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Hybrid forecasting and spatial clustering support climate-informed dengue early warning in urban Malaysia

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Abstract

Dengue surveillance requires models that convert routine case and environmental data into actionable temporal and spatial signals. We developed a climate-informed early warning framework for an urban district in Malaysia by integrating autoregressive distributed lag (ARDL) modelling, support vector machine (SVM) residual correction, endemic-channel interpretation and Local Indicators of Spatial Association (LISA). Weekly dengue onset and meteorological data from 2019 to 2023 were used for model development, and a 12-week 2024 period was used for short-horizon validation and operational interpretation. Dengue onset lagged by four weeks was the strongest predictor of current activity, while temperature lagged by five weeks provided an additional climate-sensitive signal. The standalone ARDL model showed positive residual autocorrelation and severe overestimation during validation, whereas hybrid ARDL-SVM reduced RMSE from 19,560 to 24. Adding a random forest-weighted intervention index produced only marginal improvement in explained variance. Although global spatial autocorrelation was weak, LISA detected localized forecasted clusters, and actual outbreak zones were concentrated in central and northern localities. This framework demonstrates how routine surveillance data can support short-horizon dengue warning and local vector-control prioritization.

Keywords: Aedes; dengue; early warning; forecasting; hybrid modelling; spatial epidemiology

Introduction

Dengue is a major Aedes-borne viral disease in tropical and subtropical settings. Its public health burden is shaped by vector ecology, human exposure, urban environments and the capacity of surveillance systems to detect transmission changes before outbreaks expand.[1-5] Global mapping studies have shown extensive dengue suitability and continuing expansion of populations at risk, highlighting the need for anticipatory surveillance in endemic countries.[6-10]

Meteorological variability is relevant to dengue transmission because temperature, rainfall and relative humidity influence Aedes mosquito development, survival, biting activity, breeding-site availability and the extrinsic incubation period of dengue virus.[11-16] In Malaysia, dengue activity has been associated with weather variability; however, the direction, strength and lag structure of these associations vary by locality.[17-20] This setting-specific behaviour means that dengue forecasting systems should be locally calibrated rather than transferred directly from one district to another.

Routine dengue surveillance systems commonly describe trends and trigger response after case counts exceed expected levels. Reviews of dengue surveillance and early warning systems suggest that case trends, meteorological indicators and locally defined thresholds can provide earlier warning when they are integrated into operational vector-control workflows.[21-25] Evidence on Aedes control also supports more targeted use of limited resources, particularly when high-risk periods and high-risk localities can be identified in advance.[26,27]

A key methodological challenge is that dengue transmission is temporal, nonlinear and spatially heterogeneous. Classical regression approaches are useful for interpretability, but they may underperform when residual patterns are nonlinear or when short-term case momentum dominates observed trends. Machine-learning approaches can improve prediction, but their operational value is stronger when outputs are translated into practical thresholds and spatial prioritization signals. Similarly, LISA can identify localized clusters and spatial outliers that may be masked by district-level summary trends.[28-31]

This study developed and evaluated a district-level dengue early warning framework that integrates interpretable time-series modelling, machine-learning residual correction, endemic-channel interpretation and spatial cluster detection. The objective was to assess whether routinely available dengue surveillance and meteorological data could be translated into short-horizon warning signals and spatial prioritization intelligence for dengue control in an urban Malaysian setting.

Results

ARDL identified recent dengue activity and lagged temperature as warning signals

The ARDL model identified dengue onset lagged by four weeks as the dominant predictor of current dengue activity. Temperature lagged by five weeks also contributed to prediction, whereas humidity lagged by eight weeks and rainfall lagged by two weeks were not significant in the district-level linear model. The Durbin-Watson statistic was 1.1877, indicating positive residual autocorrelation and incomplete capture of temporal dependence by the standalone ARDL model.

Hybrid residual correction improved short-horizon forecast accuracy

The standalone ARDL forecast substantially overestimated dengue incidence during the 12-week 2024 validation period. In week 1, the ARDL model forecasted 216 cases compared with 30 observed cases; by week 12, the forecast increased to 54,632 cases compared with 13 observed cases. In contrast, hybrid ARDL-SVM forecasts were closer to observed values, including 75 cases in week 1 and 40 cases in week 12 (**Table 1**).

Table 1. Summary of model performance and surveillance signals for the dengue early warning framework, Melaka Tengah, Malaysia, 2019-2024.

