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Research article

Forecasting dengue incidence based on entomological indices, population density, and meteorological and environmental variables in the Gampaha District of Sri Lanka

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1. Background

The occurrence of infectious diseases and the high transmissibility of such infections is one of the unavoidable public issues in the world. The issue would be more severe if the transmission is multifactorial and there is no curative or prophylactic treatment for such infection. Dengue is an infectious mosquito-borne viral disease found in tropical and sub-tropical climates worldwide, and it mainly exists in urban and semi-urban environmental setups [1].

A virus causes dengue under the Flaviviridae family, which has four distinct serotypes [1,2] transmitted by mosquitoes belonging to the genus *Aedes*. Dengue has been identified as a fast-spreading infection in the world, and about half of the world's population is now at risk of dengue, with an estimated 100–400 million infections occurring yearly [3]. It has been evidenced that the number of dengue cases reported to WHO has increased over eight-fold over the last two decades [1]. Thus far, no successful treatment has been introduced for this infection. Therefore, reducing vector breeding habitats and suppressing disease vectors have been the main focus of disease control programmes worldwide. In control programmes, systematized vector surveillance programmes and interpretations by the entomological indices are the backbone of such efforts. Therefore, control approaches aided with scientific evidence would provide a better outcome in control interventions. In dengue vector surveillance and control programmes, larval-based indices such as House Index (HI), Breteau Index (BI), and Container Index (CI) are widely used in decision-making and disease prediction approaches [4–7]. On the other hand, these indices can estimate the likelihood of disease transmission and ultimately set thresholds for initiating vector control interventions in a given area based on larval concentrations. The BI is primarily used as a decision-making parameter for vector management programmes in Sri Lanka. According to the current practice in Sri Lanka, chemical fogging is advised when the BI value is > 5 with reported dengue cases or BI > 20, even if there is no dengue case [8]. Nonetheless, this national standard uses common threshold values to handle dengue epidemics, which is typically ineffective due to the dynamics of local vector populations that differ from place to place [7].

Prediction of novel or re-emerging infectious diseases can effectively control and prevent large-scale outbreaks and epidemics. In predicting an infectious disease, the main work is to collect and analyze information using statistical/mathematical approaches and

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estimate temporal/spatial transmission/regular epidemic patterns [9,10]. In Sri Lanka, there are several attempts have been made, which include mathematical modeling [11–13], ARIMA-based modeling based on the larval indices [4,14], and meteorological variables [15]. Some studies have emphasized that dengue incidence is significantly related to meteorological variables such as maximum monthly temperature [16], minimum monthly temperature [16], weekly average maximum temperature [17], relative humidity [16], and rainfall with a two-month lag [11,15,16]. Several other studies used meteorological and vector density variables to forecast dengue disease outbreaks [12]. However, only a few studies have used solely vector indices correlated with dengue incidence [4,18].

The main objective of developing a prediction mechanism is to forecast distribution patterns and magnitude of dengue outbreaks to assess the risk of an epidemic. However, many of the attempts conducted in Sri Lanka have been accompanied by limited surveillance data collected from a few sampling locations for a short period. Further, all of these threshold values for disease prediction may be subjective to different places or localities depending on various elements such as environmental conditions, climate, geography, and socioeconomic/cultural behaviour of the community. Therefore, it is necessary to construct threshold values based on regional or city-level data to successfully perform vector control efforts based on entomological indices [6,7,19]. Unfortunately, such crucial thresholds for the larval indices have rarely been found, which would allow for the effective adoption of preventative measures during a dengue outbreak.

Meanwhile, selecting suitable prediction methods is the premise of implementing prevention and control of infectious diseases. It indirectly reduces the incidence rate and mortality and decreases economic/social losses, which lay the foundation for relevant follow-up policies. Therefore, the present study was conducted to establish localized threshold levels to reflect the frequency of dengue outbreaks and facilitate decision-making and implementation of effective, economic, and sustainable dengue vector control measures in the district of Gampaha using empirical-based modeling approaches.

2. Methodology

2.1. Study area

Gampaha District (7°05′22″ N, 80° 04′E) is located in the Western Province of Sri Lanka, covering an area of 1387 km^2. It has a human population 2,574,324, recorded as the highest residential population in Sri Lanka. The annual rainfall is about 2500 mm, mainly received during two monsoonal periods from April to June and October to December [20]. The mean average temperature ranges from 22.7 to 34.3 °C. In Sri Lanka, Gampaha District reports the second-highest dengue incidence in the country during the past two decades. Therefore, Gampaha District was selected for the present investigation.

2.2. Selection of study sites

In selecting sites, areas with different environmental settings, such as urban, suburban, and rural, were selected randomly. "Urban areas" were defined as areas within towns and cities with a high population density, a low per capita land consumption, a low household land consumption, a low agricultural land consumption and increased reliance on piped-born water supplies. In contrast, the areas located outside towns and cities that are typically less developed, with a more significant proportion of land covered by agriculture and natural vegetation, a higher per capita/household land consumption, and a greater reliance on well water were considered "Rural." Areas with mixed characteristics were considered "Suburban" [21–23]. The criteria used for the site classification is indicated in Table 1.

Based on those criteria, three MOH areas in the Gampaha district were selected to represent **Urban** (Kelaniya, Negombo, and Wattala), **Suburban** (Attanagalla, Minuwangoda, and Gampaha) and **Rural** (Dompe, Mirigama, and Divulapitiya) environmental settings. In each selected MOH area, four sentinel sites (as Grama Niladhari [GN] divisions) were identified for entomological surveillance (Fig. 1). The human population, population density, dengue incidence over the last five years, and feasibility of field operations to collect relevant data were considered factors in selecting the sentinel sites.

2.3. Entomological surveillance

Entomological surveys were conducted monthly from April 2016 to December 2019 using standard entomological techniques according to the guidelines specified by the World Health Organization [24]. At each sampling attempt, a location was selected, considering a central point for entomological surveillance. The surveys were conducted, and random surveillance was continued within a 200 m–300 m radius.

Table 1
Classification of Urban, Suburban, and, Rural areas.

Environmental setting	Land area (km^2)	Household land consumption (Hectares)	Per capita land consumption (Hectares)	Household and agricultural land extend (Hectares)	Population density (per km^2)	Pipe born water supply (no of households)
Urban	<100	<0.1	<0.01	<1500	>2500	>5000
Suburban	100–150	0.1–0.3	0.01–0.1	1500–2000	1500–2500	3000–5000
Rural	>150	>0.3	>0.1	>2000	<1500	<3000

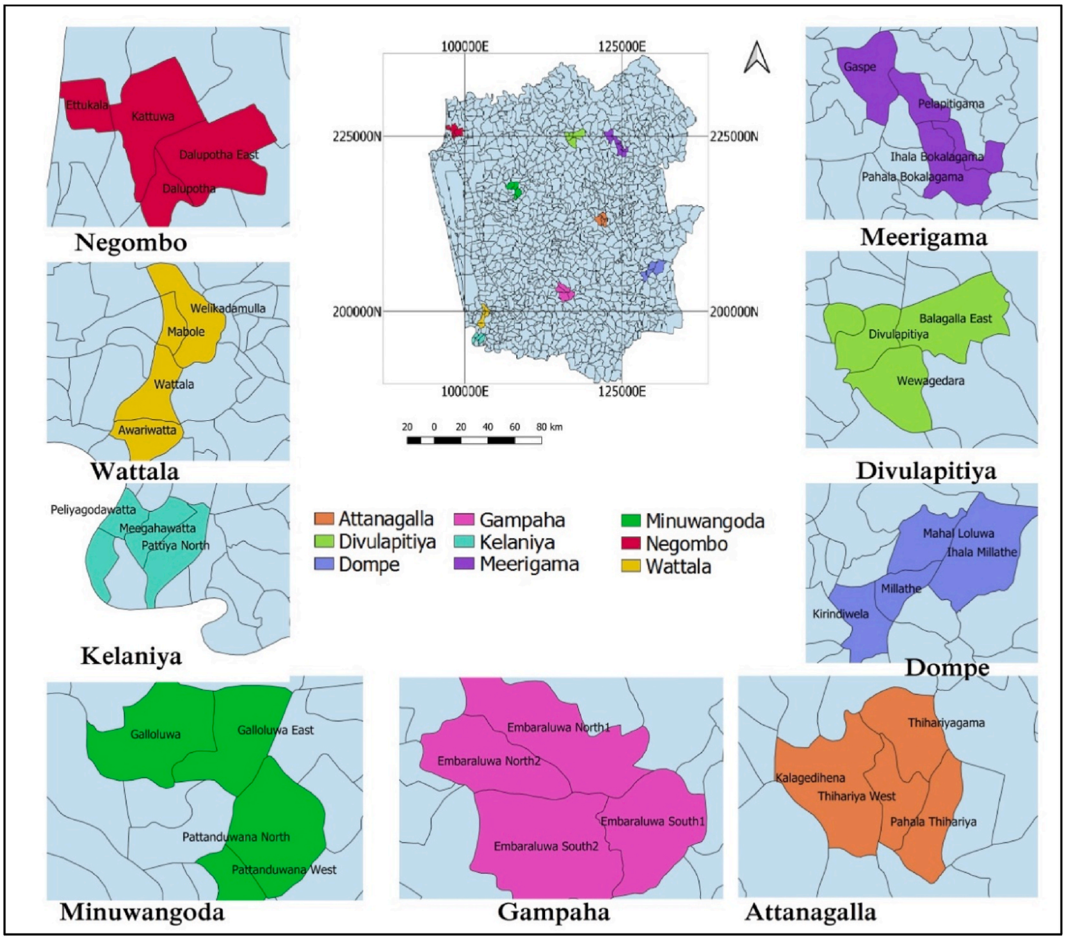

Fig. 1. Selected sentinel sites at each selected MOH area in Gampaha District, Sri Lanka.

