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Impact of Climate Factors on Hand, Foot, and Mouth Disease in Malaysia: A Generalised Linear Models Approach

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Abstract: Hand, Foot, and Mouth Disease (HFMD) is a re-emerging infectious disease in the Asia-Pacific region, particularly in Malaysia. To the best of our knowledge, studies focusing on analyzing the relationship between climate factors and HFMD in Malaysia have not used 10 years of climate data or conducted research covering all states in the country. These existing studies have suggested that examining more data would produce more precise results. Therefore, this study employs generalized linear models (GLMs) to examine the relationship between climate factors and HFMD incidences and to forecast the HFMD cases. Data from 2009 to 2019 were analyzed using five different distributions across fourteen Malaysian states, considering daily HFMD cases, temperature, relative humidity, and rainfall. The Zero-inflated Negative Binomial model was identified as the most appropriate for analyzing and predicting HFMD cases in multiple states, providing valuable insights for policymakers and health authorities.

Keywords: Hand Foot Mouth Disease (HFMD), Zero-inflated Models, Generalised Linear Models, Climate Factors Analysis, Model Fitting and Prediction.

1. Introduction

Hand, Foot, and Mouth Disease (HFMD) is a significant public health issue in the Asia-Pacific region, primarily affecting children under five years of age. The disease is caused by enteroviruses, predominantly Coxsackievirus A16 (CVA16) and Enterovirus A71 (EV-A71), and is characterised by symptoms including painful mouth sores and a rash with blisters on the hands, feet, and buttocks (Chang et al., 2002). While the disease is generally mild, severe cases may result in complications like meningitis, encephalitis, and polio-like paralysis, which can be fatal (Puenpa et al., 2019). HFMD is transmitted directly with contaminated bodily secretions, including blister fluid and faeces, or via contaminated objects (Sun et al., 2016).

The incidence of HFMD exhibits distinct seasonal patterns, indicating that climate factors such as temperature, relative humidity, and rainfall play an important role in the spread of the disease (Luo et al., 2022; Wu et al., 2022; Kim et al., 2016; Onozuka & Hashizume, 2011). Temperature affects viral survival and transmission rates, rainfall contributes to environmental contamination and increased human contact, and relative humidity influences virus stability and vulnerability. This study focuses specifically on these three climate factors because they have consistently shown the strongest associations with HFMD outbreaks in previous research. Other climate variables, such as wind speed and air pressure, have demonstrated inconsistent or weaker relationships with HFMD cases and are thus not included in this analysis.

Motivated by the prevalence of HFMD in Malaysia in recent years, this study aims to evaluate the fit of generalized linear models (GLMs) for HFMD incidence data, identify the most suitable model, and use it to predict HFMD cases in Malaysia based on climate factors. Additionally, the study employs daily data from a span of ten years to examine which climate factors significantly influence HFMD by conducting factor analysis and evaluating the statistical significance of the variables through p-values. By identifying the best model for HFMD prediction, the findings will offer valuable insights for early warning systems and targeted public health interventions to prevent HFMD outbreaks effectively.

2. Literature review

Several studies have examined the relationship between climatic factors and HFMD incidences. Onozuka and Hashizume (2011) investigated the impact of temperature on HFMD incidence in Japan, finding that the disease exhibited a seasonal pattern with peaks during summer in temperate regions, and both spring and autumn in subtropical regions. The study indicated that within a high temperature range, the risk of HFMD increased, but extremely high temperatures led to a decline in cases, suggesting an optimal temperature range for the survival and transmission of the virus.

In Singapore, studies conducted during epidemic years from 2005 to 2007 revealed two distinct peaks in HFMD incidence. The dominant circulating strain of the virus during these outbreaks varied, with CVA16 being prevalent in 2005 and 2007, while EV-

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A71 was prevalent in 2006 (Ang et al., 2009). The Ministry of Health in Singapore reported significant variations in the number of HFMD clusters affecting preschools and childcare centres from 2018 to 2022, further underscoring the influence of climate on HFMD spread.

Thailand experienced its first major HFMD outbreak in 2012, with over 45,000 reported cases, followed by another notable outbreak four years later. These events highlighted HFMD as a growing public health concern in Thailand (Verma et al., 2021). Similarly, in India, the first documented HFMD outbreak occurred in Kerala in 2005, attributed to EV-A71, with subsequent reports of over 1,150 cases from 2012 to 2017 (Chavan et al., 2023).