Component	Indicator	Result	Operational interpretation
Temporal ARDL model	Dominant predictor	Dengue onset lagged 4 weeks	Recent dengue activity carried the strongest short-term warning signal.
Meteorological predictor	Significant climate signal	Temperature lagged 5 weeks	Temperature contributed a delayed climate-sensitive signal.
ARDL diagnostic	Durbin-Watson statistic	1.1877	Positive residual autocorrelation remained in the standalone model.
Forecast accuracy	RMSE	ARDL = 19,560; ARDL-SVM = 24	SVM residual correction substantially improved short-horizon forecasting.
Intervention sensitivity	Explained variance	R-squared: 0.6741 to 0.6754	The intervention index produced marginal improvement only.
Intervention weights	Random forest importance	PTP = 0.356; LC = 0.252; SRT = 0.242; ULV = 0.149	House inspection contributed the largest intervention weight.
Spatial autocorrelation	Moran's I	0.018	Global spatial dependence was weak, but localized clusters were detected.
LISA classification	Forecasted clusters	2 high-high; 4 high-low; 1 low-high	Forecast-informed spatial targeting can prioritize zones for verification and control.

Abbreviations: ARDL = autoregressive distributed lag; LC = larviciding; LISA = Local Indicators of Spatial Association; PTP = house inspection; RMSE = root mean squared error; SRT = thermal fogging; SVM = support vector machine; ULV = ultra-low volume spraying.

Forecast accuracy improved markedly after SVM residual correction. The standalone ARDL model produced an RMSE of 19,560, whereas the hybrid ARDL-SVM model reduced RMSE to 24. This large reduction reflected the instability of the standalone ARDL trajectory during the validation period and the ability of SVM residual correction to recover a more operationally realistic forecast pattern.

Intervention sensitivity analysis showed limited additional explanatory value

Random forest weighting assigned the greatest importance to house inspection (0.356), followed by larviciding (0.252), thermal fogging (0.242) and ultra-low volume spraying (0.149). Adding the intervention index marginally increased explained variance from 0.6741 to 0.6754, but residual autocorrelation persisted (Durbin-Watson statistic = 1.1496).

Endemic-channel and LISA outputs translated forecasts into operational warning signals

When hybrid forecasts were plotted against the endemic curve, forecasted dengue activity rose into higher-risk bands during later epidemiological weeks, particularly around weeks 50-52 (**Figure. 1**). This transformed numerical forecasts into operational warning signals that could be used for field verification, preparedness and targeted prevention.