2.4. Collection of secondary data

The reported number of dengue cases, case density, and incidence data of selected MOH areas from 2014 to 2019 were collected in all the nine MOH areas chosen for the study from the Regional Director of Health Services office, Gampaha. The larval indices for 2014–2016 in the Gampaha district were also collected. Selected meteorological data (Monthly average rainfall, number of rainy days, monthly average temperature, and monthly average relative humidity) collected from the Katunayake monitoring station in the Gampaha District from January 2014 to December 2019 were obtained from the Department of Meteorology, Colombo 07, Sri Lanka.

2.5. Selection of entomological indices for prediction model

Since the traditional *Stegomyia* indices are considered important measures [24] for monitoring dengue vector populations and forecasting dengue outbreaks, the Breteau Index (BI) was used as one of the explanatory variables of the dengue forecasting model. It was assumed that vector density and meteorological variables such as rainfall, temperature, and humidity relate directly and indirectly to the occurrence of dengue cases within the district. The temporal patterns of mosquito species presence were studied using time series models built for each species, and cross-correlation was employed separately to determine the lagging effect for each covariate. The meteorological variables such as monthly average rainfall, number of rainy days per month, monthly average temperature and monthly average relative humidity were used to capture the periodic pattern of dengue dynamics. Further, vector indices such as the Breteau Index *Ae. aegypti* (BIA) and Breteau Index *Ae. albopictus* (BIB) were also considered as explanatory variables. The case incidence (number of reported cases per 100,000 population) was used as a response variable to develop the model because it provides more reliable data than direct dengue patient counts.

2.6. Assessing the relationship of meteorological variables with dengue incidence and vector indices

Pearson correlation analysis with cross-correlation (CCF) was performed to investigate the relationship between meteorological variables and vector indices on dengue case incidence. Only significant associations were further examined using regressions to determine the best predictor variables associated with the case incidence. The CCF analysis revealed that dengue case incidence had a medium significant positive correlation with average rainfall and average relative humidity ($r = 0.511$ to $r = 0.566$) at a two-month lag. Therefore, all other meteorological variables (such as the number of rainy days and average monthly temperature) were ignored from further consideration of the model development due to multi-collinearity in the meteorological variables used in the study (Table 2).

2.7. Development of dengue prediction models

All meteorological and entomological variables were standardized before being used in the models. Based on the CCF data analysis, four models were developed under each environmental setup to forecast dengue outbreak situations in the district using multiple linear regression (MLR). This mathematical technique employs multiple explanatory variables to predict the result of a response variable. Case incidence without a lag period [DI (t)] was used as the response variable during the model development. The BIA with one-month lag [BIA (t-1)], BIB with one-month lag [BIB (t-1)], monthly average rainfall at lag two [RFavg (t-2)], and monthly average humidity with two-month lag period [RHavg (t-2)] were used as the explanatory variables based on the findings according to the past literature [4,11,15,16,25] and Cross-Correlation Analysis performed. Four models were developed using stepwise multiple linear regression correlation with selected parameters (Table 3).

2.8. Selection of the best fitting model for dengue prediction

At each time, Pearson's Coefficient of Correlation (r) was used to determine how well the data fit the regression model, and the value R-squared and adjusted R-squared were calculated. The value of r is always between -1 and $+1$. When the r value approaches zero, the correlation is said to be unrelated. If the value of r is $+1$, the variables are strongly correlated and if the value of r is -1, the variables are said to be negatively correlated. The P-value was also calculated to determine the significance of each explanatory variable. The SPSS version 26 was used to develop the model in MLR. Each time, heteroscedasticity and normality of residuals were tested to ascertain the influence of explanatory (independent) variables in the model. Heteroscedasticity was determined by mapping the residual value against the explanatory variables and normality was determined using the Kolmogorov- Smirnov and Shapiro- Wilk tests. The log-transformed case incidence (Lg DI) was employed for subsequent analysis.

2.9. Cross-validation of the model

Leave-one-out cross-validation approach was used to determine the fitness of the model [26]. In each iteration, one sample is left out (for a validation set), and the rest of the data (a training set) is used to fit the model. The procedure is repeated until every year has been used for a validation set. The distribution of residuals of the developed models was analyzed, and normality plots were created to validate fitted models. The model was tested using three different MOH areas representing each environmental configuration from 2014 to 2018. The MOH areas of Jaela, Mahara, and Katana were chosen to represent urban, suburban, and rural settings, respectively. Spearman rank correlation test was performed to analyze the relationship between actual and predicted cases at each environmental setup. The model's good fit was further examined by plotting the model-fitted predicted values with actual reported dengue cases in the field.

2.10. Developing areas specific threshold values for different setups

The epidemic level was visualized separately for each environmental setup using the epidemic channel concept when developing area-specific thresholds for predicting dengue outbreaks. Based on the quartile values (Q) taken from 2013 to 2016 data of the MOH area in the Gampaha district, the MOH areas were classified into three risk zones based on the case incidence.

Table 2
Cross-correlation function summary for case incidence with meteorological variables and vector indices.

Monthly Lag period	Explanatory variables					
	Average rainfall/mm	Number of rainy days/months	Monthly average Relative humidity	Monthly average temperature/^{0}C	Breteau Index for *Aedes aegypti*	Breteau Index for *Aedes albopictus*
−3	0.131	0.005	0.017	−0.053	−0.170	−0.383
−2	−0.224	−0.412	−0.400	−0.095	−0.532	−0.457
−1	−0.367	−0.430	−0.390	−0.194	−0.388	−0.093
0	−0.206	−0.187	−0.052	−0.232	0.294	0.543
1	0.301	0.384	0.471	−0.218	**0.777**	**0.802**
2	**0.566**	**0.440**	**0.501**	0.009	0.433	0.314
3	0.198	0.163	0.144	**0.249**	−0.163	−0.202

*The highest significant positive correlations were highlighted in red.

Table 3
Explanatory variables used in different prediction models in the study.

Model	Variables used	Explanatory variables	Regression equations
Model I	BI for *Ae. aegypti* BI for *Ae. albopictus* All selected meteorological variables	BIA, BIB, RFavg, RHavg	$logDI_{(t)} = \beta_0 + \beta_1 \times BIA_{(t-1)} + \beta_2 \times BIB_{(t-1)} + \beta_3 \times RFavg_{(t-2)} + \beta_4 \times RHavg_{(t-2)}$
Model II	BI for *Ae. aegypti* BI for *Ae. albopictus* Monthly average RF	BIA,BIB, RFavg	$logDI_{(t)} = \beta_0 + \beta_1 \times BIA_{(t-1)} + \beta_2 \times BIB_{(t-1)} + \beta_3 \times RFavg_{(t-2)}$
Model III	BI for *Ae. aegypti* BI for *Ae. albopictus* Monthly average RH	BIA,BIB,RHavg	$logDI_{(t)} = \beta_0 + \beta_1 \times BIA_{(t-1)} + \beta_2 \times BIB_{(t-1)} + \beta_3 \times RHavg_{(t-2)}$
Model IV	BI for *Ae. aegypti* BI for *Ae. albopictus*	BIA, BIB	$\log\left(DI_{(t)}\right) = \beta_0 + \beta_1 \times BIA_{(t-1)} + \beta_2 \times BIB_{(t-1)}$

DI (t): Case incidence without a lag period, **BIA$_{(t-1)}$:** Breteau Index *Ae. aegypti* at lag 1, **BIB $_{(t-1)}$:** Breteau Index *Ae. albopictus* at lag 1, **RFavg $_{(t-2)}$:** Monthly average rainfall at lag 2, **RHavg $_{(t-2)}$:** Monthly average relative humidity at lag 2.

2.11. Temporal distribution of Ae. aegypti and Ae. albopictus

The BI for both the vectors indicated a seasonal pattern from May–June and October–November each year, with two distinct peaks in urban settings (Fig. 2), with a significant peak in the latter part of the year by *Ae. aegypti*. However, in suburban (Fig. 3) and rural areas (Fig. 4), a major peak was observed mainly during the May–June period, followed by the first inter monsoonal rain in the April–May season.

2.12. Climatic effect on density and abundance of Ae. aegypti and Ae. albopictus

The climatic variables, except temperature, demonstrated statistically significant, weak (0.20–0.30) to moderate (0.40–0.59) positive correlation with *Ae. aegypti, Ae. albopictus* and Cumulative BI in urban and suburban areas at a 95 % confidence level. On most occasions, the positive association was strongest with relative humidity and weakest with maximum monthly rainfall. It was also noted that the correlation of climatic variables with BI was statistically insignificant in rural areas except for relative humidity and cumulative BI, which demonstrated a weak correlation ($r = 0.236$; $P = 0.050$).

