ORIGINAL ARTICLE

Developing a time series prediction modelling for dengue in Kota Kinabalu, Sabah

Norsyahida Md Taib, MPH[1,2], Azman Atil,DrPH[1,3], Rahmat Dapari, DrPH[4], Mohd Rohaizat Hassan, PhD[5], Priya Dharishini Kunasagran, DrPH[1,2], Adora J Muyou, DrPH[1,2], S Muhammad Izuddin Rabbani Mohd Zali, MPH[1,2], Zahir Izuan Azhar, DrPH[6], Syed Sharizman Syed Abdul Rahim, DrPH[1,3]

[1]Faculty of Medicine and Health Sciences, Department of Public Health Medicine, Universiti Malaysia Sabah, Sabah, Malaysia, [2]Sabah State Health Department, Ministry of Health Sabah, Malaysia, [3]Borneo Medical & Health Research Centre, Faculty of Medicine & Health Sciences, Universiti Malaysia Sabah, Sabah, Malaysia, [4]Faculty of Medicine and Health Sciences, Universiti Putra Malaysia, Serdang,Selangor, Malaysia, [5]Department of Community Health, Faculty of Medicine, National University of Malaysia, Kuala Lumpur, Malaysia, [6]Department of Public Health Medicine, Faculty of Medicine, Universiti Teknologi MARA, Sungai Buloh, Selangor, Malaysia

ABSTRACT

Introduction: Dengue is a major public health issue, with 3,900,000 people living in 129 dengue-endemic countries globally facing a risk of contracting dengue fever. Dengue incidence in Sabah is among the highest in Malaysia. In 2022, Kota Kinabalu District reported 22% of the total number of dengue cases in Sabah. The objective of this study was to develop a prediction model for dengue incidence using meteorological, entomological, and environmental parameters in Kota Kinabalu, Sabah.

Materials and Methods: An ecological study was conducted from 2016 to 2021 using the dengue database and meteorological data. The forecasting model for dengue incidence was performed with R software using the seasonal autoregressive integrated moving average (SARIMA) model. The model was fitted based on the reported weekly incidence of dengue from 2016 to 2020 and validated using data collected between January and December 2021.

Results: SARIMA (1,1,1) (1,1,0)52 with the external regressor maximal temperature, Aedes index, and vacant lot were the models with minimal measurement errors, as indicated by the Mean Absolute Error (MAE) values of 3.04, Root Mean Squared Error (RMSE) of 4.43, and Akaike Information Criterion (AIC) of 1354.82.

Conclusions: The predicted values in 2021 accurately forecasted the capability to serve as an early warning system for proactive dengue measures. This information is deemed valuable to healthcare administrators for enhancing the level of preparedness.

KEYWORDS:
Dengue, environmental parameters, entomological parameters, meteorological parameters, prediction modelling

INTRODUCTION

Dengue fever is a viral infection transmitted by infected female Aedes mosquito bites from humans to humans and occurs in tropical and subtropical areas of the world. According to the World Health Organization (WHO) reports on dengue fever, 3,900,000 people live in 129 dengue-endemic countries globally and are at risk of contracting dengue fever.[1] The Western Pacific Region represents 75% of the global disease burden. The number of dengue cases in the Western Pacific Region increasingly doubled from 200,000 people in 2011 to more than 450,000 people in 2015 and 680,000 people in 2019.[2]

Kota Kinabalu had the highest occurrence of dengue cases in Sabah compared to the other districts.[3] Even though the Ministry of Health (MOH) has comprehensive guidelines for the management and treatment of dengue fever, the number of dengue cases in Kota Kinabalu has risen from 2012 to 2021. To meet the objectives of the National Dengue Strategic Plan, which aims to reduce the burden and threat of dengue through effective, locally adapted, and sustainable vector control, Kota Kinabalu district should establish its own framework to anticipate and respond accordingly.[4]

The unpredictable nature of dengue outbreaks presents challenges for public health authorities in terms of resource allocation and preparedness. Advanced predictive modelling techniques have emerged as promising methods for forecasting dengue outbreaks, allowing timely intervention and improved disease management. With prediction, early notification of the dengue epidemic and timely allocation of scarce resources for dengue management in the Kota Kinabalu District Health Office. Thus, dengue cases can be reduced and control improved, while the Kota Kinabalu Vector Borne Diseases Unit can focus more on prevention activities.

