	0.005*	0.176	0.097	0.080	0.456	—	
Pressure	-0.303	0.004*	-0.016	0.879	-0.145	0.173	-0.559	<0.001*
Temperature	0.123	0.247	-0.001	0.990	-0.016	0.884	0.272	0.010*
Relative humidity	0.820	0.024*	0.123	0.247	0.345	<0.001*	0.442	<0.001*
Rainfall	0.051	0.630	0.141	0.184	0.263	0.012*	0.491	<0.001*
Sunshine	-0.219	0.041*	-0.108	0.316	-0.260	0.014*	-0.576	<0.001*
Evaporation	0.111	0.296	-0.054	0.616	-0.114	0.286	0.037	0.729

Table 5 The Generalized Linear Model of the monthly HFMS, leptospirosis and mushroom poisoning cases

Names	Coefficient	Estimate	exp(B)	Lower	Upper	z	p
The Quasi-Poisson model of monthly HFMD cases							
(Intercept)	a	4.597	99.184	74.263	128.735	32.85	<0.001*
Sunshine	b	-0.241	0.786	0.705	0.876	-4.36	<0.001*
The Quasi-Poisson model of monthly Leptospirosis cases							
(Intercept)	a	0.9249	2.52	1.97	3.15	7.75	<0.001*
Rh	b	0.0616	1.06	1.04	1.1	4.26	<0.001*
The negative binomial model of monthly mushroom poisoning cases							
(Intercept)	a	0.3052	1.357	0.998	1.831	1.970	0.049*
Rh	b1	0.0707	1.073	1.034	1.117	4.070	<0.001*
Pressure	b2	-0.2482	0.780	0.710	0.853	-5.410	<0.001*

* p<0.05

The number of monthly HFMD cases

The number of monthly HFMD cases – HFMD
 $= e^{a+bSun}$

The Quasi-Poisson model with R^2 0.198

Sunshine (h) – Loglikelihood ratio test $\chi^2=18.90$
 p -value<.001

The predicted equation for the monthly HFMD reported cases (using the parameters in Table 5) is: HFMD cases = $99.184xe^{(-0.241Sun)}$. A 1% increase in the daily average monthly sunshine (hours) is projected to reduce the number of reported HFMD cases to 0.786 times the baseline of 99.184 cases for that month as shown in Figure 1.

The number of monthly melioidosis cases

There was no fitted model.

The number of monthly leptospirosis cases

The number of monthly HFMD cases – leptospirosis = $e^{(a+bRh)}$

The Quasi-Poisson model with R^2 0.198

Relative Humidity (Rh) – Loglikelihood ratio test
 $\chi^2=22.10$ p -value< 0.001

The monthly leptospirosis reported cases (using

the parameters in Table 5) . A 1% increase in average monthly relative humidity is expected to raise the number of reported leptospirosis cases to 1.06 times the baseline of 2.52 cases for that month as shown in Figure 2.

The number of monthly mushroom poisoning cases

The number of monthly mushroom poisoning cases, Mushroom Poisoning= $e^{(a+b1Rh+b2Pressure)}$

The negative binomial model with R^2 0.438

An increase of 1% in the average monthly relative humidity is projected to raise the number of reported mushroom poisoning cases to 1.073 times the baseline of 1.357 cases. Conversely, an increase of 1 hPa in air pressure is expected to reduce the reported cases to 0.780 times the baseline of 1.357 cases.

Discussion

Association between meteorological factors and HFMD

This study found that Hand, Foot, and Mouth Disease (HFMD) in Chiang Mai Province was asso-

Figure 1 The Quasi-Poisson model of the number of monthly HFMD cases and sunshine