In Malaysia, HFMD incidences peak during the Southeast Monsoon season (May to August), which is typically dry, and decline during the Northeast Monsoon season (November to February), associated with heavy rainfall (Abdul Wahid et al., 2021). This seasonal variation highlights the potential influence of climate factors on HFMD transmission.

Previous studies in Malaysia have provided valuable insights into HFMD patterns and related risk factors. A study in Kota Kinabalu analysed HFMD occurrences and demographic risk factors, using logistic regression to estimate the odds ratios for severe cases. The findings indicated significant associations between severe HFMD and factors such as age and ethnicity (Chin et al., 2022). In Sarawak, researchers applied an autoregressive moving average (ARMA) model to seven years of HFMD data, achieving a 94% confidence interval for predicting HFMD cases (Sham et al., 2014). Another study in Kelantan used multiple logistic regression to examine the relationship between risk factors and HFMD incidences, identifying factors like preschool attendance and home care as significant (Wan Mohamad et al., 2021). In Selangor, a study from 2010 to 2016 performed correlation analysis and GLM to estimate the relationship between HFMD occurrences and temperature, considering a lag-time effect (Abdul Wahid et al., 2020). The research concluded that temperature could serve as an early warning indicator for HFMD outbreaks, with a 2-week lag time being significant (Wahid et al., 2021).

While previous studies have examined the relationship between climate factors and HFMD, there are key gaps that this study aims to address. First, this study analyses ten years of HFMD data. In contrast, most existing studies have only covered an average of five years, as suggested by Abdul Wahid et al. (2020), who emphasized the importance of using longer time spans for more reliable conclusions. Additionally, this study uses daily HFMD data, following the recommendation of Chen et al. (2019) that analysing daily data can yield more precise findings compared to weekly or monthly data. Furthermore, Wahid et al. (2021) highlighted the need to explore the impact of climate variables on HFMD at the state level in Malaysia, which this study addresses by assessing regional variations in climate effects.

Despite these studies, there remains a gap in understanding the impact of climate factors across all Malaysian states using statistical models like Zero-inflated models. This study aims to bridge this gap by evaluating the fit of different GLMs and identifying the most appropriate model for predicting HFMD cases based on climate factors.

3. Methodology

3.1 Data Sources

HFMD data from 2009 to 2019 were obtained from the Institute of Medical Research, Malaysia, covering daily reported cases across fourteen states. Climate data, including temperature, rainfall, and relative humidity, were acquired from the Malaysia Meteorological Department.

3.2 Generalised Linear Models

To model Hand, Foot, and Mouth Disease (HFMD) cases, several count models are considered, including the Poisson model, Conway-Maxwell Poisson (COM-Poisson) model, Zero-inflated Poisson (ZIP) model, Zero-inflated Geometric (ZIGeo) model, and Zero-inflated Negative Binomial (ZINB) model. These models address key characteristics observed in HFMD data, such as overdispersion and excess zero counts.

The Poisson model serves as a baseline and assumes that HFMD cases follow a Poisson distribution. The COM-Poisson model extends this by allowing for variable dispersion levels, making it useful for under-dispersed and over-dispersed data. However, since daily HFMD data often contain an excess number of zeros, zero-inflated models are applied. Each of these models is mathematically formulated as shown in Table 1.

3.3 Statistical Analysis

The analysis was conducted using R version 4.2.2 with the ‘pscl’ package. Five models were evaluated: Poisson, Conway-Maxwell Poisson (COM-Poisson), Zero-inflated Poisson (ZIP), Zero-inflated Geometric (ZIGeo), and Zero-inflated Negative Binomial (ZINB). The data were divided 80:20 for model training and testing. Model selection was based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Accuracy was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percent Error (MAPE).

4. Results

4.1 Model Fitting Performance

The model fitting performance for the five evaluated models is presented in Table 2. The Zero-inflated Negative Binomial (ZINB) model demonstrated the lowest AIC and BIC values across most states, indicating it as the most appropriate fit for analysing HFMD data. The results for selected states are summarized as in Table 2.

The model fitting results indicate that the Zero-inflated Negative Binomial (ZINB) model consistently outperformed other models across several states. In Sabah, the ZINB model had the lowest AIC (17,273.85) and BIC (17,328.52), indicating the best fit. Similarly, in Sarawak, it achieved the lowest AIC (26,647.21) and BIC (26,701.88), confirming its superior performance. In Selangor, both the Zero-inflated Geometric (ZIGeo) and ZINB models

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Table 1. Statistical Models for HFMD Data.