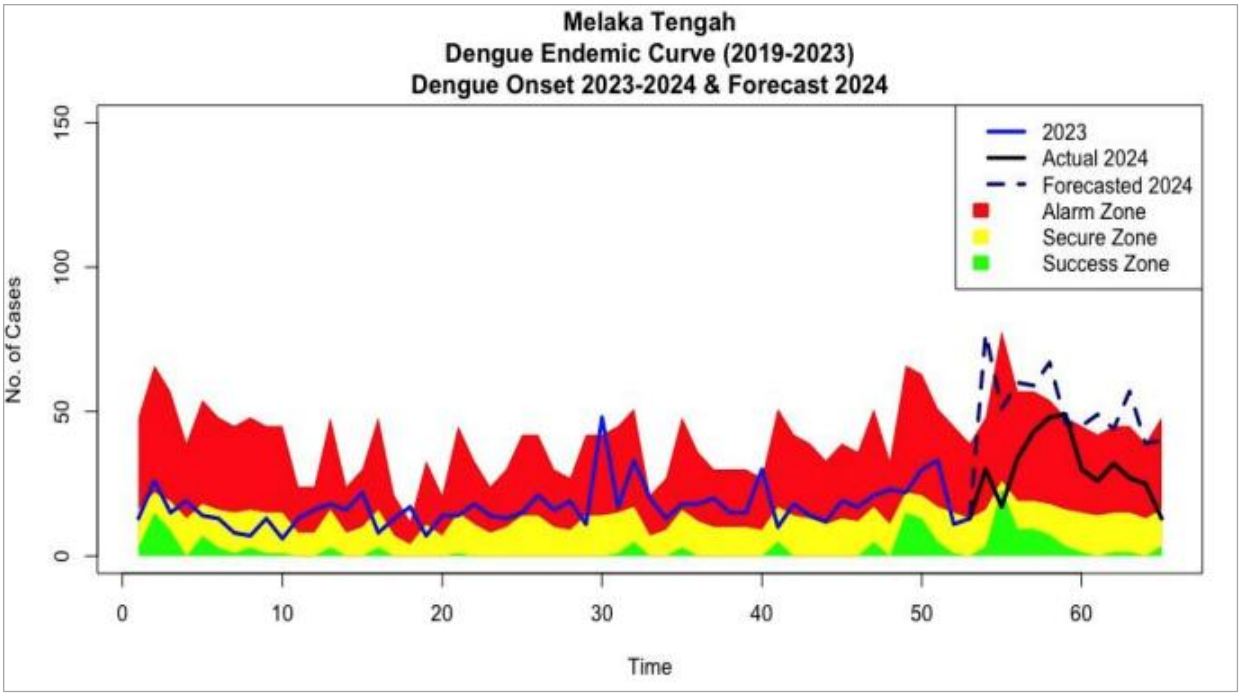


Figure 1. Melaka Tengah dengue endemic curve (2019-2023), observed dengue onset (2023-2024) and hybrid forecast for 2024. The coloured bands represent endemic-channel risk zones. Source: authors' analysis using anonymized dengue surveillance and meteorological data. Figure generated using R software.

Spatial analysis of forecasted zonal values showed weak positive global spatial autocorrelation (Moran's I = 0.018). Nevertheless, LISA identified localized spatial signals, including two high-high clusters, four high-low clusters and one low-high cluster (**Figure. 2**). Mapping of actual outbreak zones showed concentration in central and northern localities, including Batu Berendam, Bukit Baru, Bukit Katil, Cheng, Bertam and Alai (**Figure. 3**).