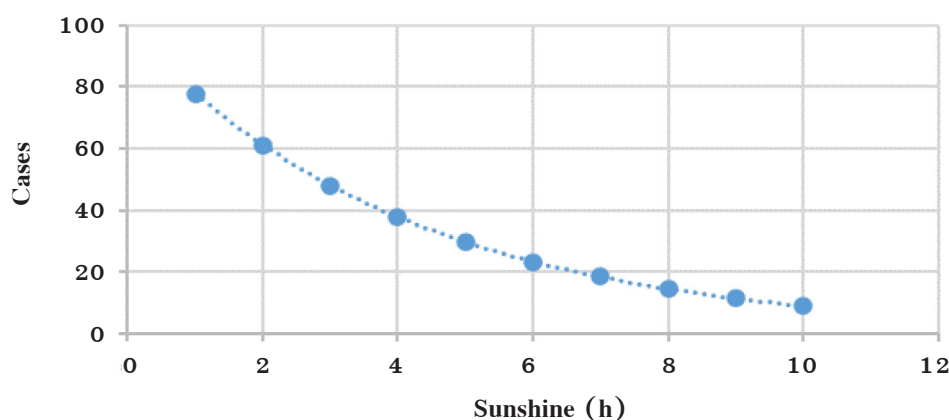
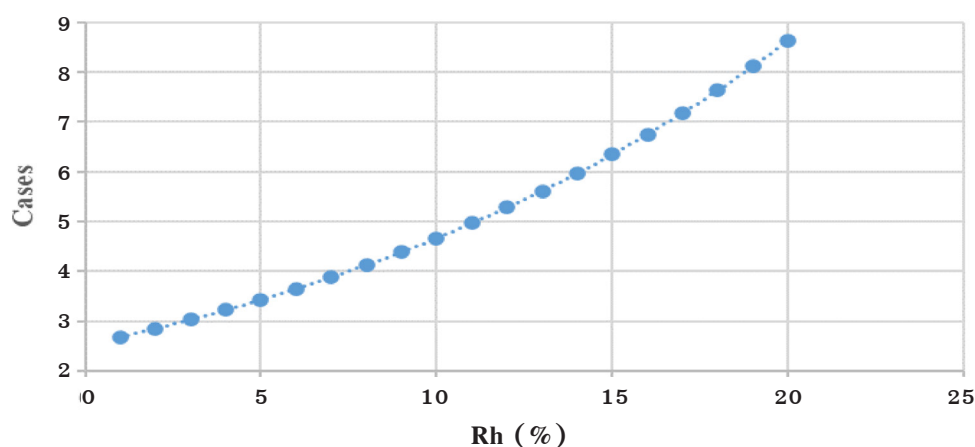


Figure 2 The Quasi-Poisson model of the number of monthly Leptospirosis cases and relative humidity



ciated with sunshine duration as the sole factor (Quasi-Poisson model, $R^2 = 0.198$, $IRR = 0.786$, $p < 0.001$). This finding differs from a study in Yangzhou, China (2017–2022), which reported that multiple meteorological factors—including temperature, sunshine duration, relative humidity, and atmospheric pressure—affected HFMD incidence⁽⁴⁾. This discrepancy may be partially attributed to the difference in data resolution; the Yangzhou study used daily data, whereas the present study used monthly aggregated data, which may not capture short-term variations in disease transmission. Furthermore, a meta-analysis of

143 cities in China (2009–2014) identified a non-linear relationship between rainfall and HFMD incidence, with significant regional variations⁽²⁹⁾, emphasizing that the impact of meteorological factors on HFMD cannot be generalized across different locations. The use of daily data combined with consideration of local geographic and climatic characteristics would improve the accuracy of disease prediction models.

Association between meteorological factors and melioidosis

For melioidosis, this study could not generate a

suitable fitted model. The primary reason was the low monthly case count (mean=0.72 cases per month) and a high proportion of months with zero cases (54.4%), consistent with the Shapiro–Wilk test indicating non-normal distribution ($p < 0.05$). In contrast, a study in northern Hainan, China (2010–2020) found that the highest number of cases occurred in summer and autumn and were positively associated with abundant rainfall⁽⁹⁾. Another study in Ubon Ratchathani Province, Thailand (2009–2018) reported that while monthly average rainfall and melioidosis incidence both peaked from July to September, they were not significantly associated ($p=0.576$). However, monthly maximum and minimum temperatures were significantly associated with melioidosis incidence in that study⁽¹⁰⁾. These contrasting findings suggest that geographic and local climatic factors play important roles in melioidosis epidemiology. The high proportion of zero counts and low case numbers in Chiang Mai are major limitations that prevent the development of a precise statistical model. Future studies in areas with higher incidence rates may yield clearer results.