Models	**Mathematical Expression**
Poisson	$P(Y=y)=\frac{e^{-\lambda}\lambda^{y}}{y!}$ $\log(\lambda)=\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_kx_k$
Conway-Maxwell (COM) Poisson (Conway & Maxwell, 1962)	$P(Y=y)=\frac{\lambda^{y}}{(y!)^{v}Z(\lambda,v)}$ $\lambda=E(y^{v})>0$ $Z(\lambda,v)=\sum_{j=0}^{\infty}\frac{\lambda_j}{(j!)^{v}}$ $v\geq 0$ denotes dispersion parameter $v=1$ denotes equi-dispersion
Zero-inflated Poisson (Greene, 1994)	$P(Y=y)=\begin{cases}\pi+(1-\pi)\mathrm{e}^{-\lambda}, if\ y=0\\ (1-\pi)\frac{\lambda^{y}\mathrm{e}^{(-\lambda)}}{y!}, if\ y>0\end{cases}$ $\lambda=\exp(\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_kx_k)$
Zero-inflated Geometric (Nanjundan & Pasha, 2015)	$P(Y=y)=\begin{cases}\pi+(1-\pi)p, if\ y=0\\ (1-\pi)pq^{y}, if\ y>0\end{cases}$ $\lambda=\exp\ (\beta_0+\beta_1x_{m+1}+\cdots+\beta_{k-m}x_k)$
Zero-inflated Negative Binomial (Greene, 1994)	$P(Y=y)=\begin{cases}\pi+(1-\pi)\left(\frac{\mathrm{r}}{r+\lambda}\right)^{r}, if\ y=0\\ (1-\pi)\left(\frac{\mathrm{r}}{r+\lambda}\right)^{r}\frac{\delta(r+y)}{y!\,\delta(r)}\left(\frac{\lambda}{r+\lambda}\right)^{y}, if\ y>0\end{cases}$ $\lambda=\exp\ (\beta_0+\beta_1x_{m+1}+\cdots+\beta_{k-m}x_k)$ $r=positive\ constant$

showed comparable performance, with the ZINB model marginally better in terms of AIC and BIC.

Wilayah Persekutuan also had the best fit with the ZINB model, with an AIC of 19,335.21 and BIC of 19,389.88. A similar trend was observed in Perak and Perlis, where the ZINB model showed the lowest AIC and BIC values, indicating its robustness across different states.

4.2 Factor Analysis p-values

Table 3 presents the p-values from the factor analysis for temperature (β_1), rainfall (β_2), and relative humidity (β_3) using the Zero-inflated Negative Binomial model. Only the count model coefficients (negbin with log link) are included, as they directly estimate the impact of climate factors on the expected number of HFMD cases. The zero-inflation model coefficients (binomial with logit link), which predict the probability of excess zero cases, are excluded since the primary focus of this study is on identifying significant climate factors that influence HFMD incidence rather than explaining the existence of true zero cases in the data. The significant climate factors ($p < 0.05$) influencing HFMD cases across various states are summarised below:

The results from Table 3 indicate that temperature significantly affects HFMD cases across different states in Malaysia. In most states, higher temperatures are associated with an increase in HFMD cases, with Johor (β1 = 0.2672 ***) and Melaka (β1 = 0.3136 ***) showing the strongest positive associations. This suggests that warmer conditions may create a more favourable environment for HFMD transmission.

An exception is observed in Sarawak, where temperature has a negative effect (β1 = -0.2140), implying that cooler weather may contribute to increased HFMD cases in this state. However, the p-values for all climate variables, including temperature, are unavailable (NA) in the output, indicating potential issues with model estimation. This could be due to collinearity among variables, insufficient data variability, or computational singularity, as suggested by the warning message.

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Table 2. Model Fitting Performance.