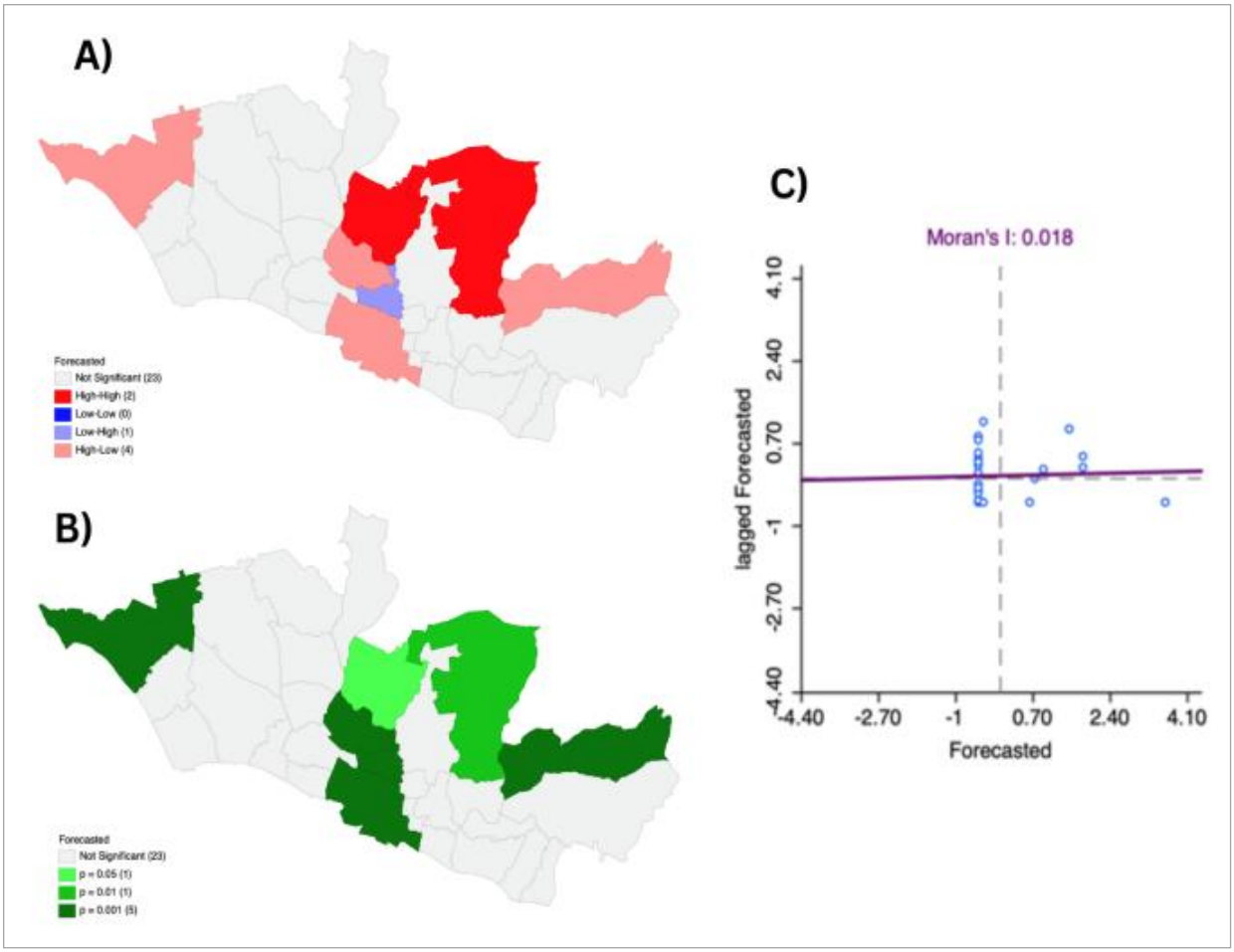


Figure 2. Spatial cluster analysis of forecasted dengue cases in Melaka Tengah: (A) LISA cluster map, (B) significance map and (C) Moran's I scatterplot. LISA = Local Indicators of Spatial Association. Source: authors' analysis using anonymized dengue surveillance and spatial data. Figure generated using GeoDa software.

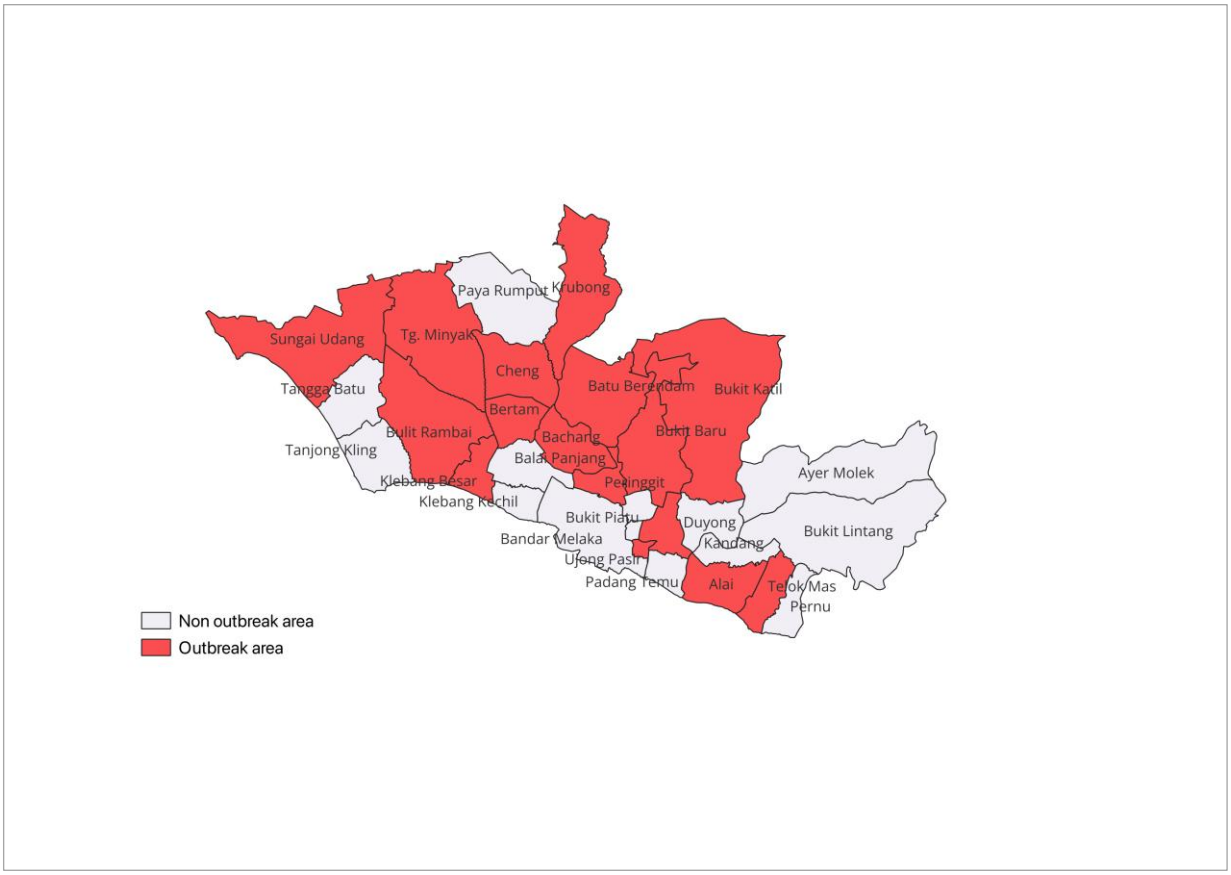


Figure 3. Spatial distribution of Melaka Tengah zones affected by actual dengue outbreaks during the study period. Red shading indicates zones affected by actual dengue outbreaks. Source: authors' analysis using anonymized dengue surveillance and spatial data. Figure generated using QGIS software.