Association between meteorological factors and leptospirosis

This study found that monthly leptospirosis cases were significantly associated with relative humidity (Quasi-Poisson model, $R^2 = 0.198$, $IRR = 1.060$, $p < 0.001$). This finding aligns with the biological principle that environmental moisture enhances the survival and growth of *Leptospira* bacteria^(13,14). However, most international studies, such as those in Salvador, Brazil (1996–2010) and Fiji (2006–2017), have demonstrated a clear association between cumulative rainfall and leptospirosis incidence^(12,15).

For example, the Fiji study found that cumulative rainfall over six weeks (lagged by one week) was strongly associated with increased cases (15). This discrepancy may be explained by the use of monthly data in the present study, which may not be sufficiently detailed to capture time-lagged relationships. Leptospirosis typically has a specific incubation period and is often associated with flooding events or exposure to stagnant water over a defined timeframe. The use of weekly or daily data would likely improve the detection of associations with rainfall.

Association between meteorological factors and mushroom poisoning

Mushroom poisoning showed the strongest association with meteorological factors in this study. The negative binomial model explained 43.8% of the variance in monthly cases ($R^2 = 0.438$). A 1% increase in average monthly relative humidity was associated with a 1.073-fold increase in cases ($IRR = 1.073$, 95%CI: 1.034–1.117, $p < 0.001$), while a 1 hPa increase in atmospheric pressure was associated with a 0.780-fold decrease ($IRR = 0.780$, 95%CI: 0.710–0.853, $p < 0.001$). A study in Guizhou Province, China (2023), using a generalized additive model, found significant non-linear relationships between mushroom poisoning cases and daily average ground temperature at 15 cm depth, daily average precipitation, daily average relative humidity, and daily average sunshine duration⁽¹⁷⁾. The present study partially aligns with that study regarding relative humidity. However, differences in other factors—such as ground temperature and precipitation—may be due to variations in mushroom species, vegetation, and climatic conditions between the two regions. Chiang Mai Province has extensive forest cover and high biodi-

versity, which may influence the types and quantities of toxic mushrooms present in different seasons.

Summary across diseases and study limitations

When comparing the results across all four diseases, it is evident that the effects of meteorological factors vary by disease type, geographic location, and time period. Specifically: (1) HFMD was associated only with sunshine duration; (2) melioidosis could not be modeled due to low case counts and excessive zeros; (3) leptospirosis was associated with relative humidity; and (4) mushroom poisoning was associated with both relative humidity and atmospheric pressure. These differences confirm that the impact of meteorological factors cannot be generalized across all settings, and location-specific studies are essential.

The main limitation of this study is the use of monthly aggregated data, which may not capture time-lagged effects or daily variations. Many infectious diseases have short incubation periods—for example, HFMD has an incubation period of 3–7 days—and monthly data may dilute or obscure true associations. Future studies should use weekly or daily data and incorporate additional factors such as land use, population density, and preventive health behaviors to improve model accuracy and comprehensiveness. Additionally, extending the study period would increase case counts and statistical power, particularly for low-incidence diseases such as melioidosis.

Comparing study results across regions with different geographic, meteorological, and public health characteristics can only provide a broad perspective and should not be used for direct generalization. Local-level studies remain essential for effective disease surveillance and control planning.

Conclusion

This study demonstrated that meteorological factors are significantly associated with the incidence of hand, foot, and mouth disease (HFMD), leptospirosis, and mushroom poisoning in Chiang Mai Province, Thailand. Specifically, sunshine duration was negatively associated with HFMD cases, while relative humidity was positively associated with leptospirosis cases. For mushroom poisoning, both relative humidity (positive association) and air pressure (negative association) were significant predictors. However, no suitable model could be fitted for melioidosis cases. The use of monthly aggregated data limits the ability to capture time-lagged effects and daily variations. These findings provide useful predictive models for local health authorities to monitor disease outbreaks and implement appropriate public health measures based on meteorological forecasts.