A more systematic Cross-Association Function analysis revealed that *Ae. aegypti* and *Ae. albopictus* had a medium to high correlation with rainfall parameters and relative humidity at a one-month lag time and the monthly average temperature at a two-month lag time in urban settings (Figs. 5 and 6). Both *Ae. aegypti* ($r = 0.679$) and *Ae. albopictus* ($r = 0.669$) demonstrated a higher cross-correlation with

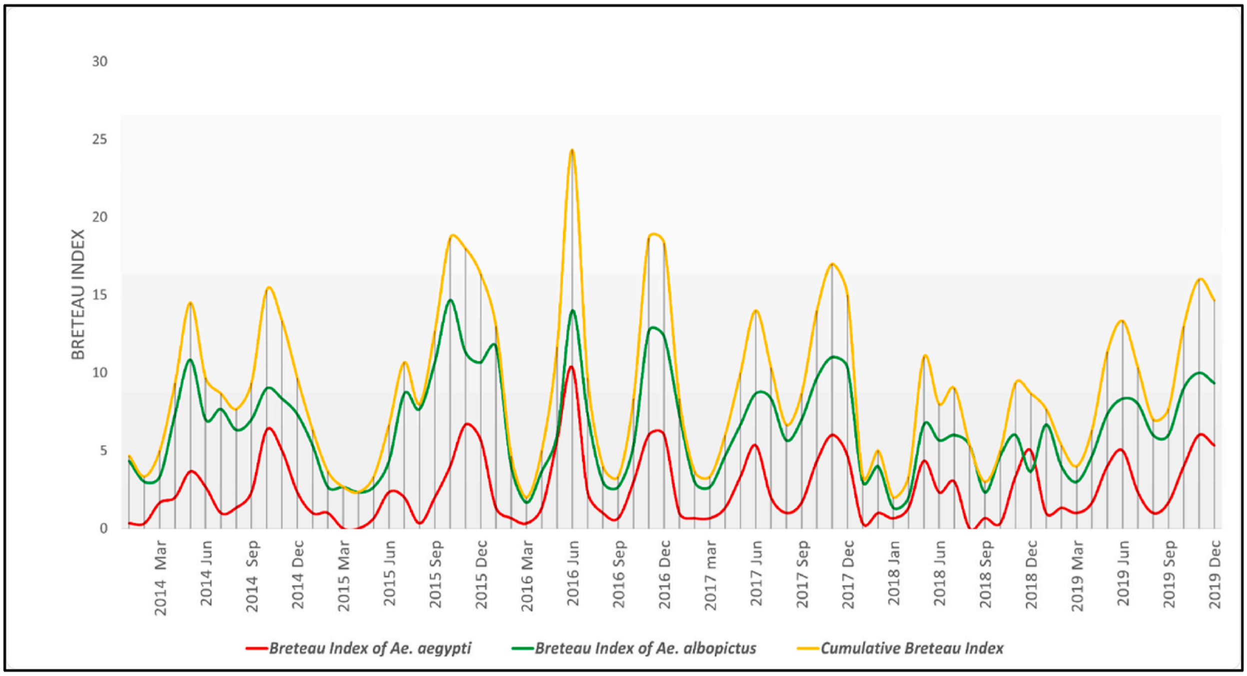

Fig. 2. Temporal distribution of *Ae. aegypti* and *Ae. albopictus* in urban settings of the District of Gampaha for the period of 2014–2019.

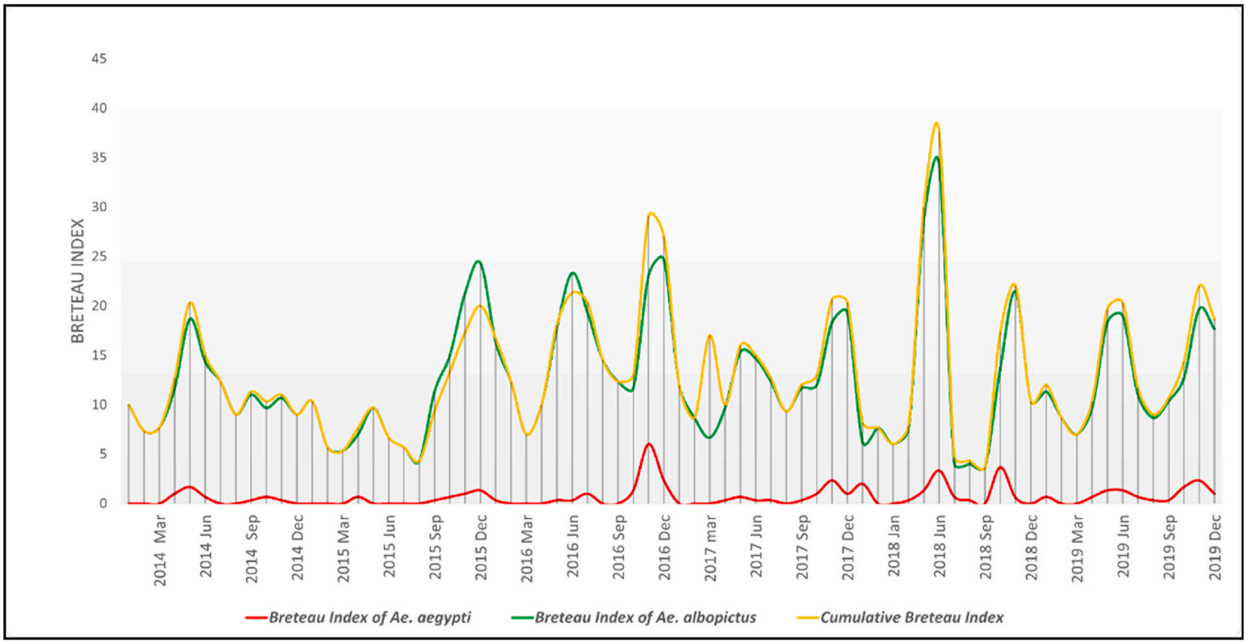

Fig. 3. Temporal distribution of *Ae. aegypti* and *Ae. albopictus* in suburban settings of the District of Gampaha from 2014 to 2019.

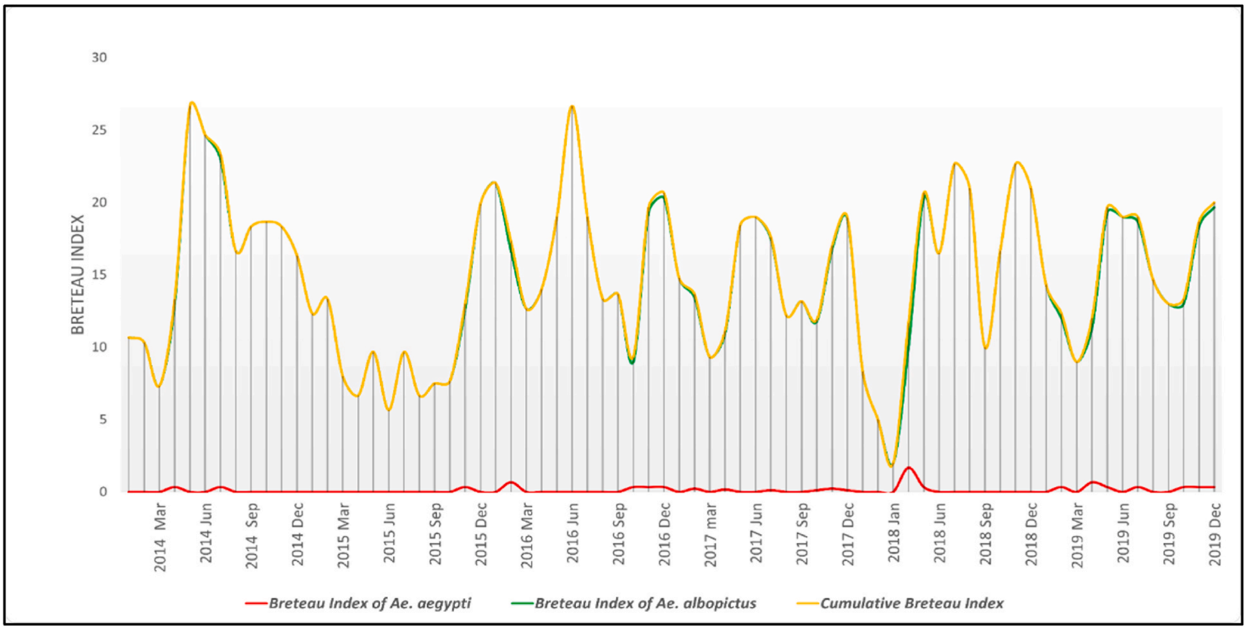

Fig. 4. Temporal distribution of *Ae. aegypti* and *Ae. albopictus* in rural settings of the District of Gampaha for the period of 2014–2019.

the number of rainy days than other climatic variables with a one-month lagging effect. During the study period, *Ae. aegypti* ($r = 0.372$) and *Ae. albopictus* ($r = 0.584$) showed a stronger positive correlation with the number of rainy days in suburban regions comparable to urban settings.

2.13. Cross-validation of the model

The residual normal probability plot depicts a realistically straight line, whereas the residual sequence plot depicts a consistent distribution of errors around zero within ±1. These findings demonstrate that residuals followed a normal distribution throughout the research period, confirming all approved models for each environmental configuration (Fig. 7). Seven dengue outbreaks (Case