Discussion

This study demonstrates that dengue early warning can be strengthened by connecting temporal forecasting, nonlinear residual correction, endemic-channel interpretation and local spatial cluster detection. The strongest predictor was recent dengue activity, reflecting short-term transmission momentum that is typical of focal urban dengue outbreaks. The contribution of lagged temperature is biologically plausible because temperature affects Aedes development, biting frequency, vectorial capacity and viral incubation.[11-16]

The principal methodological finding was the contrast between the interpretable but unstable ARDL model and the more operationally realistic hybrid ARDL-SVM model. ARDL was useful for identifying lagged predictors, but residual autocorrelation and substantial overestimation indicated that a linear model alone was insufficient for operational forecasting in this setting. SVM residual correction substantially reduced forecast error, consistent with evidence that machine-learning methods can improve dengue prediction when relationships are nonlinear and setting-specific.[36-38]

The modelling contribution of this study is the integration of interpretability and operational translation. ARDL provided a transparent representation of lagged dengue-climate signals, SVM corrected nonlinear residual structure, the endemic channel converted predictions into warning bands and LISA translated forecasts into local spatial intelligence. This combination is important for public health practice because a model with good numerical performance is not automatically useful unless its outputs can guide decisions about timing and location of response.

The intervention sensitivity analysis showed only marginal improvement after adding the composite intervention index. This should not be interpreted as evidence that vector-control interventions are unimportant. Routine intervention data may not fully capture the timing, coverage, quality, entomological effect or community response associated with control activities. Evidence from vector-control literature supports integrated Aedes management, but effectiveness depends on implementation context and high-quality operational data.[26,27,40]

The public health value of this framework lies in translation. Endemic-channel interpretation converts forecasts into warning bands that can trigger field verification, risk communication and preparedness. LISA further identifies where forecasted risk is clustered or spatially unusual. This is important for urban dengue control because a district-level trend may appear moderate while specific localities experience localized risk. Combining these components can help programme managers prioritize inspection, source reduction, larviciding and adulticiding in zones with forecasted or observed clustering.

Several methodological issues require cautious interpretation. First, the large RMSE reduction should be interpreted in relation to the instability of the standalone ARDL forecast, rather than as evidence that the hybrid model is universally superior. Second, the framework was demonstrated in one urban district and should be validated in areas with different ecological, demographic and intervention profiles. Third, population mobility, land use, entomological indices, socioeconomic indicators and reporting delays were not fully incorporated. Fourth, the maps are operational zonal products and should be interpreted as local public health intelligence rather than causal evidence. Finally, prospective evaluation is needed to determine whether the framework improves lead time, resource allocation and outbreak prevention compared with routine surveillance alone.

In conclusion, a climate-informed hybrid ARDL-SVM model combined with endemic-channel thresholds and LISA can convert routine dengue surveillance data into actionable early warning intelligence. With regular recalibration, prospective validation and improved intervention and entomological inputs, this framework could support proactive and localized dengue vector control in Malaysia and other dengue-endemic urban settings.

Methods

Study design and setting

A retrospective analytical study was conducted using an urban dengue-endemic district in Melaka, Malaysia, as the demonstration setting. The workflow was designed as a prototype early warning approach for vector-borne disease surveillance rather than as a purely explanatory model. The analysis combined temporal modelling, hybrid residual correction, endemic-channel interpretation and zonal spatial analysis.

Data sources and variables

Weekly dengue onset data from January 2019 to December 2023 were obtained from the E-Dengue web-based surveillance system managed by the Vector Borne Disease Unit, Melaka Health Department, Ministry of Health Malaysia. Meteorological predictors comprised weekly temperature, relative humidity and rainfall obtained from the Malaysian Meteorological Department. Forecasting was conducted for a 12-week horizon in 2024 and compared with observed dengue onset during the same period. For spatial analysis, the district was divided into 30 operational zones. Sensitivity analysis incorporated routine vector-control indicators: house inspection, larviciding, thermal fogging and ultra-low volume spraying.

ARDL modelling

ARDL modelling was used to estimate delayed associations between dengue onset and meteorological variables because it allows lagged predictors to be represented in a transparent regression framework.[32]

The candidate model included dengue onset lagged by four weeks, temperature lagged by five weeks, humidity lagged by eight weeks and rainfall lagged by two weeks. The fitted model was expressed as:

$$D_t = \alpha + \beta_1 D_{\{t-4\}} + \beta_2 T_{\{t-5\}} + \beta_3 H_{\{t-8\}} + \beta_4 R_{\{t-2\}} + \varepsilon_t$$

where D_t is weekly dengue onset at time t, T is temperature, H is relative humidity, R is rainfall, α is the intercept, β_1-β_4 are regression coefficients for lagged predictors and ε_t is the model error. Residual autocorrelation was assessed using the Durbin-Watson statistic.