State	Model	AIC	BIC
Sabah	Poisson	39002.28	39026.58
	COM-Poisson	21983.75	22014.12
	Zero-inflated Poisson	30847.28	30895.88
	Zero-inflated Geometric	17495.82	17544.42
	Zero-inflated Negative Binomial	**17273.85**	**17328.52**
Sarawak	Poisson	75514.18	75538.47
	COM-Poisson	35637.58	35667.95
	Zero-inflated Poisson	72396.65	72445.24
	Zero-inflated Geometric	26665.26	26713.85
	Zero-inflated Negative Binomial	**26647.21**	**26701.88**
Selangor	Poisson	82233.46	82257.75
	COM-Poisson	33095.37	33125.74
	Zero-inflated Poisson	78530.65	78579.24
	Zero-inflated Geometric	26115.44	**26164.04**
	Zero-inflated Negative Binomial	**26111.79**	26166.46
Wilayah Persekutuan	Poisson	36931.83	36956.13
	COM-Poisson	21229.43	21259.80
	Zero-inflated Poisson	32587.58	32636.17
	Zero-inflated Geometric	19353.25	19401.85
	Zero-inflated Negative Binomial	**19335.21**	**19389.88**
Kelantan	Poisson	22823.43	22847.72
	COM-Poisson	14389.53	14419.90
	Zero-inflated Poisson	18486.72	18535.32
	Zero-inflated Geometric	13332.44	13381.04
	Zero-inflated Negative Binomial	**13122.71**	**13177.38**
Pahang	Poisson	13862.97	13887.27
	COM-Poisson	10874.74	10905.12
	Zero-inflated Poisson	11839.62	11888.21
	Zero-inflated Geometric	10405.88	10454.48
	Zero-inflated Negative Binomial	**10345.73**	**10400.40**
Terengganu	Poisson	10837.39	10861.69
	COM-Poisson	9096.156	9126.528
	Zero-inflated Poisson	9663.740	9713.335
	Zero-inflated Geometric	8922.715	8971.309
	Zero-inflated Negative Binomial	**8883.816**	**8938.485**
Kedah	Poisson	21062.40	21086.70
	COM-Poisson	15205.62	15235.99
	Zero-inflated Poisson	18919.42	18968.01
	Zero-inflated Geometric	14872.84	**14921.43**
	Zero-inflated Negative Binomial	**14870.34**	14925.00
Perak	Poisson	31047.72	31072.02
	COM-Poisson	18583.35	18613.73
	Zero-inflated Poisson	27160.56	27209.15
	Zero-inflated Geometric	17427.22	17475.81
	Zero-inflated Negative Binomial	**17369.45**	**17424.11**

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Table 2. Model Fitting Performance (continue).

State	Model	AIC	BIC
Perlis	Poisson	8358.494	8382.791
	COM-Poisson	7476.174	7506.546
	Zero-inflated Poisson	7728.705	7777.300
	Zero-inflated Geometric	7443.517	7492.112
	Zero-inflated Negative Binomial	**7425.571**	**7480.240**
Penang	Poisson	28363.47	28387.76
	COM-Poisson	19370.06	19400.43
	Zero-inflated Poisson	25965.96	26014.55
	Zero-inflated Geometric	**17667.38**	**17715.97**
	Zero-inflated Negative Binomial	17667.60	17722.27
Johor	Poisson	31317.07	31341.37
	COM-Poisson	20394.95	20425.32
	Zero-inflated Poisson	28221.37	28269.97
	Zero-inflated Geometric	18454.17	**18502.76**
	Zero-inflated Negative Binomial	**18448.59**	18503.26
Melaka	Poisson	20887.61	20911.90
	COM-Poisson	13986.04	14016.41
	Zero-inflated Poisson	17514.96	17563.56
	Zero-inflated Geometric	13602.45	13651.04
	Zero-inflated Negative Binomial	**13523.83**	**13578.50**
Negeri Sembilan	Poisson	20424.16	20448.46
	COM-Poisson	14133.61	14163.98
	Zero-inflated Poisson	17329.83	17378.43
	Zero-inflated Geometric	13590.85	13639.45
	Zero-inflated Negative Binomial	**13543.00**	**13597.67**

insights into potential relationships, they cannot be statistically proven. This means that no definitive conclusions can be drawn regarding the significance of climate factors in Sarawak.

Rainfall exhibits varied effects on HFMD cases depending on the state. In Sabah, Wilayah Persekutuan, Kelantan, Johor, Melaka, and Negeri Sembilan, greater rainfall is associated with increased HFMD cases, with Johor (β2 = 0.0260 ***) and Melaka (β2 = 0.0377 ***) showing significant positive correlations. Conversely, in Perak (β2 = -0.0281 ***) and Perlis (β2 = -0.0203 ***), higher rainfall appears to reduce HFMD cases.

Relative humidity has a negative effect on HFMD cases, indicating that increased humidity levels are linked with a decrease in reported infections. This effect is particularly notable in Sabah (β3 = -0.0109 ***), where significant negative coefficients were observed. However, in Perlis, higher humidity corresponds with an increase in HFMD cases (β3 = 0.0108 **).