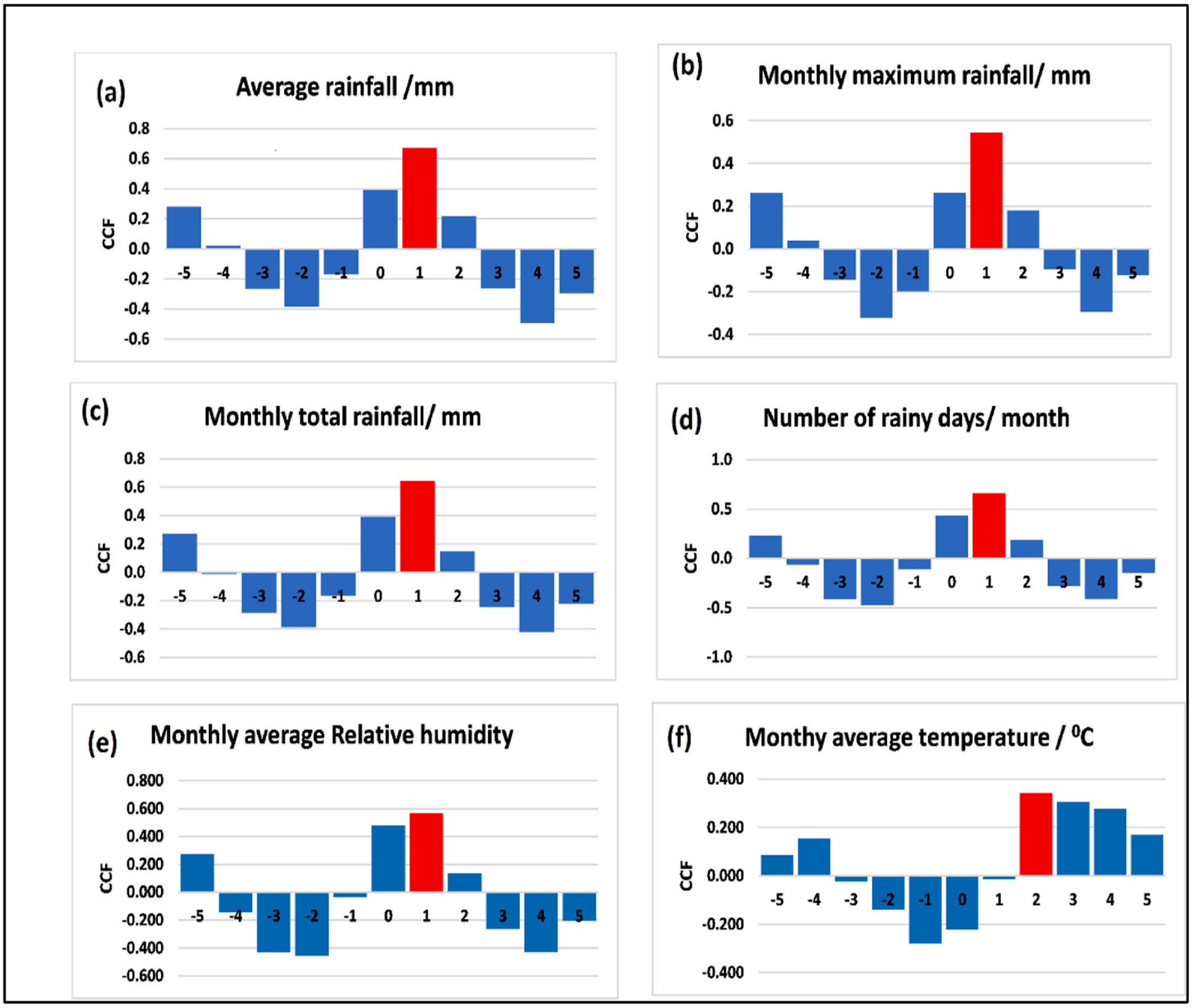

Fig. 5. Cross-correlation analysis (CCF) between climatic variables [**(a)** monthly average rainfall/mm, **(b)** Monthly total rainfall/mm, **(c)** monthly maximum rainfall/mm, **(d)** monthly average relative humidity, **(e)** number of rainy days per month **(f)** Monthly average temperature] with *Ae. aegypti* Breteau Index (urban). ***The highest significant correlation was marked in red**.

incidence >44) were observed in the Jaela MOH region throughout the model development period. The suggested model for urban environmental setup accurately predicted all outbreaks occurring over the 58-month testing period (Fig. 8). When applied to suburban regions of Gampaha district; Biyagama MOH area, the model indicated seven out of eight epidemics occurred in (case incidence >26) with an accuracy of 88 % (Fig. 9), whereas in rural areas, Katana MOH area, the generated model predicted all seven outbreaks (case incidence >18) with an accuracy of 100 % preciseness (Fig. 10).

2.14. Developing areas specific threshold values for different setups

Cross-association function analysis revealed that disease incidence had a medium significant positive correlation with rainfall (r = 0.397) and relative humidity (r = 0.566) at a two-month lag and a weaker positive correlation with monthly average temperature (r = 0.249) at a three-month lag time. Most interestingly, the disease incidence had a strong to very strong positive correlation with BI A (r = 0.777), BIB (r = 0.802) and Cumulative BI (r = 0.828) at a one-month time lag. Based on the case incidence, the areas in the district were classified into three zones, namely, Secured zone" (<Q2), "Alarm zone" (Q2-Q3), and "Epidemic zone" (>Q3) (Fig. 11). The values of case incidence related to different zones are indicated in Table 4.

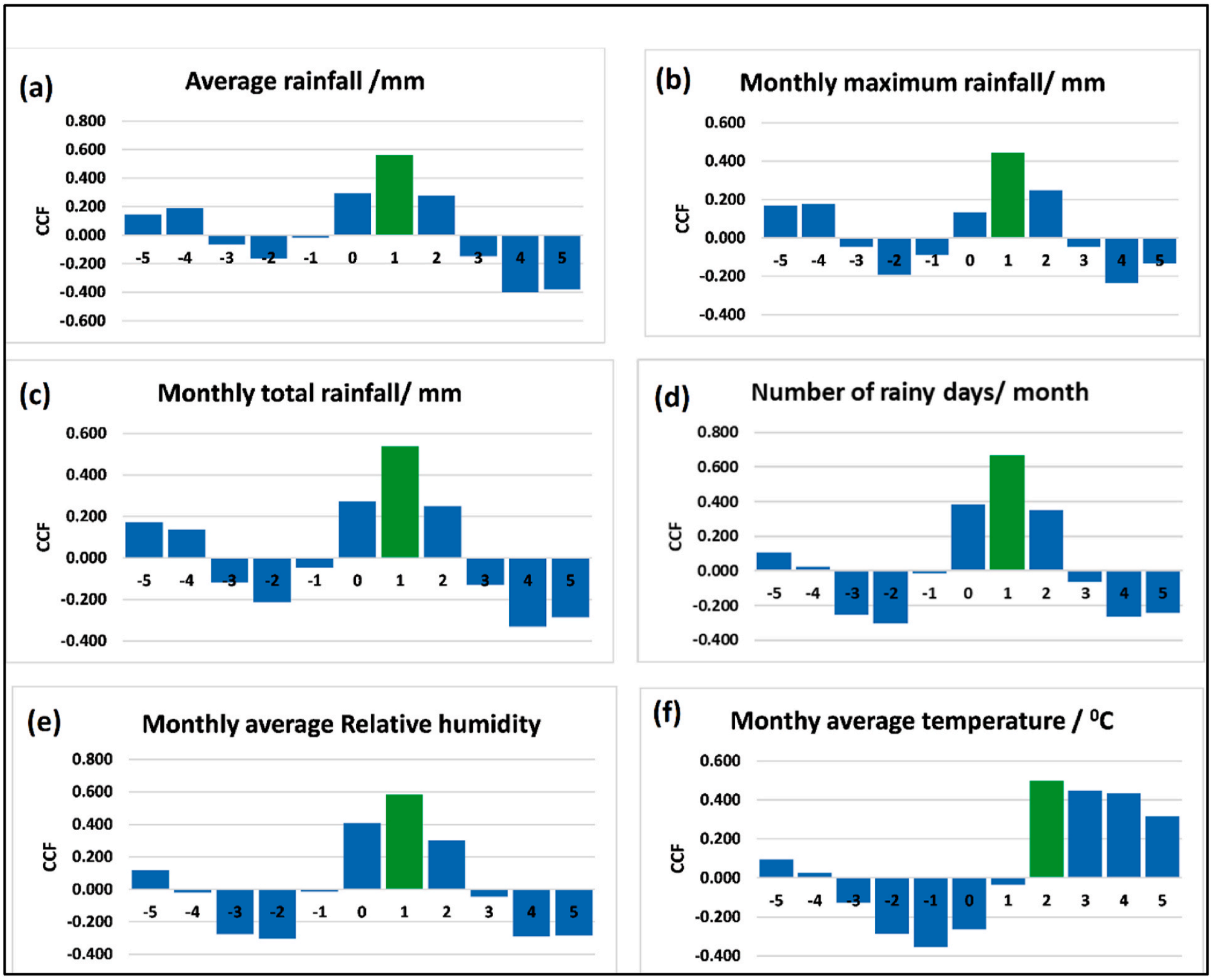

Fig. 6. Cross-correlation analysis (CCF) between climatic variables [**(a)** monthly average rainfall/mm, **(b)** Monthly total rainfall/mm, **(c)** monthly maximum rainfall/mm, **(d)** monthly average relative humidity, **(e)** number of rainy days per month, **(f)** Monthly average temperature] with *Ae. albopictus* Breteau Index (urban). * The highest significant correlation was marked in green.

2.15. Development of prediction model for different environmental settings

2.15.1. Urban environmental setup

Pearson correlation coefficient values and regression equations used to develop the prediction models for urban setup are indicated in Table 5. Based on the linear regression analysis results, it was noted that the stepwise multiple regression model with BI for one month lag and average monthly relative humidity at two lag months ($r = 0.775$) was the best model to fit the case incidence in urban settings, as indicated below.

$$\boldsymbol{DI}_{(U,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIA}_{(U,t-1)} + \beta_2 \times \boldsymbol{RHavg}_{(t-2)}$$

The regression equation of best-fitted model urban areas was,

$$\boldsymbol{DI}_{(U,t)} = -\ 0.5222 + 0.0218 \times \boldsymbol{BIA}_{(U,t-1)} + 0.0844 \times \boldsymbol{RHavg}_{(t-2)}$$

The regression plots developed based on the selected model in the urban environmental setup are included in Fig. 12. Relative humidity exceeds 81 %, and the model implies an early outbreak scenario inside the urban areas. An early epidemic situation is also indicated when the $BIA_{(U,t-1)}$ is more than three and the RHavg (t-2) >77 %. Most significantly, when the $BIA_{(U)}$ is more significant than three with an average $RHavg_{(t-2)}$ of 88 %, when the $BIA_{(U)}$ is equal to or greater than four with an average RHavg $_{(t-2)}$ of 84 %, when the $BIA_{(U)}$ is 5.0 with an average $RHavg_{(t-2)}$ of 81 %, and whenever the $BIA_{(U,\ t-1)}$ is > 6.0 with an average $RHavg_{(t-2)}$ of 77 %, it reached up to a severe epidemic condition (Table 6).