The use of autoregressive integrated moving average (ARIMA) modelling, in conjunction with time-series analysis, has become increasingly important in epidemiological research, specifically in the study of infectious diseases, such as malaria, influenza, COVID-19, tuberculosis, and dengue fever. A study in Wuhan, China presented an analysis of the epidemiology of influenza viruses in children over the influenza seasons (2007-2015) to forecast the future positive rate of various types of influenza viruses.[5] In Pakistan, ARIMA, SARIMA, and the Holt-Winter method are used to

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Corresponding Author: Syed Sharizman Syed Abdul Rahim
Email: syedsharizman@ums.edu.my

forecast malaria cases.6 This study aimed to identify covariates that could be used to develop a model for predicting dengue outbreaks in Kota Kinabalu to facilitate timely outbreak notification and resource management.

MATERIALS AND METHODS

Kota Kinabalu, the capital city of the state of Sabah, served as the research site because it has the highest rate of dengue fever among all districts.[3] This was an ecological study design involving eDengue data, which included vacant lots, construction sites, Aedes species, Aedes indices, dengue case data, and meteorological parameters collected from 3rd January 2016 to 25th December 2021 from the Kota Kinabalu Meteorological Office. Daily data for all years were categorized into weekly data based on epidemiological weeks.

The dengue surveillance data from the eDengue and meteorological parameters were input into Microsoft Excel. The analysis was conducted by aggregating daily data into weeks based on epidemiological weeks (with an epidemiological week beginning on Sundays).[7] The data were analysed in R programming software, utilizing the forecast, tseries, and ggplot[2] packages. Time-series data were decomposed into fundamental components and seasonal components described using an addictive method 8 as in Figure 1.

Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were applied to determine the stationarity of data.[9] Subsequently, the dataset was split into training and testing datasets. The training dataset spans from 1st March 2016 to 27th December 2020 whereas the testing dataset covers the period from 28th December 2020 to 19th December 2021. This study utilised Auto ARIMA for selecting the best ARIMA model parameters (p, d, q) by testing different combinations of parameters and comparing model performance based on information criteria like the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC).[10]

The accuracy of the model was verified by measuring the errors of the ARIMA model, such as the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Akaike Information Criterion (AIC) with an external regressor. The correlogram and Ljung-Box test were employed to assess the correlation between the consecutive forecast errors.[11] A p-value below a predetermined significance level suggested the presence of autocorrelation in the values. If the p-value is greater than 0.05, it can be inferred that the residuals of the data are independent.[10] The chosen model, referred to as the predictive model, was then applied for data forecasting. This approach, however, utilizes a static learning model, which has limited applicability in public health contexts.

RESULTS

Descriptive time series of dengue cases and independent variables

Figure 2 shows the time series between meteorological parameters and dengue incidence over the study period. The weekly maximum temperature at Kota Kinabalu fluctuated between 2016 and 2021. The highest temperature was 33 °C in January 2020 and the lowest in May 2016 (35.6 °C).

This study investigated relative humidity (RH) as a climatic factor under examination. The minimum weekly humidity in Kota Kinabalu fluctuated within a relatively narrow range. The maximum RH recorded in January 2020 was 76.4%. The lowest recorded cases occurred at a RH of 77.7% in May 2016, as depicted in Figure 2.

The increase in the number of dengue cases can be attributed to weekly maximum rainfall. The weekly maximum rainfall in Kota Kinabalu between 2016 and 2021 can be classified as falling within the medium. In January 2020, the recorded maximum dengue fever case rate was 12.2 mm/hour, while the minimum case rate was observed at 10.88 mm/hour.

The distribution of the dengue vector Aedes aegypti is potentially influenced by wind speed. In January 2020, the incidence of dengue cases peaked at a rate of 4.6 knots of wind speed. The minimum recorded number of cases, as illustrated in Figure 2, was 4.9 knots during May 2016.