4.3 Model Prediction Accuracy

Table 4 presents the prediction accuracy for the five models using MAE, RMSE, and MAPE. The key findings include the following. The model prediction accuracy varied among different states. The Poisson model had the lowest MAE and RMSE in Sabah and Sarawak, indicating strong predictive performance. Similarly, in Selangor, the Poisson model performed best with the lowest MAE (17.3880) and RMSE (25.2163). For Wilayah Persekutuan, the Zero-inflated Poisson (ZIP) model demonstrated slightly better prediction accuracy compared with other models. In contrast, for Kelantan, Pahang, Terengganu, Kedah, Perak, Perlis, Penang, Johor, Melaka, and Negeri Sembilan, the ZINB model consistently exhibited the best prediction accuracy, particularly for Perak, Perlis, and Penang.

5. Discussion

The analysis highlights the ZINB model as the most appropriate for fitting and predicting HFMD cases based on climate factors in Malaysia. This model is particularly effective because HFMD data often display overdispersion and excess zeros (Greene, 1994).

The negative binomial component of the model handles overdispersion by introducing a dispersion parameter, which permits the variance to be greater than the mean (Greene, 1994):

$$\frac{Var[y_i]}{\mathbb{E}[y_i]} = 1 + \alpha\mathbb{E}[y_i] > 1 \quad (1)$$

where y_i represents HFMD case counts. This property makes the negative binomial distribution more flexible than the Poisson distribution, which assumes $Var[y_i] = \mathbb{E}[y_i]$ and may not capture HFMD's fluctuating case numbers (Greene, 1994). The

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Table 3. Factor Analysis of Climate Variables on HFMD Cases.

State	Temperature β_1	Rainfall β_2	Relative Humidity β_3
Sabah	0.1560 ***	0.0408 ***	-0.0109 ***
Sarawak	-0.2140	-0.0571	-0.0078
Selangor	0.0923 ***	-0.0072	0.0062 ***
Wilayah Persekutuan	0.1645 ***	0.0106 *	0.0043 *
Kelantan	0.0510	0.0277 *	-0.0022
Pahang	0.2297 ***	0.0055	-0.0012
Terengganu	0.1175 **	-0.0032	0.0026
Kedah	0.0024	0.0021	0.0014
Perak	0.0306 *	-0.0281 ***	0.0072 *
Perlis	0.0968 ***	-0.0203 ***	0.0108 **
Penang	0.0120	0.0018	0.0021
Johor	0.2672 ***	0.0260 ***	-0.0037
Melaka	0.3136 ***	0.0377 ***	-0.0052
Negeri Sembilan	0.1452 ***	0.0242 **	-0.0036

Significance levels: *** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$

zero-inflation component improves model performance by differentiating between true zero cases and zeros due to randomness (Greene, 1994). The model assumes that each observation follows a mixture process:

$$Prob[y_i = 0] = Prob[z_i = 0] + Prob[z_i = 1, y_i^* = 0] \\ = q_i + (1 - q_i)f(0)$$

$$Prob[y_i = k] = (1 - q_i)f(k), k = 1,2, \ldots \quad (2)$$

where q_i is the probability of true zero cases, and $f(k)$ represents the probability mass function of the negative binomial distribution (Greene, 1994). This formulation allows the model to better capture regions or periods where HFMD is zero.

Combining these two components, the ZINB model offers a flexible and accurate framework for modelling HFMD data, with better predictions than traditional count models. Its ability to account for overdispersion and excess zeros makes it highly suitable for HFMD forecasting and public health planning in general.

5.1 Key Climate Factors

The results show that climate factors significantly impact HFMD incidences across different Malaysian states. Temperature plays a critical role in HFMD transmission. Optimal temperature ranges can facilitate viral survival and transmission, while extremely high or low temperatures might reduce it. States such as Sarawak, Pahang, and Kedah showed significant temperature impacts, suggesting a need for region-specific temperature monitoring. Rainfall affects HFMD cases in states such as Selangor and Wilayah Persekutuan, as heavy rainfall can influence virus transmission by affecting human behaviour, such as increased indoor activities that facilitate close contact among children. Relative humidity is significant in several states, including Sabah and Selangor, where high humidity levels might support viral persistence in the environment, enhancing transmission risks. These insights can support public health strategies by allowing for targeted interventions based on seasonal and regional climate conditions to better prevent HFMD outbreaks.

5.2 Regional Differences

The variation in significant climate factors across states demonstrates the importance of localized approaches to HFMD prevention and control. For instance, while temperature was a significant factor in northern states, rainfall and relative humidity were more influential in central and southern regions. These differences require tailored public health strategies to address HFMD risks effectively.