When the case incidence exceeds 25, it suggests an early epidemic stage (Alarm), but when it surpasses 44, it signals an epidemic

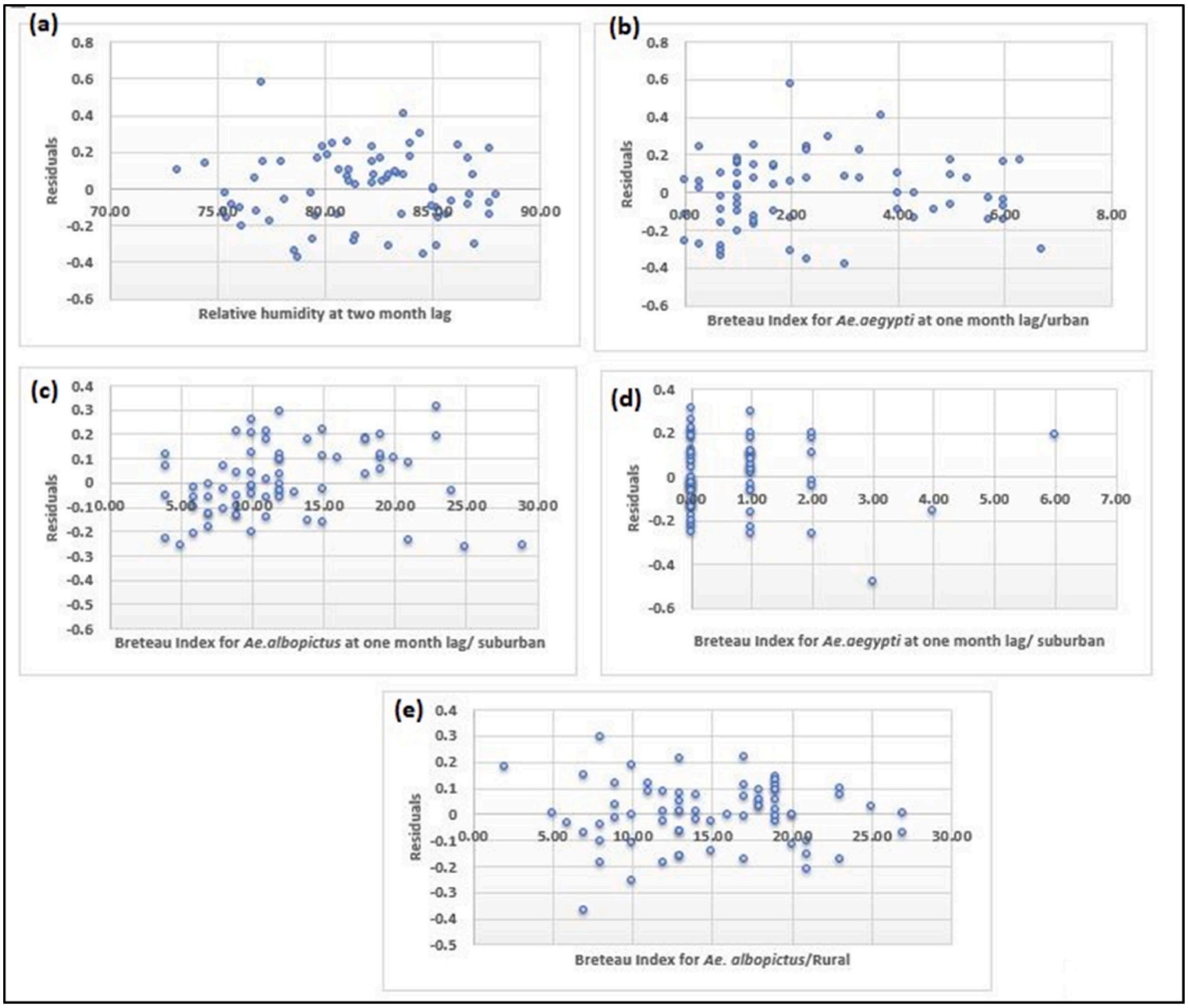

Fig. 7. Residual normality plots of the developed models; **a, b;** urban setting, **c, d;** suburban settings, **e;** rural settings.

condition in the Gampaha district's urban districts. The indicators were determined using the National Dengue Action Plan 2019–2023 [27] and the technical handbook for dengue monitoring and epidemic prediction [28].

2.15.2. Suburban environmental setup

The third model indicated a strong significant association between vector indices and monthly average relative humidity with a two-month lag with case occurrence (Table 7). The best correlation was found when both *Ae. aegypti* and *Ae. albopictus* BI at one month lag was used together with the monthly average relative humidity at a two-month lag in MLR ($r = 0.779$) (Fig. 13). In suburban areas, the BIA and BIB with one month lag time was identified as the best predictor that affected the likelihood of higher dengue incidences. Therefore, the regression equation was fitted as follows.

$$\boldsymbol{DI}_{(SU,t)} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \times \boldsymbol{BIA}_{(SU,t-1)} + \boldsymbol{\beta_1} \times \boldsymbol{BIB}_{(SU,t-1)}$$

The regression equation of the best-fitted model for suburban setup,

$$\boldsymbol{DI}_{(SU,t)} = \mathbf{0.9086} + \mathbf{0.0547} \times \boldsymbol{BIA}_{(SU,t-1)} + \mathbf{0.0251} \times \boldsymbol{BIB}_{(SU,t-1)}$$

In suburban areas, the BIA varied from 0 to 6, with most records ≤ 2.0 (96 %, n = 66 months). The BIB on the other hand, had a broader range (4–34). An early outbreak situation was noted when Cumulative BI reached >10 at one month lagged time where $BIA_{(t-1)} \geq 3$ and $BIAB_{(t-1)} \geq 7$. However, BIA rarely reached >3 three in suburban areas. Early outbreak situation can also be observed whenever $BIAB_{(t-1)}$ reached >9.0and with $(BIA_{(t-1)}) \geq 2$, cumulative BI reached >13 with $BIB_{(t-1)} \geq 12$ and $BIA_{(t-1)} = 1$. If the sole index of BIB(t-1) is > 14, case incidence reaches an alarming zone. Epidemic situations arise when research is > 21, even without the presence of *Ae. aegypti*

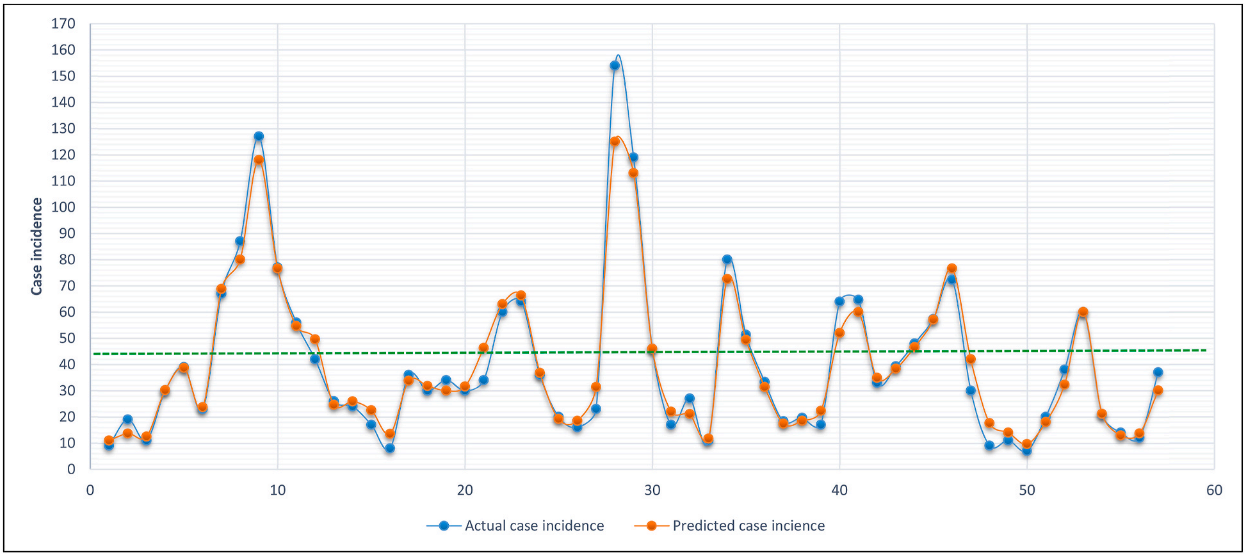

Fig. 8. The goodness of fitness of the model was developed for urban settings in the Gampaha district. Fitted and forecasted dengue case incidence from the developed model illustrated for a period of 2014–2018 in the Jaela MOH area. The epidemic threshold level is denoted with a dotted line on the graph at 44 cases per 100,000 population.

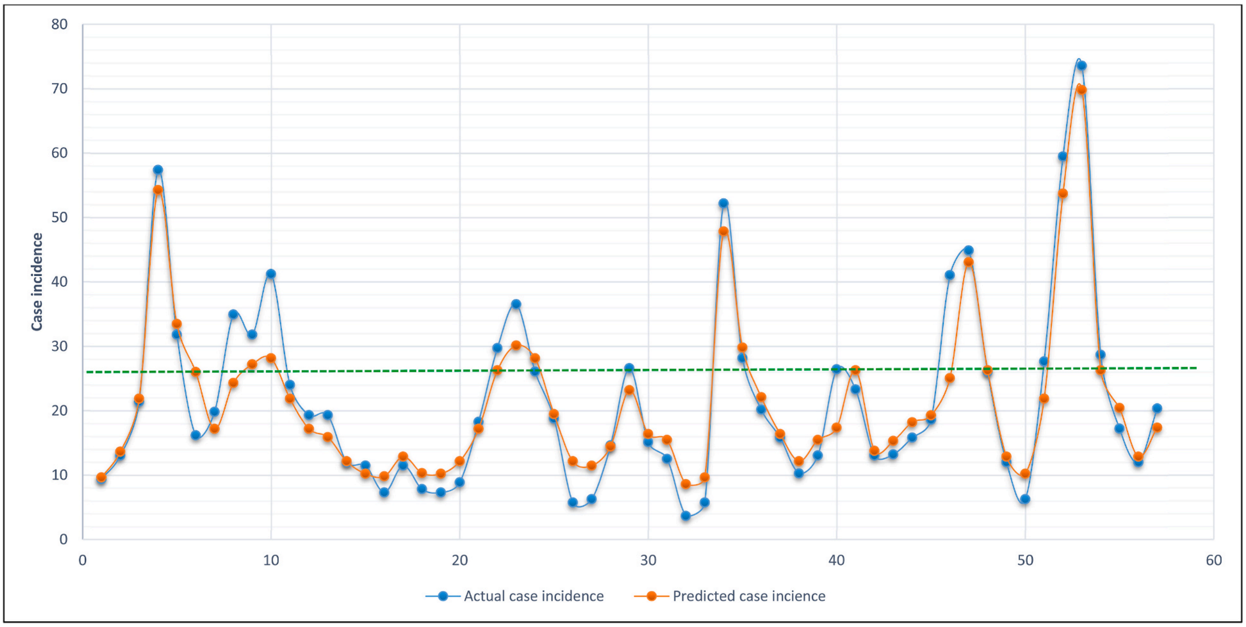

Fig. 9. The goodness of fitness of the model developed for suburban settings of the Gampaha district. Fitted and forecasted dengue case incidence from the developed model illustrated for a period of 2014–2018 in the Biyagama MOH area. The epidemic threshold level is denoted with a dotted line on the graph at 26 cases per 100,000 population.