The time-series analysis presented in Figure 3 illustrates the relationship between the entomological parameters and dengue incidence throughout the study period. The weekly population of Aedes albopictus in Kota Kinabalu from 2016 to 2021 exhibited minimal fluctuations on a weekly basis. The peak incidence of Aedes albopictus infection occurred in January 2020, with a weekly count of 61. Conversely, the lowest recorded incidence of Aedes albopictus was observed in May 2016, with no reported instances.

This study examined the Aedes Index as a variable of interest within the field of entomology. Analysis of the weekly Aedes Index data in Kota Kinabalu revealed minimal fluctuations. In January 2020, the weekly Aedes Index reached 69. Notably, the lowest recorded weekly Aedes Index of 0 was observed in May 2016, as illustrated in Figure 3.

This study investigated vacant lots as an environmental parameter. The weekly number of vacant lots in Kota Kinabalu varied. In January 2020, 11 vacant lots were recorded weekly. Figure 3 illustrates the occurrence of the lowest recorded cases of the weekly number of vacant lots in May 2016, which amounted to 29.

Furthermore, the increase in the number of dengue cases could be attributed to the weekly number of construction sites. The weekly frequency of construction sites in Kota Kinabalu from 2016 to 2021 can be categorised as belonging to a small range. In January 2020, the highest recorded incidence rate of dengue fever was zero, whereas the lowest incidence rate of dengue cases was zero.

Developing Seasonal Autoregression Integrated Moving Average (SARIMA) model with External Regressor

An external regressor was introduced to the SARIMA models with the parameters (1,1,1) (0,1,1) and (0,1,2) (0,1,1) after selecting the two best models. The maximum temperature, Aedes index, vacant lot, and Aedes albopictus, which exhibited an association with dengue cases, were all included

Table I: Measurement errors of the SARIMA model with external regressor

SARIMA model (1,1,1) (0,1,1) with external regressor	**Measurement Error**		**Ljung-Box Test**	
	MAE	**RMSE**	**AIC**	**p-value**
Maximal Temperature, Aedes Index, Vacant Lot, Aedes Albopictus	3.036	4.430	1356.81	0.045
Maximal Temperature, Aedes Index, Vacant Lot	3.029	4.457	1357.40	0.047
Maximal Temperature, Vacant Lot, Aedes Albopictus	3.038	4.430	1354.82	0.045
Aedes Index, Vacant Lot, Aedes Albopictus	3.053	4.436	1355.41	0.039
Maximal Temperature, Aedes Index	3.312	4.797	1385.36	0.248
Maximal Temperature, Vacant Lot	3.341	4.925	1396.79	0.192
Maximal Temperature, Aedes Albopictus	3.316	4.776	1383.21	0.197
Aedes Index, Vacant Lot	3.036	4.466	1356.23	0.040
Aedes Index, Aedes Albopictus	3.387	4.875	1385.11	0.156
Vacant Lot, Aedes Albopictus	3.054	4.436	1353.41	0.039
Maximal Temperature	3.630	5.283	1423.98	0.373
Aedes Index	3.398	4.920	1385.66	0.198
Vacant Lot	3.342	4.947	1396.64	0.162
Aedes Albopictus	3.393	4.881	1383.12	0.153
External Regressor	**Measurement Error**		**Ljung-Box Test**	
SARIMA model (0,1,2) (0,1,1) with external regressor	**MAE**	**RMSE**	**AIC**	**p-value**
Maximal Temperature, Aedes Index, Vacant Lot, Aedes Albopictus	3.051	4.451	1358.79	0.087
Maximal Temperature, Aedes Index, Vacant Lot	3.038	4.458	1357.40	0.077
Maximal Temperature, Vacant Lot, Aedes Albopictus	3.047	4.451	1356.81	0.086
Aedes Index, Vacant Lot, Aedes Albopictus	3.060	4.454	1357.04	0.084
Maximal Temperature, Aedes Index	3.336	4.869	1387.66	0.224
Maximal Temperature, Vacant Lot	3.349	4.944	1398.47	0.193
Maximal Temperature, Aedes Albopictus	3.309	4.794	1384.88	0.183
Aedes Index, Vacant Lot	3.043	4.490	1358.43	0.076
Aedes Index, Aedes Albopictus	3.462	5.001	1386.33	0.157
Vacant Lot, Aedes Albopictus	3.056	4.454	1355.07	0.084
Maximal Temperature	3.618	5.300	1424.93	0.346
Aedes Index	3.498	5.081	1387.33	0.197
Vacant Lot	3.340	4.961	1397.84	0.187
Aedes Albopictus	3.463	5.002	1384.33	0.157