6. Conclusion

This study highlights the significant impact of climate factors on HFMD incidences in Malaysia and identifies the Zero-inflated Negative Binomial model as the most suitable for data analysis and prediction. The findings guide developing targeted public health interventions and can serve as a reference for other regions with comparable climatic conditions. By enhancing our understanding of the climate-HFMD relationship, this research contributes to improved disease management and prevention strategies, ultimately protecting public health. The findings offer valuable insights for policymakers and health authorities, allowing them to implement timely interventions to mitigate HFMD outbreaks. By identifying key climate factors and utilizing the ZINB model for accurate predictions, authorities can take proactive measures such as public awareness campaigns to educate communities about the influence of climate on HFMD and promote preventive measures.

For future research, the study implication can be applied to other Asia-Pacific countries with similar climates, such as Singapore, Thailand, and Brunei. The ZINB model adoption may be useful in their public health system. One can consider an alternative method such as the Cox Proportional Hazards Regression Models for impact analysis (Khoo et al., 2022).

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Table 4. Model Prediction Accuracy.

State	Model	MAE	RMSE	MAPE
Sabah	Poisson	5.536938	**8.703627**	**98.92037**
	COM-Poisson	4807.440	136032.7	147.0561
	Zero-inflated Poisson	5.533498	8.707670	98.92683
	Zero-inflated Geometric	**5.531052**	8.711916	98.95993
	Zero-inflated Negative Binomial	5.532531	8.713534	98.99258
Sarawak	Poisson	16.82827	23.75413	72.76203
	COM-Poisson	46.00056	753.6395	95.94758
	Zero-inflated Poisson	16.82671	23.74165	72.76128
	Zero-inflated Geometric	16.80448	23.70645	**72.59127**
	Zero-inflated Negative Binomial	**16.80379**	**23.70450**	72.59155
Selangor	Poisson	17.38799	25.21629	**82.09430**
	COM-Poisson	18.99343	29.28693	93.02014
	Zero-inflated Poisson	**17.38590**	25.21893	82.09531
	Zero-inflated Geometric	17.39162	**25.21359**	82.09465
	Zero-inflated Negative Binomial	17.39151	25.21362	82.09614
Wilayah Persekutuan	Poisson	6.042738	8.839537	84.72911
	COM-Poisson	6.352827	9.509369	90.31472
	Zero-inflated Poisson	**6.042544**	8.840781	84.76679
	Zero-inflated Geometric	6.045528	8.842220	84.86904
	Zero-inflated Negative Binomial	6.043901	**8.838485**	**84.61422**
Kelantan	Poisson	2.859967	4.614232	110.1171
	COM-Poisson	3.099292	5.711534	124.9455
	Zero-inflated Poisson	2.858334	4.612774	110.0435
	Zero-inflated Geometric	**2.857076**	**4.611442**	**109.9434**
	Zero-inflated Negative Binomial	2.862506	4.613632	23650.59
Pahang	Poisson	1.587677	2.622078	111.8821
	COM-Poisson	1.614908	2.659068	116.2612
	Zero-inflated Poisson	**1.587451**	**2.621841**	111.8816
	Zero-inflated Geometric	1.588179	2.622170	**111.8491**
	Zero-inflated Negative Binomial	1.589665	2.622696	113.4683
Terengganu	Poisson	1.294917	2.334898	128.5674
	COM-Poisson	1.313821	2.350453	134.4711
	Zero-inflated Poisson	**1.294782**	2.334745	**128.5229**
	Zero-inflated Geometric	1.294963	**2.334688**	128.5535
	Zero-inflated Negative Binomial	1.295264	2.334885	128.6255
Kedah	Poisson	2.848100	4.811941	89.24372
	COM-Poisson	2.868848	4.817015	89.48412
	Zero-inflated Poisson	2.848474	4.812269	89.21289
	Zero-inflated Geometric	2.843152	**4.805715**	**88.84789**
	Zero-inflated Negative Binomial	**2.843143**	4.806401	88.88041
Perak	Poisson	4.765443	7.027617	91.84752
	COM-Poisson	4.817328	7.249890	94.53100
	Zero-inflated Poisson	4.764963	7.029099	91.87115
	Zero-inflated Geometric	**4.761979**	7.027808	91.91114
	Zero-inflated Negative Binomial	4.762420	**7.027417**	**91.76178**

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Table 4. Model Prediction Accuracy (continue)