in suburban MOH areas. With the presence of *Ae. aegypti*, case incidence reached above the epidemic level when the $BIA_{(t-1)} = 1$ with $BIB_{(t-1)} \geq 19$, $BIA_{(t-1)} \geq 2$ with $BIB_{(t-1)} \geq 17$ or above index (Table 8). The model suggested it was essential to maintain the cumulative $BI < 21$ to maintain case incidence below the epidemic situation in suburban areas.

When the case incidence exceeds 17, it suggests an early epidemic stage, but when it surpasses 25, it signals an epidemic condition in the Gampaha district's suburban areas.

The indicators were determined using the National dengue action plan 2019–2023 [27] (and the technical handbook for dengue monitoring and epidemic prediction [28].

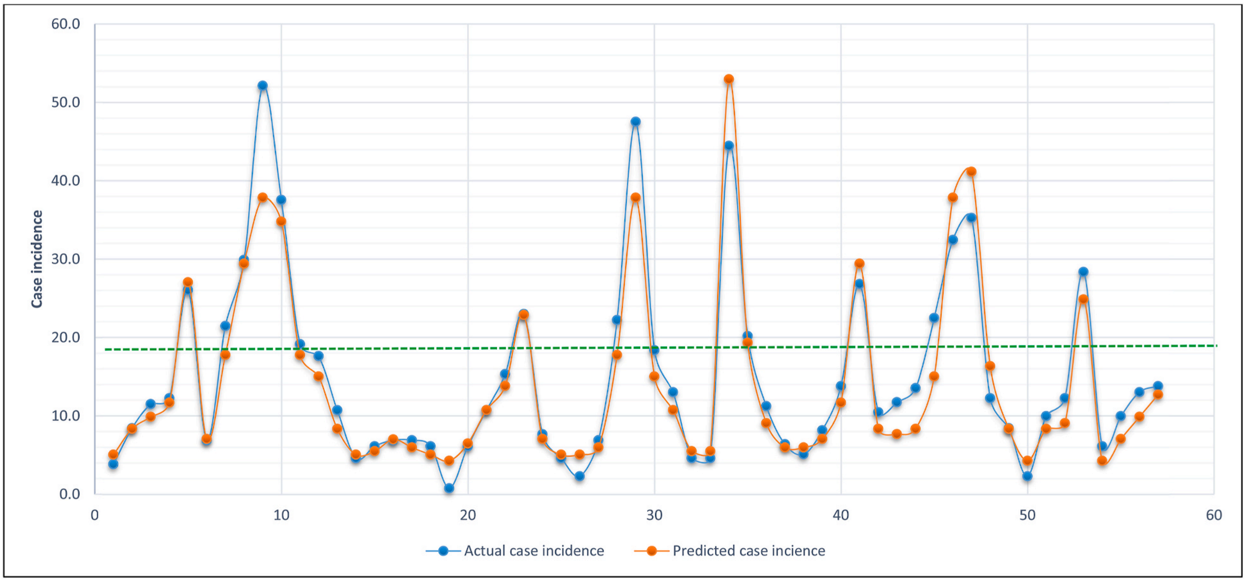

Fig. 10. The goodness of fitness of model developed for rural settings of Gampaha district. Fitted and forecasted dengue case incidence from the developed model illustrated for a period of 2014–2018 in the Katana MOH area. The epidemic threshold level is denoted with a dotted line on the graph at 18 cases per 100,000 population.

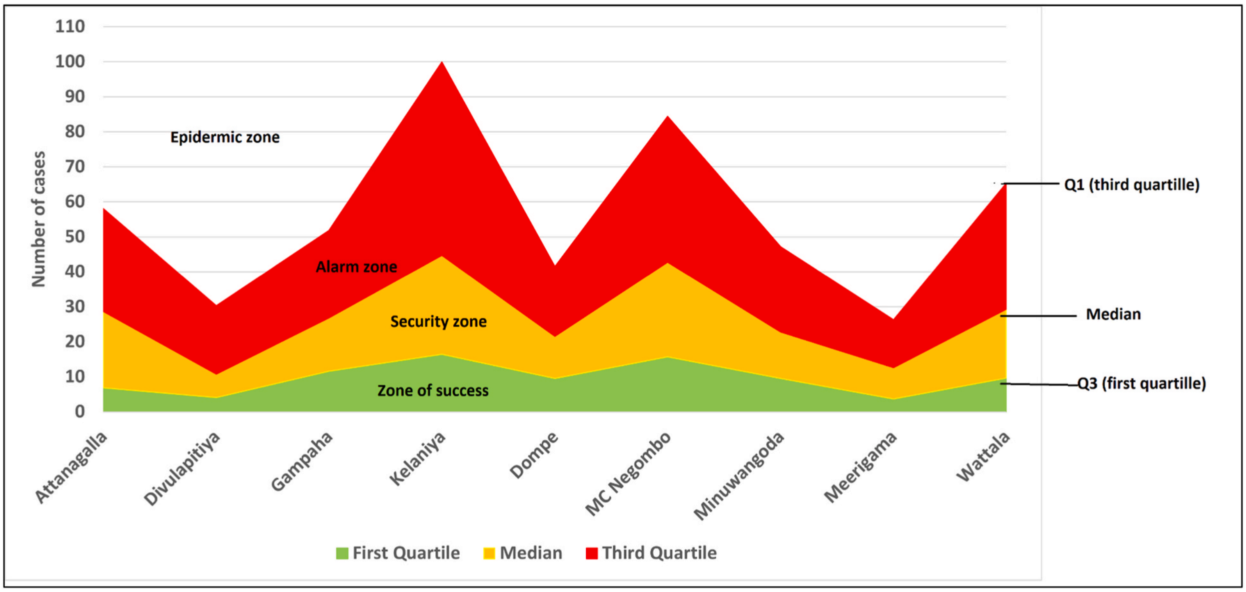

Fig. 11. Illustration of the epidemic-level selected MOH areas of Gampaha district.

Table 4
Case incidence values used to categorize different zone levels in the selected MOH areas.

Environmental setting	Case incidence per 100,000 population		
	Secured Zone	Alarm Zone	Epidemic Zone
Urban	14–25	25–44	>44
Suburban	9–17	17–26	>26
Rural	6–9	9–18	>18

Table 5
Pearson correlation coefficient values and regression equations for prediction models for urban setup.

Model	Regression equations	R	R square	Adjusted R square	Sig.	F value
Model I	$DI_{(U,t)} = \beta_0 + \beta_1 \times BIA_{(U,t-1)} + \beta_2 \times RHavg_{(t-2)}$ ①	0.775^b	0.600	0.588	<0.001	49.573
Model II	$DI_{(U,t)} = \beta_0 + \beta_1 \times BIA_{(U,t-1)} + \beta_1 \times BIB_{(U,t-1)}$ ②	0.770^b	0.593	0.581	<0.001	48.162
Model III	$DI_{(U,t)} = \beta_0 + \beta_1 \times BIA_{(U,t-1)} + \beta_2 \times RHavg_{(t-2)}$ ①	0.775^b	0.600	0.588	<0.001	49.573
Model IV	$DI_{(U,t)} = \beta_0 + \beta_1 \times BIA_{(U,t-1)} + \beta_2 \times BIB_{(U,t-1)}$ ②	0.770^b	0.593	0.581	<0.001	48.162
Model V	$DI_{(U,t)} = \beta_0 + \beta_1 \times RD_{(t-2)}$ ③	0.640^a	0.409	0.400	<0.001	81.544

DI (U,t): Case incidence without a lag period in urban areas, **$BIA_{(U,t-1)}$:** Breteau Index *Ae. aegypti* at lag 1 in urban areas, **$BIB_{(U,t-1)}$:** Breteau Index *Ae. albopictus* at lag 1 in urban areas, **$RFavg_{(t-2)}$:** Monthly average rainfall at lag 2, **$RHavg_{(t-2)}$:** Monthly average relative humidity at lag 2.
Regression equations were developed using significant correlations followed by multiple regression analysis.
*Best fitted model for urban setup is highlighted in red colour.