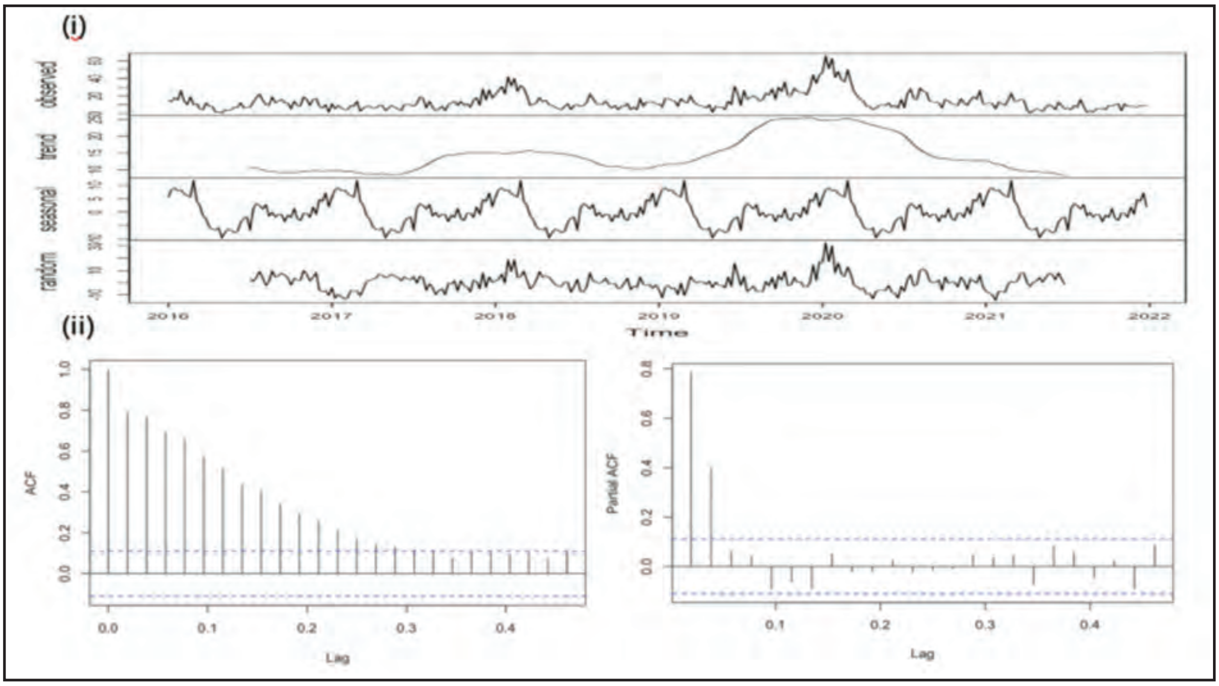

Fig. 1: (i)Decomposition of dengue cases reported years 2016 – 2021 (a) Time series of dengue cases in Kota Kinabalu 2016-2021 (b) Trend of dengue cases in Kota Kinabalu 2016-2021 (c) Seasonality of dengue cases in Kota Kinabalu 2016-2021 (d) Random of dengue cases in Kota Kinabalu 2016-2021
(ii) ACF plot of and PACF plot for time series of dengue cases in Kota Kinabalu from 2016 to 2021