Limitations of the study

Only historical data was utilized, with no additional supplementary information.

Acknowledgements

The authors would like to express their sincere gratitude to the Northern Meteorological Center⁽¹⁸⁾ for providing the meteorological data of Mueang District, Chiang Mai Province, which were essential for this research. The data were kindly responded via email and greatly contributed to the completion of this study.

References

1. Centers for Diseases Control and Prevention. Hand, foot, and mouth disease (HFMD) [Internet]. 2024 [cited 2025 Apr 10]. Available from: <https://www.cdc.gov/hand-foot-mouth/about/index.html>

2. Zhu Z, Cai J, Feng Y, Gu L, Guan X, Liu N, et al. Association between air pollution, meteorological factors and hand, foot, and mouth disease incidence in Zhejiang province: a Bayesian spatio-temporal modelling study. *Atmos Environ* 2024;336:120745.
3. Musa HI, Hassan L, Panchadcharam C, Zakaria Z, Aziz SA. Correlations between melioidosis seroprevalence in livestock and meteorological factors in peninsular Malaysia. *J Anim Health Prod* 2024;12(4):562–73.
4. Guo Z, Wang Y, Li Y, Zhou L. Impact of meteorological factors on the incidence of hand-foot-mouth disease in Yangzhou from 2017 to 2022: a time series study. *Front Public Health* 2023;10(11):1278516.
5. Peng H, Chen Z, Cai L, Liao J, Zheng K, Li S, et al. Relationship between meteorological factors, air pollutants and hand, foot and mouth disease from 2014 to 2020. *BMC Public Health* 2022;22:998.
6. Wahid NAA, Suhaila J, Rahman HA. Effect of climate factors on the incidence of hand, foot, and mouth disease in Malaysia: A generalized additive mixed model. *Infect Dis Model* 2021;6:997–1008.
7. Min N, Ong YHB, Han AX, Ho SX, Yen EWP, Ban KHK, et al. An epidemiological surveillance of hand foot and mouth disease in paediatric patients and in community: A Singapore retrospective cohort study, 2013–2018. *PLOS Negl Trop Dis* 2021;15:e0008885.
8. Centers for Diseases Control and Prevention. Clinical overview of melioidosis [Internet]. 2024 [cited 2025 Apr 10]. Available from: <https://www.cdc.gov/melioidosis/hcp/clinical-overview/index.html>
9. Zheng W, Kuang S, Zhong C, Zhou J, Long W, Xiao S, et al. Risk factors for melioidosis mortality and epidemics: a multicentre, 10-year retrospective cohort study in Northern Hainan. *Infect Dis Ther* 2023;12(3):951–64.
10. Wongbutdee J, Saengnil W, Jittimanee J, Panomket P, Saenwang P. The association between the mapping distribution of melioidosis incidences and meteorological factors in an endemic area: Ubon Ratchathani, Thailand (2009–2018). *J Nat Sci CMUJ* 2021;20(4):e2021083.
11. Centers for Diseases Control and Prevention. Clinical overview of leptospirosis [Internet]. 2024 [cited 2025 Apr 10]. Available from: <https://www.cdc.gov/leptospirosis/hcp/clinical-overview/index.html>
12. Cunha M, Costa F, Ribeiro G, Carvalho M, Reis R, Nery Jr N, et al. Rainfall and other meteorological factors as drivers of urban transmission of leptospirosis. *PLOS Negl Trop Dis* 2022;16:e0007507.
13. Desvars A, Jégo S, Chiroleu F, Bourhy P, Cardinale E, Michault A. Seasonality of human leptospirosis in Reunion Island (Indian Ocean) and its association with meteorological data. *PLOS ONE* 2011;6(5):e20377.
14. Pawar SD, Kore MR, Athalye A, Thombre PA. Seasonality of leptospirosis and its association with rainfall and humidity in Ratnagiri, Maharashtra. *Int J Health Sci* 2018; 7:37–40.
15. Rees EM, Batista ML, Kama M, Kucharski AJ, Lau CL, Lowe R. Quantifying the relationship between climatic indicators and leptospirosis incidence in Fiji: a modelling study. *PLOS Glob Public Health* 2023;3(10):e0002400.
16. O'Malley BF, O'Malley R. Merck. Manual professional version: mushroom poisoning [Internet]. 2022 [cited 2025 Apr 10]. Available from: <https://www.merck-manuals.com/professional/injuries-poisoning/poisoning/mushroom-poisoning>
17. Xiong S, Wu A, Weng L, Zhang L, Wu M, Li H, et al. Study on the correlation between the number of mushroom poisoning cases and meteorological factors based on the generalized additive model in Guizhou Province, 2023. *BMC Public Health* 2023;24(1):2628.