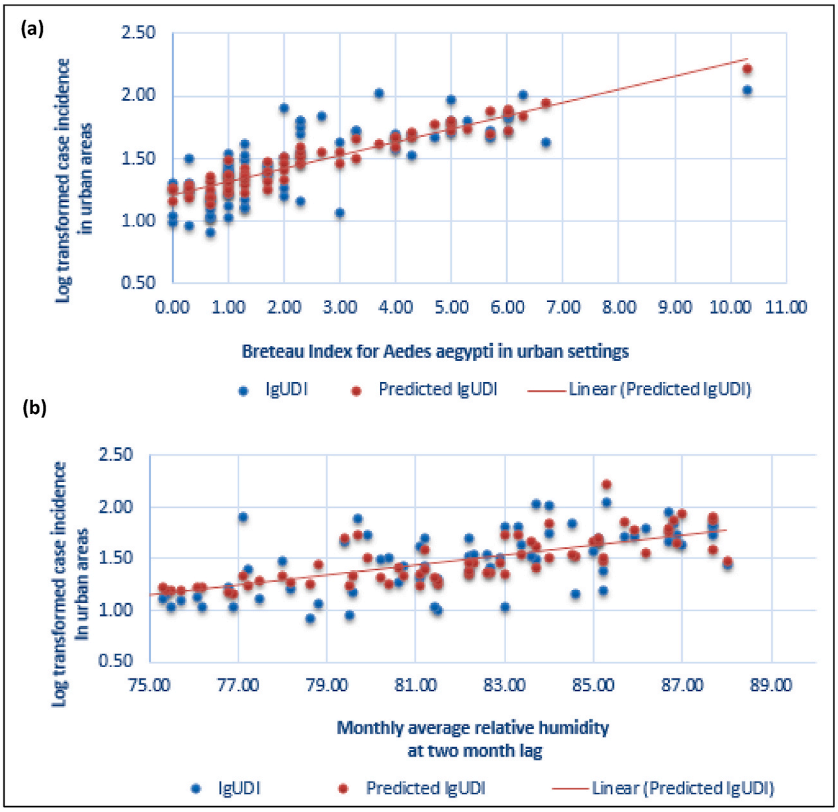

Fig. 12. Regression plots of case incidence with **(a):** Breteau Index for *Ae. aegypti* at one month lag, **(b):** monthly average relative humidity at a two-month lag in an urban setting.

2.15.3. Rural environmental setup

Aedes aegypti was rarely observed in rural regions in the Gampaha District and *Ae. albopictus* was found as the primary vector in the areas. Similar data were found from all four modeling methodologies, demonstrating that the emergence of dengue cases and case incidence had an influential significant association with the BIB with a one-month lag ($r = 0.854$). Regression statistics used to forecast impending dengue epidemics under all four models are indicated in Table 9. Based on the results obtained by SLR, the BIA at one-month lagging effect was identified as the best predictor model to forecast increasing case incidence and emerging dengue outbreaks in rural areas of the Gampaha District (Fig. 14).

Incidences with the developed model. The developed model was,

$$\boldsymbol{DI_{(R,t)} = \beta_0 + \beta_1 \times BIB_{(R,t-1)}}$$

The regression equation of best fitted model for rural areas was,

Table 6
Predicted case incidences for urban areas of Gampaha District based on the selected model.

BI of *Ae. aegypti*	Monthly average relative humidity (%)											
	77	78	79	80	81	82	83	84	85	86	87	88
1.0	17	18	19	20	21	23	24	25	26	28	29	31
2.0	21	22	24	25	26	27	29	30	32	33	35	37
3.0	26	27	29	30	32	33	35	37	39	41	43	**45**
4.0	31	33	35	37	37	40	42	45	49	49	52	55
5.0	38	40	42	44	47	49	54	57	59	60	63	66
6.0	46	49	51	54	57	60	63	69	73	74	77	81
7.0	56	59	62	65	62	72	76	80	84	89	93	98
8.0	68	72	76	80	69	88	92	97	102	108	113	119
9.0	83	87	92	97	102	107	112	118	124	131	137	144
10.0	101	106	112	117	123	130	136	143	151	159	167	175

Note: Values in the parenthesis include: Case incidence data calculated based on the best-fitted model.

Table 7
Pearson correlation coefficient values and regression equations for prediction models for suburban setup.

Model	Regression equations	R	R square	Adjusted R square	Sig.	F value
Model I	$\boldsymbol{DI}_{(SU,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIA}_{(SU,t-1)} + \beta_1 \times \boldsymbol{BIB}_{(SU,t-1)}$ ——①	0.779^{b}	0.607	0.595	<0.001	51.004
Model II	$\boldsymbol{DI}_{(SU,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIA}_{(SU,t-1)} + \beta_1 \times \boldsymbol{BIB}_{(SU,t-1)}$ ——①	0.779^{b}	0.607	0.595	<0.001	51.004
Model III	$\boldsymbol{DI}_{(SU,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIA}_{(SU,t-1)} + \beta_1 \times \boldsymbol{BIB}_{(SU,t-1)}$ ——①	0.779^{b}	0.607	0.595	**<0.001**	51.004
Model IV	$\boldsymbol{DI}_{(SU,t)} = \beta_0 + \beta_1 \times BIB_{(SU,t-1)} + \beta_2 \times RFavg_{(t-2)}$ ——②	0.631^{b}	0.398	0.380	**<0.001**	88.149
Model V	$\boldsymbol{DDI}_{(SU,t)} = \beta_0 + \beta_1 \times RFavg_{(t-2)} + \beta_2 \times Tavg_{(t-3)}$ ——③	0.605^{b}	0.366	0.347	**<0.001**	89.320

DI (SU,t): Case incidence without a lag period in sub urban areas, **$BIA_{(SU,t-1)}$:** Breteau Index *Ae. aegypti* at lag 1 in sub urban areas, **$BIB_{(SU,\ t-1)}$:** Breteau Index *Ae. albopictus* at lag 1 in sub urban areas, **$RFavg_{(t-2)}$:** Monthly average rainfall at lag 2, **$RHavg_{(t-2)}$:** Monthly average relative humidity at lag 2.
Regression equations were developed using significant correlations followed by multiple regression analysis.
*Best fitted model for suburban setup is highlighted in red.

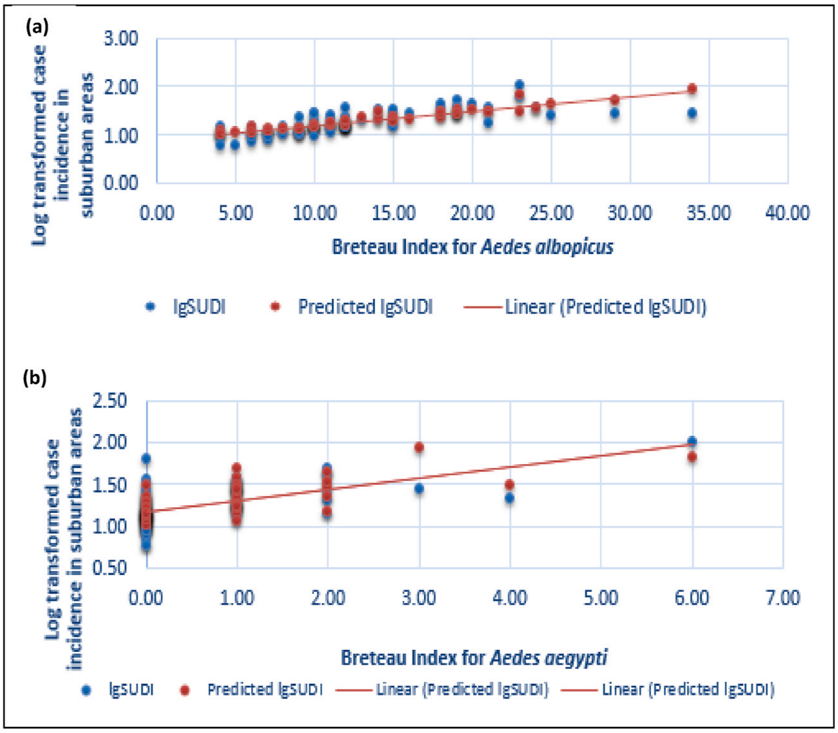

Fig. 13. Regression plots of case incidence with **(a):** Breteau Index for *Ae. albopictus* at one month lag, **(b):** Breteau Index for *Ae. aegypti* at one month lag in a suburban setting.

Table 8
Predicted case incidences for suburban areas of the Gampaha district based on the selected model.

Breteau Index for *Ae. albopictus*	Breteau index for *Ae. aegypti*			
	0.0	1.0	2.0	3.0
4.0	10	12	13	15
5.0	11	12	14	16
6.0	11	13	15	17
7.0	12	14	16	18
8.0	13	15	17	19
9.0	14	15	18	20
10.0	14	16	19	21
11.0	15	17	20	22
12.0	16	18	21	24
13.0	17	19	22	25
14.0	18	21	23	27
15.0	19	22	25	28
16.0	20	23	26	30
17.0	22	25	28	32
18.0	23	26	30	33
19.0	24	28	31	35
20.0	26	29	33	38
21.0	27	31	35	40
22.0	29	33	37	42

Note: Values in the parenthesis include: Case incidence data calculated based on the best-fitted model.

Table 9
Pearson correlation coefficient values and regression equations for prediction models for rural setup.

Model	Regression equations	R	R square	Adjusted R square	Sig.	F value
Model I	$\boldsymbol{DI}_{(R,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIB}_{(R,t-1)}$ —— ①	0.854[a]	0.730	0.726	<0.001	186.269
Model II	$\boldsymbol{DI}_{(R,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIB}_{(R,t-1)}$ —— ①	0.854[a]	0.730	0.726	<0.001	186.269
Model III	$\boldsymbol{DI}_{(R,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIB}_{(R,t-1)}$ —— ①	0.854[a]	0.730	0.726	<0.001	186.269
Model IV	$\boldsymbol{DI}_{(R,t)} = \beta_0 + \beta_1 \times \boldsymbol{BIB}_{(R,t-1)}$ —— ①	0.854[a]	0.730	0.726	<0.001	186.269
Model V	$DI_{(R,t)} = \beta_0 + \beta_1 \times RHavg_{(t-2)} + \beta_2 \times Tavg_{(t-3)}$ —— ②	0.512[b]	0.262	0.240	<0.001	78.432

DI (R,t): Case incidence without a lag period in rural areas, **BIA$_{(R,t-1)}$:** Breteau Index *Ae. aegypti* at lag 1 in rural areas, **BIB $_{(R, t-1)}$:** Breteau Index *Ae. albopictus* at lag 1 in rural areas, **RFavg $_{(t-2)}$:** Monthly average rainfall at lag 2, **RHavg $_{(t-2)}$:** Monthly average relative humidity at lag 2.
Regression equations were developed using significant correlations followed by multiple regression analysis.
*Best fitted model for rural setup is highlighted.