State	Model	MAE	RMSE	MAPE
Perlis	Poisson	0.885055	1.318105	123.8650
	COM-Poisson	0.885864	1.319426	124.5666
	Zero-inflated Poisson	0.885095	1.318152	123.8726
	Zero-inflated Geometric	0.885037	1.318042	123.8427
	Zero-inflated Negative Binomial	**0.884852**	**1.317895**	**123.5608**
Penang	Poisson	4.135669	**6.090004**	78.45892
	COM-Poisson	4.164218	6.125970	**78.11093**
	Zero-inflated Poisson	4.136250	6.091779	78.37926
	Zero-inflated Geometric	4.132330	6.091060	78.15331
	Zero-inflated Negative Binomial	**4.131520**	6.090470	78.13294
Johor	Poisson	**5.232985**	7.531515	86.55955
	COM-Poisson	5.456939	7.949198	91.26989
	Zero-inflated Poisson	5.245626	**7.523421**	85.84830
	Zero-inflated Geometric	5.245267	7.525213	85.77475
	Zero-inflated Negative Binomial	5.245637	7.524500	**85.67280**
Melaka	Poisson	2.769605	**4.312197**	**104.6849**
	COM-Poisson	2.871048	4.432487	111.0587
	Zero-inflated Poisson	**2.769525**	4.312394	104.6876
	Zero-inflated Geometric	2.769760	4.312516	104.6922
	Zero-inflated Negative Binomial	2.770196	4.312783	104.7040
Negeri Sembilan	Poisson	2.597698	4.021901	99.74504
	COM-Poisson	2.642547	4.089556	101.6317
	Zero-inflated Poisson	2.595862	4.020736	99.71958
	Zero-inflated Geometric	2.591382	**4.019127**	**99.62895**
	Zero-inflated Negative Binomial	**2.591132**	4.019977	99.72834

during high-risk periods. Improved surveillance can also help monitor climate data to predict and prepare for HFMD outbreaks, with quicker responses. Developing region-specific strategies based on significant climate factors ensures more effective and customized HFMD control measures.

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8. References

Abdul Wahid, N. A., Suhaila, J., & Rahman, H. Abd. (2021). Effect of climate factors on the incidence of hand, foot, and mouth disease in Malaysia: A generalized additive mixed model. Infectious Disease Modelling, 6, 997–1008. https://doi.org/10.1016/j.idm.2021.08.003

Abdul Wahid, N. A., Suhaila, J., & Sulekan, A. (2020). Temperature effect on HFMD transmission in Selangor, Malaysia. Sains Malaysiana, 49(10), 2587–2597. https://doi.org/10.17576/jsm-2020-4910-24

Ang, L. W., Koh, B. K., Chan, K. P., Chua, L. T., James, L., & Goh, K. T. (2009). Epidemiology and control of hand, foot and mouth disease in Singapore, 2001-2007. Annals of the Academy of Medicine, Singapore, 38(2), 106–112. https://doi.org/10.47102/annals-acadmedsg.v38n2p106

Chang, L.-Y., King, C.-C., Hsu, K.-H., Ning, H.-C., Tsao, K.-C., Li, C.-C., Huang, Y.-C., Shih, S.-R., Chiou, S.-T., Chen, P.-Y., Chang, H.-J., & Lin, T.-Y. (2002). Risk factors of enterovirus 71 infection and associated hand, foot, and mouth disease/herpangina in children during an epidemic in Taiwan. Pediatrics, 109(6). https://doi.org/10.1542/peds.109.6.e88

Chavan, N. A., Lavania, M., Shinde, P., Sahay, R., Joshi, M., Yadav, P. D., Tikute, S., Waghchaure, R., Ashok, M., Gupta, A., Mittal, M., Khan, V., Fomda, B. A., Ahmad, M., Tiwari, V. P., Pote, P., Dhongade, A. R., Mohanty, A., Mohan, K., … Bhardwaj, A. (2023). The 2022 outbreak and the pathobiology of the Coxsackie virus [hand foot and mouth disease] in India. Infection, Genetics and Evolution, 111, 105432. https://doi.org/10.1016/j.meegid.2023.105432

Chen, S., Liu, X., Wu, Y., Xu, G., Zhang, X., Mei, S., Zhang, Z., O'Meara, M., O'Gara, M. C., Tan, X., & Li, L. (2019). The application of meteorological data and search index data in improving the prediction of HFMD: A study of two cities in Guangdong Province, China. *Science of The Total Environment*, *652*, 1013–1021. https://doi.org/10.1016/j.scitotenv.2018.10.304

Chin, S. N., Lem, F. F., Toh, J. Y., Chee, F. T., Yew, C. W., Saptu, A. R., Sampil, N. S., Mathew, M. G., & Sharip, J. (2022). A retrospective analysis on incidence of hand, foot, and mouth disease in Kota Kinabalu, district of Sabah Malaysia. International Journal of Public Health Science (IJPHS), 11(2), 369. https://doi.org/10.11591/ijphs.v11i2.21294

Conway, R.W. & Maxwell, W.L. (1962) A queuing model with state dependent service rates. Journal of Industrial Engineering, 12, 132-136.