Hybrid ARDL-SVM residual correction

To address remaining nonlinear residual structure, ARDL residuals were modelled using SVM regression. SVM was selected because support-vector methods can represent nonlinear patterns while controlling model complexity.[33,34] The hybrid design retained the interpretability of ARDL for identifying lagged signals, while using SVM as a residual-correction layer for remaining nonlinear structure. Residuals and hybrid forecasts were defined as:

$$e_t = D_t - \widehat{D}_t^{ARDL}$$

$$\widehat{D}_t^{Hybrid} = \widehat{D}_t^{ARDL} + \hat{e}_t^{SVM}$$

where e_t is the ARDL residual, D_t is the observed dengue onset, $\widehat{D}_t^{ARDL}$ is the standalone ARDL forecast and $\hat{e}_t^{SVM}$ is the residual correction predicted by the SVM model. Forecast accuracy was assessed using mean squared error (MSE) and root mean squared error (RMSE):

$$MSE = \frac{1}{n}\sum_{t-1}^{n}(D_t - \widehat{D}_t)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t-1}^{n}(D_t - \widehat{D}_t)^2}$$

The 2024 period was treated as a short-horizon validation and operational interpretation period. This retrospective validation was used to assess whether the hybrid framework produced forecasts closer to observed dengue activity than the standalone ARDL model.

Intervention sensitivity analysis

Routine vector-control indicators were incorporated in a sensitivity analysis to explore whether operational intervention data improved model explanation. Random forest variable-importance weights were used to construct a composite intervention index.[35-38] The intervention index was defined as:

$$I_t = \sum_{m=1}^{4} w_m \, x_{m,t}, subject\ to \sum_{m=1}^{4} w_m = 1$$

where I_t is the intervention index at time t, w_m is the normalized importance weight for intervention component m and $x_{m,t}$ is the corresponding intervention that measured. This sensitivity analysis was interpreted cautiously because routine intervention records may not fully capture timing, coverage, quality of implementation, entomological impact or community participation.

Endemic-channel and spatial analysis

Hybrid forecast values were plotted against endemic-channel zones derived from historical dengue activity to classify whether expected incidence fell within lower-risk, alert or action-oriented bands. This threshold-based interpretation is consistent with dengue early warning frameworks that combine surveillance indicators with operational triggers.[21,25,39] Forecasted zonal values were then analysed using LISA to identify high-high clusters, low-low clusters and spatial outliers.[28-31] This step was intended to translate district-level forecasts into localized risk intelligence that could guide field verification and targeted vector-control preparedness.

Ethical approval

This study used anonymized routine dengue surveillance data and meteorological records. Ethical approval for the parent study, "Spatial temporal relationship between climate variables and dengue incidence in Peninsular Malaysia: A time-series modelling", was granted by the Medical Research & Ethics Committee, Ministry of Health Malaysia (NMRR ID: 23-03375-UXY [IIR]; Ref: 23-03375-UXY). All methods were performed in accordance with the relevant guidelines and regulations, including the International Council for Harmonisation guidelines and the Malaysia Guidelines for Good Clinical Practice, as stated by the Medical Research & Ethics Committee, Ministry of Health Malaysia. No identifiable individual-level information was accessed, analysed or reported in this manuscript. As this study involved secondary analysis of anonymized routine surveillance and meteorological data, with no direct contact with human participants, no clinical intervention and no tissue samples, the requirement for individual informed consent was formally waived by the Medical Research & Ethics Committee, Ministry of Health Malaysia.

Use of artificial intelligence tools

AI-assisted language-editing support was used to improve clarity, grammar and formatting during manuscript preparation. All analyses, interpretations and final content were reviewed and approved by the authors, who take full responsibility for the submitted manuscript.

Data availability

The data used in this study were derived from routine Ministry of Health Malaysia dengue surveillance records and meteorological records from the Malaysian Meteorological Department. Because the surveillance data are subject to institutional and Ministry of Health Malaysia data-governance restrictions, the full dataset cannot be made publicly available. An anonymized analytical dataset and R scripts may be made available from the corresponding author upon reasonable request and subject to institutional approval.