18. Meteorological Information Division, Northern Regional Meteorological Center, Thai Meteorological Department. Monthly meteorological data from the Northern Regional Meteorological Station (Chiang Mai Station), Mueang District, Chiang Mai Province [Internet]. 2024 [cited 2025 Jan 5]. Available from https://drive.google.com/drive/folders/1ApWc-82J2YEUplI0QjlbufIxS6Iaa7_w
19. Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health. National disease surveillance (Report 506), communicable diseases: HFM, melioidosis, leptospirosis, and mushroom poisoning [Internet]. 2024 [cited 2025 Jan 5]. Available from: <http://doe.moph.go.th/surdata/index.php17>
20. Melato C. An Introduction to the Shapiro-Wilk test for normality [Internet]. 2023 [cited 2025 Apr 10]. Available from: <https://builtin.com/data-science/shapiro-wilk-test>
21. Statistics Solutions. Correlation (Pearson, Kendall, Spearman) [Internet]. 2026 [cited 2026 Apr 5]. Available from: <https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/correlation-pearson-kendall-spearman/>
22. Walker JA. Statistics for the experimental biologist a guide to best (and worst) practices. Chapter 20 generalized linear models I: count data [Internet]. 2024 [cited 2025 Apr 10]. Available from: https://www.middleprofessor.com/files/applied-biostatistics_book-down/_book/generalized-linear-models-i-count-data.html
23. Sarakarn P, Jumparway D. Coverage and flexibility: issues should be considered for analyzing by generalized linear model in health science research. Thai Health Science Journal and Community Public Health 2020; 3(2):144-58.
24. Gallucci M. GAMLj: General analyses for linear models [Internet]. 2019 [cited 2025 Apr 10]. Available from: <https://gamlj.github.io/>
25. Jamovi Stat Open Now. Jamovi desktop, download and install jamovi onto your computer [Internet]. 2024 [cited 2025 Apr 10]. Available from: <https://www.jamovi.org/>
26. Gallucci M, Jonathon LJ. Introducing GAMLj: GLM, LME and GZLMs in jamovi [Internet]. 2024 [cited 2025 Apr 10]. Available from: <https://blog.jamovi.org/2018/11/13/introducing-gamlj.html>
27. MU Central-IRB (MU-CIRB). Self-Assessment form whether an activity is human subject research which requires ethical approval [Internet]. 2022 [cited 2025 Apr 10]. Available from: <https://sp.mahidol.ac.th/th/ethics-human/forms/checklist/2022-Human%20Research%20Checklist-researcher.pdf>
28. Mahidol University. Announcement of Mahidol University on guidelines for research projects that do not qualify as human research, 2022 [Internet]. [cited 2025 Apr 10]. Available from: <https://sp.mahidol.ac.th/th/LAW/policy/2565-MU-Non-Human.pdf>
29. Yang F, Ma Y, Liu F, Zhao X, Fan C, Hu Y, et al. Short-term effects of rainfall on childhood hand, foot and mouth disease and related spatial heterogeneity: evidence from 143 cities in mainland China. BMC Public Health 2020;20(1):1528.