Greene, William H., Accounting for Excess Zeros and Sample Selection in Poisson and Negative Binomial Regression Models (March 1994). NYU Working Paper No. EC-94-10, Available at SSRN: https://ssrn.com/abstract=1293115

Kim, B. I., Ki, H., Park, S., Cho, E., & Chun, B. C. (2016). Effect of climatic factors on hand, foot, and mouth disease in South Korea, 2010-2013. PLOS ONE, 11(6). https://doi.org/10.1371/journal.pone.0157500

Khoo, W. C., Yeah, K. L., Hong, S. Y. (2022). Modeling unemployment duration, determinants and insurance premium pricing of Malaysia: insights from an upper middle-income developing country. SN Business & Economics 2(8), 116.

Luo, C., Qian, J., Liu, Y., Lv, Q., Ma, Y., & Yin, F. (2022). Long-term air pollution levels modify the relationships between short-term exposure to meteorological factors, air pollution and the incidence of hand, foot and mouth disease in children: A DLNM-based multicity time series study in Sichuan Province, China. BMC Public Health, 22(1). https://doi.org/10.1186/s12889-022-13890-7

Nanjundan, N.G., & Pasha, S.S. (2015). A characterization of zero-inflated geometric model. *International Journal of Mathematics Trends and Technology*, *23*(1), 71–73. https://doi.org/10.14445/22315373/ijmtt-v23p510

Onozuka, D., & Hashizume, M. (2011). The influence of temperature and humidity on the incidence of hand, foot, and mouth disease in Japan. Science of The Total Environment, 410–411, 119–125. https://doi.org/10.1016/j.scitotenv.2011.09.055

Puenpa, J., Wanlapakorn, N., Vongpunsawad, S., & Poovorawan, Y. (2019). The history of enterovirus A71 outbreaks and molecular epidemiology in the Asia-Pacific region. Journal of Biomedical Science, 26(1). https://doi.org/10.1186/s12929-019-0573-2

Sham, N. M., Krishnarajah, I., Shitan, M., & Lye, M.-S. (2014). Time series model on hand, foot and mouth disease in Sarawak, Malaysia. Asian Pacific Journal of Tropical Disease, 4(6), 469–472. https://doi.org/10.1016/s2222-1808(14)60608-3

Sun, L., Lin, H., Lin, J., He, J., Deng, A., Kang, M., Zeng, H., Ma, W., & Zhang, Y. (2016). Evaluating the transmission routes of hand, foot, and mouth disease in Guangdong, China. American Journal of Infection Control, 44(2). https://doi.org/10.1016/j.ajic.2015.04.202

Verma, S., Razzaque, M. A., Sangtongdee, U., Arpnikanondt, C., Tassaneetrithep, B., Arthan, D., Paratthakonkun, C., & Soonthornworasiri, N. (2021). Hand, foot, and mouth disease in Thailand: A comprehensive modelling of epidemic dynamics. Computational and Mathematical Methods in Medicine, 2021, 1–15. https://doi.org/10.1155/2021/6697522

Wahid, N. A., Suhaila, J., & Rahman, H. Abd. (2021). The influence of climate factors on hand-foot-mouth disease: A five-state study in Malaysia. Universal Journal of Public Health, 9(5), 324–331. https://doi.org/10.13189/ujph.2021.090515

Wan Mohamad, W. M., Ismail, N. A., & Mohd Fuzi, N. M. (2021). Risk factors of hand, foot and mouth disease (HFMD) outbreak cases among children under five years old in North Eastern State of Malaysia. Malaysian Journal of Public Health Medicine, 21(2), 315–320. https://doi.org/10.37268/mjphm/vol.21/no.2/art.1028

Wu, Y., Wang, T., Zhao, M., Wang, S., & Shi, J. (2022). Spatiotemporal cluster patterns of hand, foot, and mouth disease at the province level in mainland China, 2011-2018. PLoS ONE, 17(8), e0270061. https://doi.org/10.21203/rs.3.rs-1601423/v1

DOI: https://doi.org/10.22452/mjs.vol45sp1.3
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