References

1. World Health Organization. Dengue and severe dengue: fact sheet. Geneva: World Health Organization; 2025. Available from: https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue, accessed 2 May 2026.
2. World Health Organization. Dengue: guidelines for diagnosis, treatment, prevention and control. New edition. Geneva: World Health Organization; 2009.
3. World Health Organization. Global strategy for dengue prevention and control, 2012-2020. Geneva: World Health Organization; 2012.
4. World Health Organization. Global vector control response 2017-2030. Geneva: World Health Organization; 2017.
5. Gubler DJ. Dengue and dengue hemorrhagic fever. Clin Microbiol Rev 1998;11(3):480-96.
6. Bhatt S, Gething PW, Brady OJ, Messina JP, Farlow AW, Moyes CL, et al. The global distribution and burden of dengue. Nature 2013;496(7446):504-7. doi:10.1038/nature12060.
7. Stanaway JD, Shepard DS, Undurraga EA, Halasa YA, Coffeng LE, Brady OJ, et al. The global burden of dengue: an analysis from the Global Burden of Disease Study 2013. Lancet Infect Dis 2016;16(6):712-23. doi:10.1016/S1473-3099(16)00026-8.
8. Messina JP, Brady OJ, Golding N, Kraemer MUG, Wint GRW, Ray SE, et al. The current and future global distribution and population at risk of dengue. Nat Microbiol 2019;4(9):1508-15. doi:10.1038/s41564-019-0476-8.
9. Brady OJ, Gething PW, Bhatt S, Messina JP, Brownstein JS, Hoen AG, et al. Refining the global spatial limits of dengue virus transmission by evidence-based consensus. PLoS Negl Trop Dis 2012;6(8):e1760. doi:10.1371/journal.pntd.0001760.
10. Kraemer MUG, Sinka ME, Duda KA, Mylne AQN, Shearer FM, Barker CM, et al. The global distribution of the arbovirus vectors Aedes aegypti and Ae. albopictus. eLife 2015;4:e08347. doi:10.7554/eLife.08347.
11. Mordecai EA, Cohen JM, Evans MV, Gudapati P, Johnson LR, Lippi CA, et al. Detecting the impact of temperature on transmission of Zika, dengue, and chikungunya using mechanistic models. PLoS Negl Trop Dis 2017;11(4):e0005568. doi:10.1371/journal.pntd.0005568.
12. Liu-Helmersson J, Stenlund H, Wilder-Smith A, Rocklov J. Vectorial capacity of Aedes aegypti: effects of temperature and implications for global dengue epidemic potential. PLoS One 2014;9(3):e89783. doi:10.1371/journal.pone.0089783.
13. Morin CW, Comrie AC, Ernst K. Climate and dengue transmission: evidence and implications. Environ Health Perspect 2013;121(11-12):1264-72. doi:10.1289/ehp.1306556.
14. Johansson MA, Dominici F, Glass GE. Local and global effects of climate on dengue transmission in Puerto Rico. PLoS Negl Trop Dis 2009;3(2):e382. doi:10.1371/journal.pntd.0000382.
15. Hii YL, Zhu H, Ng N, Ng LC, Rocklov J. Forecast of dengue incidence using temperature and rainfall. PLoS Negl Trop Dis 2012;6(11):e1908. doi:10.1371/journal.pntd.0001908.
16. Lowe R, Gasparrini A, Van Meerbeeck CJ, Lippi CA, Mahon R, Trotman AR, et al. Nonlinear and delayed impacts of climate on dengue risk in Barbados: a modelling study. PLoS Med 2018;15(7):e1002613. doi:10.1371/journal.pmed.1002613.
17. Cheong YL, Burkart K, Leitao PJ, Lakes T. Assessing weather effects on dengue disease in Malaysia. Int J Environ Res Public Health 2013;10(12):6319-34. doi:10.3390/ijerph10126319.
18. Hii YL, Zaki RA, Aghamohammadi N, Rocklov J. Research on climate and dengue in Malaysia: a systematic review. Curr Environ Health Rep 2016;3(1):81-90. doi:10.1007/s40572-016-0078-z.
19. Mohd-Zaki AH, Brett J, Ismail E, L'Azou M. Epidemiology of dengue disease in Malaysia (2000-2012): a systematic literature review. PLoS Negl Trop Dis 2014;8(11):e3159. doi:10.1371/journal.pntd.0003159.
20. Jayaraj VJ, Avoi R, Gopalakrishnan N, Raja DB, Umasa Y. Developing a dengue prediction model based on climate in Tawau, Malaysia. Acta Trop 2019;197:105055. doi:10.1016/j.actatropica.2019.105055.
21. Racloz V, Ramsey R, Tong S, Hu W. Surveillance of dengue fever virus: a review of epidemiological models and early warning systems. PLoS Negl Trop Dis 2012;6(5):e1648. doi:10.1371/journal.pntd.0001648.
22. Runge-Ranzinger S, Horstick O, Marx M, Kroeger A. What does dengue disease surveillance contribute to predicting and detecting outbreaks and describing trends? Trop Med Int Health 2008;13(8):1022-41. doi:10.1111/j.1365-3156.2008.02112.x.
23. Runge-Ranzinger S, McCall PJ, Kroeger A, Horstick O. Dengue disease surveillance: an updated systematic literature review. Trop Med Int Health 2014;19(9):1116-60. doi:10.1111/tmi.12333.
24. Badurdeen S, Valladares DB, Farrar J, Gozzer E, Kroeger A, Kuswara N, et al. Sharing experiences: towards an evidence based model of dengue surveillance and outbreak response in Latin America and Asia. BMC Public Health 2013;13:607. doi:10.1186/1471-2458-13-607.
25. Bowman LR, Tejeda GS, Coelho GE, Sulaiman LH, Gill BS, McCall PJ, et al. Alarm variables for dengue outbreaks: a multi-centre study in Asia and Latin America. PLoS One 2016;11(6):e0157971. doi:10.1371/journal.pone.0157971.
26. Bowman LR, Donegan S, McCall PJ. Is dengue vector control deficient in effectiveness or evidence? Systematic review and meta-analysis. PLoS Negl Trop Dis 2016;10(3):e0004551. doi:10.1371/journal.pntd.0004551.
27. Roiz D, Wilson AL, Scott TW, Fonseca DM, Jourdain F, Muller P, et al. Integrated Aedes management for the control of Aedes-borne diseases. PLoS Negl Trop Dis 2018;12(12):e0006845. doi:10.1371/journal.pntd.0006845.
28. Anselin L. Local indicators of spatial association-LISA. Geogr Anal 1995;27(2):93-115. doi:10.1111/j.1538-4632.1995.tb00338.x.
29. Moran PAP. Notes on continuous stochastic phenomena. Biometrika 1950;37(1-2):17-23. doi:10.1093/biomet/37.1-2.17.
30. Parra-Amaya ME, Puerta-Yepes ME, Lizarralde-Bejarano DP, Arboleda-Sanchez S. Early detection for dengue using Local Indicator of Spatial Association (LISA) analysis. Diseases 2016;4(2):16. doi:10.3390/diseases4020016.