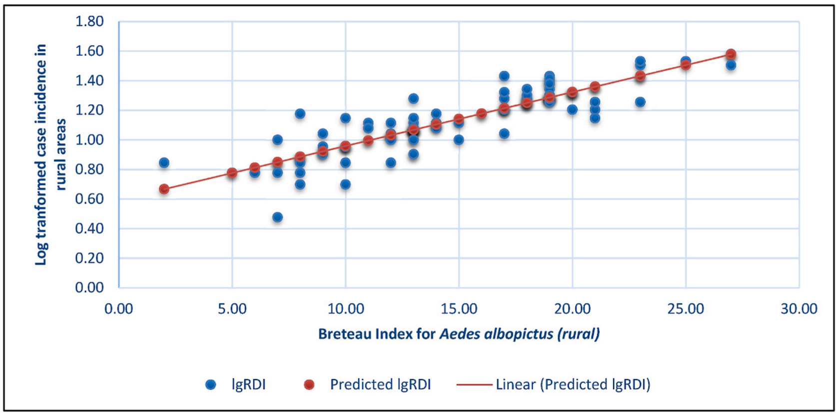

Fig. 14. Regression plot of case incidence with Breteau Index for *Ae. albopictus* at one month lag in a rural setting.

$$DI_{(R,t)} = 0.59434 + 0.03646 \times BIB_{(R,t-1)}$$

In rural areas, the BIB varied from 2 to 27. Based on the prediction model, an early outbreak was noted when the BIB is > 10 at one month lagged time, similar to suburban MOH areas. It was also pointed out that case incidence reaches the epidemic situations whenever the sole index of BIB(R,t-1) is > 19.

3. Discussion

The spatial and temporal distribution of dengue vectors is determined mainly by local vector dynamics and meteorological conditions. Thus, the prevalence of dengue cases in a given area is predicted through the frequency and density of vectors [25]. An epidemic of vector-borne disease may not evolve immediately after the incline of vectors or receiving favorable environmental factors for disease transmission. Therefore, it leaves considerable time to implement vector control measures in action and thereby reduce vector populations well in advance of an epidemic [29,30]. As a result, the current study sought to establish a relationship between meteorological variables and vector densities to forecast emerging dengue outbreaks in the Gampaha district, enabling public health authorities to promptly target high-risk areas.

The standard entomological indicators (Premise Index, Container Index, and the Breteau Index) for dengue vectors were developed primarily to monitor the progress of the *Ae. aegypti* eradication campaign in the Americas in the late 1940s [24]. Several research suggests that appropriately defined threshold values for entomological indicators represent dynamics of disease vector population in particular endemic locations and they produce trustworthy and evident forecasts on upcoming dengue outbreaks [4,5,11,29,31–36].

In Sri Lanka, vector surveillance and larval survey findings were utilized to determine monthly fluctuations of vector larval densities in terms of Breteau index. A dengue outbreak should always be preceded by vector breeding to build up to a substantial level of adult mosquito population to advance transmission into outbreak proportions. Thus, the Breteau index could predict an approaching dengue outbreak in the country. Simultaneously, many researchers have proposed that rainfall, temperature and humidity are the most vital meteorological variables possibly impacting dengue transmission [11,37,38]. (However, the effect of climate conditions on dengue transmission depends on regional location. As a result, we cannot directly apply the findings from these studies to forecasting dengue outbreaks in diverse environmental settings in the Gampaha district; instead, they must be combined with regional-level vector indices to predict dengue outbreaks, as the district receives ample rainfall, has few seasonal temperature variations, and has high humidity throughout the year.

During the model development process, modified data sets for 2017 were employed. In 2017, Sri Lanka had an unprecedented dengue outbreak. There were 186,101 suspected dengue cases and 440 dengue-related fatalities [39–41]. According to Thissera et al., 2020, the weekly average of reported dengue cases in all districts in Sri Lanka was significantly higher than the average for the prior five years. Entomological and meteorological variables did not explain the increased incidence in 2017. Serological research conducted in Sri Lanka in recent years suggests that this unexpected dengue outbreak occurred mainly due to the change in the dengue virus serotype in Sri Lanka. As a result, the present model was developed by replacing this 2017 data with average-case incidence data from 2012 to 2016 to minimize the anomalies and deviation of the proposed model.

The findings of the current study illustrate Breteau Index can be used as a strong predictor of upcoming dengue outbreaks in all the different environmental settings in the Gampaha district and it provides a more meaningful association with dengue transmission than all other determinants. The study findings are corroborated by a few comparable studies conducted in Sri Lanka [4,11,29]. Currently, BI < 5 is considered a cutoff value in Sri Lanka, where chemical control is unnecessary. Additionally, a scenario in which the BI value is between 5 and 20, but there are no reported cases, has been recommended to be dealt with solely through source reduction campaign without the use of chemical approaches such as fogging, whereas scenarios in which there are reported cases or the BI value is > 20 have been recommended to be dealt with fumigation in Sri Lanka [4,9,24]. However, when considering the dynamics of the BI within different environmental settings of the Gampaha district, it was noted that larval vector densities vary significantly across three environmental setups in the Gampaha district, owing to urbanization patterns, socio-economic backdrop, and population dynamics.

Additionally, it was discovered that a single model cannot adequately account for the entomological, environmental, and socio-economic features of dengue transmission throughout the district. Furthermore, a recent modeling study conducted by Withanage et al., 2018 also underlined the importance of developing distinct models with significant characteristics specific to each MOH area to forecast imminent dengue outbreaks due to socio-economic and meteorological variance between MOH areas in the Gampaha district. However, the current model was developed evaluating the characteristics in the Gampaha district's MOH areas and was evidenced that all fifteen MOH areas could be classified into three environmental setups. As a result, the current research study concentrated on developing the best-fit model capable of representing all MOH areas within a certain category and an empirical model was developed following Multiple Linear Regression considering three entomological parameters (BI for *Ae. aegypti,* BI for *Ae. albopictus* and Cumulative BI), six meteorological variables (average monthly rainfall, average monthly humidity, average monthly temperature, monthly total rainfall, maximum monthly rainfall and number of rainy days) and population density on dengue case incidence.

The district of Gampaha is mainly affected by two monsoon seasons each year, from April to June and October to December [20]. The cross-correlation analysis revealed a substantial positive correlation between rainfall and larval vector density and the risk of experiencing high dengue incidences. Rainfall had a moderate to high link with larval vector density after a one-month lag and with case density after a two-month lag, which was consistent with prior research conducted in Sri Lanka [4,11,15,37] and other parts of the world [42,43].

Mosquitoes complete immature stages of their life cycles in water and later hatch into adult mosquitoes. Considering the time required for an egg to mature into an adult mosquito, the effect of climate change should be noticeable one or two months later.

Rainfall's beneficial effect is justified because increased rain mainly creates more breeding grounds for mosquitos. This results in an increase in mosquito density, which results in an increase in dengue incidence rates and the danger of infection spreading. Once adult mosquitoes emerge, meteorological variables affect their survival. Temperature and humidity affect adult mosquitoes' survival and average lifespan [44]. Even though the mosquito life cycle is completed within a short period with the increase in temperature, high temperatures may increase adult mosquito mortality while the rise in temperature increases the life span of mosquitoes [44,45].

Due to the rarity of *Ae. aegypti* in rural regions of the district, vector control entities must focus on *Ae. albopictus* reproduction in order to manage dengue, as it has been identified as the sole vector of dengue in those locations. Therefore, the study highlighted the importance of defining the area-specific thresholds for vector management, considering all individual vector population dynamics and regional meteorological variations.

Some limitations of the study are discussed here. In cross-validation of the models, a set of data collected from different MOH areas with similar setups and conditions was used due to data limitations. Therefore, this could lead to micro-level variations in the prediction outcome. Another fact is that meteorological parameters were obtained from the one monitoring station available for the district. Therefore, variations within different MOH areas could not be tracked.

Further, entomological investigations were conducted in selected locations (in general, 4 localities

in each MOH area) every month. Therefore, better accuracy and sensitivity could be obtained if the survey frequency increases with more sampling sites. One possible extension for the proposed model is to use monthly dengue case data. However, as mentioned, monthly delayed effects may still exist to predict monthly dengue cases. Notably, the consequences of human intervention, including disease control, between different years are not measured to count possible impacts on annual incidences. However, with all these limitations, the present study successfully predicts dengue outbreaks at three identified environmental setups in the Gampaha district of Sri Lanka. Therefore, findings in the present study could benefit plant vector control interventions in the district.

In conclusion, the findings of the present study could be used for dengue control efforts by reducing the magnitude of the epidemic, preventing disease transmission, lowering healthcare burden/operating costs, and maximizing limited vector control resources. Finally, the high precision and sensitivity in the prediction model will reduce resource utilization and wasteful vector control operations prompted by false alarms, high running expenses and excessive psychosocial stress in the population due to false alarms may deter the adoption of a dengue early warning system.

Ethics approval and consent to participate

Ethical clearance for the present study was obtained from the Ethics Review Committee of the Institute of Biology, Sri Lanka (IOBSL161 09 17). Written consents were obtained from all adults who participated in human-baited double-net traps. Verbal permission was also obtained from household heads for conducting entomological investigations at their houses and compounds.

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Data availability

Data will be made available on request.

CRediT authorship contribution statement

Rasika Dalpadado: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Deepika Amarasinghe:** Supervision, Project administration, Conceptualization. **Nayana Gunathilaka:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Data curation, Conceptualization. **Annista N. Wijayanayake:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation.

Declaration of competing interest

We the authors certify here that we have no conflicts of interest regarding publication of the manuscript titled "**Forecasting dengue incidence based on entomological indices, population density, and climatic and environmental variables in the Gampaha District of Sri Lanka**.

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