ปัจจัยอุตุนิยมวิทยาที่สัมพันธ์กับการเกิดโรคมือ เท้า ปาก โรคเมลิออยโดสิส โรคเลปโตสไปโรสิส และ โรคพิษจากเห็บในจังหวัดเชียงใหม่ ประเทศไทย

ฉัตรสิริ ฉัตรฤติ พย.ม. (การบริหารทางการแพทย์)*; วัฒนา ชยธวัช ปร.ด. (คณิตศาสตร์ประยุกต์)**; พุทธิพงษ์ จรูญสิริพันธ์ ปร.ด. (วิศวกรรมไฟฟ้าและคอมพิวเตอร์)***

* สาขาการพยาบาลอนามัยชุมชน คณะพยาบาลศาสตร์ มหาวิทยาลัยนอร์ทกรุงเทพ; ** สาขาการแพทย์แผนไทย คณะสหเวชศาสตร์ มหาวิทยาลัยปทุมธานี; *** สาขาวิศวกรรมพลังงานใหม่ คณะวิศวกรรมศาสตร์และเทคโนโลยี มหาวิทยาลัยชินวัตร

วารสารวิชาการสาธารณสุข 2569;35(5):829-42.

ติดต่อผู้เขียน: วัฒนา ชยธวัช Email: vadhana.j@ptu.ac.th

บทคัดย่อ: ปัจจัยอุตุนิยมวิทยามีผลต่ออุบัติการณ์และการแพร่กระจายของโรคในประเทศไทย ได้แก่ โรคมือ เท้า ปาก (HFMD) โรคเลปโตสไปโรสิส โรคเมลิออยโดสิส และโรคพิษจากเห็บ การศึกษานี้เป็นการวิจัยเชิงสหสัมพันธ์ โดยมีวัตถุประสงค์เพื่อหาปริมาณความสัมพันธ์ระหว่างปัจจัยทางอุตุนิยมวิทยากับจำนวนผู้ป่วยโรคติดต่อใน จังหวัดเชียงใหม่ ข้อมูลอุตุนิยมวิทยาได้มาจากศูนย์อุตุนิยมวิทยาภาคเหนือ ส่วนข้อมูลรายงานผู้ป่วยโรค HFMD โรคเมลิออยโดสิส โรคเลปโตสไปโรสิส และโรคพิษจากเห็บ ได้มาจากสำนักโรคควบคุมโรค ช่วงเวลาที่ศึกษาเป็นระยะเวลา 90 เดือน ตั้งแต่เดือนมกราคม พ.ศ. 2560 ถึงเดือนมิถุนายน พ.ศ. 2567 การวิเคราะห์ทางสถิติประกอบด้วย สถิติเชิงพรรณนา การทดสอบ Shapiro-Wilk การหา Pearson's correlation และการวิเคราะห์แบบ generalized linear model โดยใช้โปรแกรมวิเคราะห์สถิติ Jamovi ร่วมกับโมดูล GAMLj - general analyses linear models ผลการศึกษาพบว่าแบบจำลองที่เหมาะสมที่สุด คือ แบบจำลองควอซี-ปัวซอง สำหรับโรคมือเท้าปาก ($R^2 = 0.198$ ช่วงโมเมนต์: IRR = 0.786, $p < 0.05$) และเลปโตสไปโรสิส ($R^2 = 0.198$, ความชันสัมพัทธ์: IRR = 1.060, $p < 0.05$) และแบบจำลองทวินามลบ สำหรับโรคเห็บพิษ ($R^2 = 0.438$, ความชันสัมพัทธ์: IRR = 1.073, $p < 0.05$; ความกดอากาศ: IRR = 0.780, $p < 0.05$) ปัจจัยทางอุตุนิยมวิทยามีความสัมพันธ์กับโรคมือเท้าปาก โรคเลปโตสไปโรสิส และพิษจากเห็บในจังหวัดเชียงใหม่ แต่ไม่พบแบบจำลองที่เหมาะสมสำหรับโรคเมลิออยโดสิส ข้อจำกัดหลักคือ การใช้ข้อมูลรายเดือน ซึ่งอาจไม่สามารถจับพลวัตแบบมีเวลานับหรือความแปรปรวนรายวันได้

คำสำคัญ: ปัจจัยอุตุนิยมวิทยา; ความสัมพันธ์; โรคติดต่อ