31. Zhu G, Liu J, Tan Q, Shi B. Inferring the spatio-temporal patterns of dengue transmission from surveillance data in Guangzhou, China. PLoS Negl Trop Dis 2016;10(4):e0004633. doi:10.1371/journal.pntd.0004633.
32. Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. J Appl Econ 2001;16(3):289-326. doi:10.1002/jae.616.
33. Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20(3):273-97. doi:10.1007/BF00994018.
34. Smola AJ, Scholkopf B. A tutorial on support vector regression. Stat Comput 2004;14(3):199-222. doi:10.1023/B:STCO.0000035301.49549.88.
35. Breiman L. Random forests. Mach Learn 2001;45(1):5-32. doi:10.1023/A:1010933404324.
36. Zhao N, Charland K, Carabali M, Nsoesie EO, Maheu-Giroux M, Rees E, et al. Machine learning and dengue forecasting: comparing random forests and artificial neural networks for predicting dengue burden at national and sub-national scales in Colombia. PLoS Negl Trop Dis 2020;14(9):e0008056. doi:10.1371/journal.pntd.0008056.
37. Guo P, Liu T, Zhang Q, Wang L, Xiao J, Zhang Q, et al. Developing a dengue forecast model using machine learning: a case study in China. PLoS Negl Trop Dis 2017;11(10):e0005973. doi:10.1371/journal.pntd.0005973.
38. Jain R, Sontisirikit S, Iamsirithaworn S, Prendinger H. Prediction of dengue outbreaks based on disease surveillance, meteorological and socio-economic data. BMC Infect Dis 2019;19(1):272. doi:10.1186/s12879-019-3874-x.
39. World Health Organization. Early warning and response system (EWARS) for dengue outbreaks: operational guide. Geneva: World Health Organization; 2018.
40. World Health Organization. Handbook for integrated vector management. Geneva: World Health Organization; 2012.

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Author contributions

M.A.A. contributed to conceptualization, study design, data curation, formal analysis, modelling, visualization and writing of the original draft. M.A.B.A.T., X.S., H.O. and M.S. contributed to supervision, methodological input, interpretation of results, and review and editing of the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

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