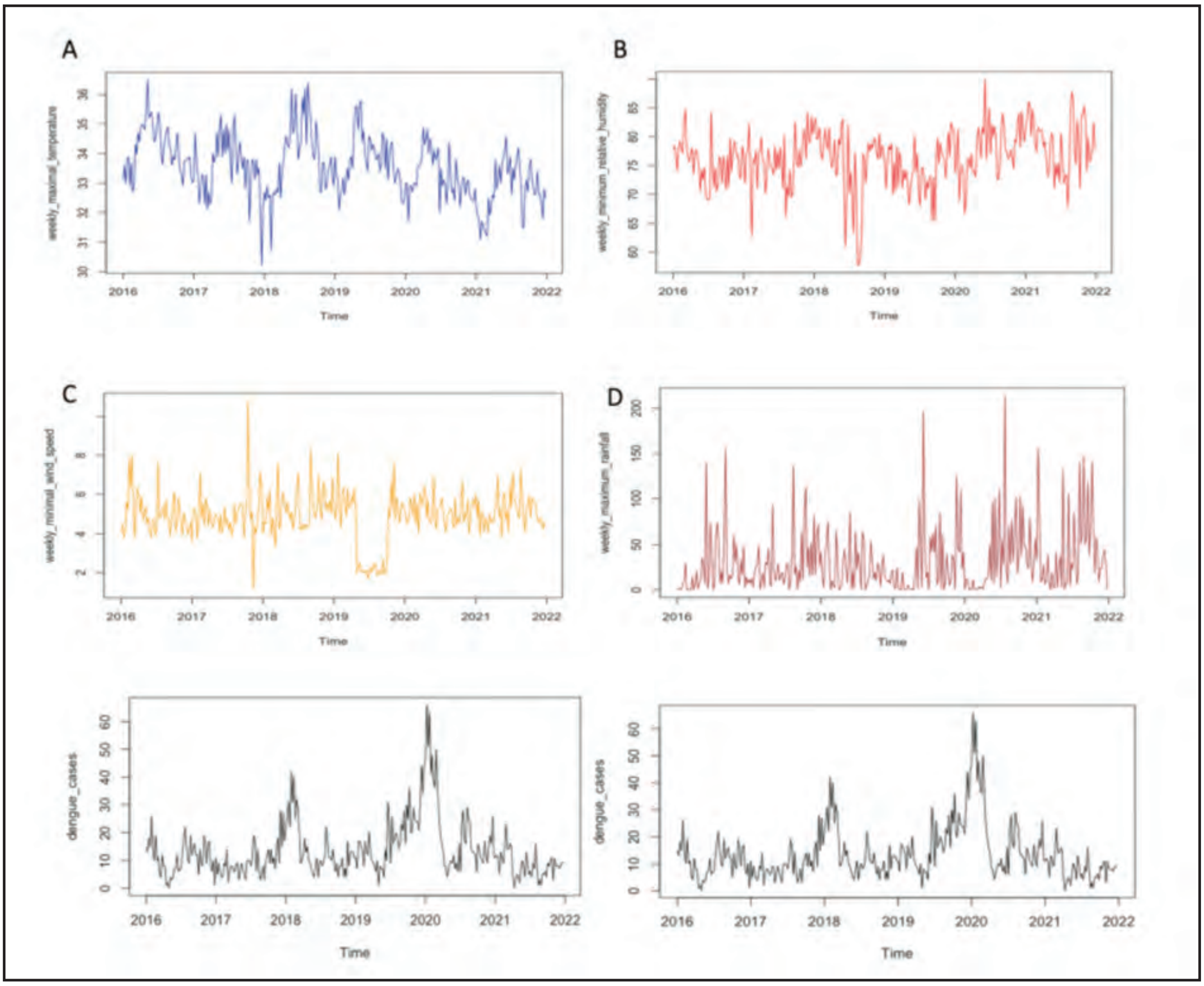

Fig. 2: Time Series of Dengue Cases in Kota Kinabalu Sabah years 2016 to 2021 and meteorological variables A) weekly maximum temperature (blue line); B) weekly minimum relative humidity (red line); C) weekly minimum wind speed (yellow line) and D) weekly maximum rainfall (brown line)

in the external regressor. SARIMA models (1,1,1) (0,1,1) and (1,1,2) (0,1,1) were constructed using the external regressors Aedes albopictus, Aedes index, vacant lot, and maximal temperature.

Among the 28 SARIMA models with external regressors, as shown in Table I, was determined to be SARIMA (1,1,1) (0,1,1) with the external regressors of maximum temperature, vacant lot, and Aedes Albopictus identified as the best model. This decision was based on the minimal measurement error, as indicated by the Mean Absolute Error (MAE) of 3.04, Root Mean Squared Error (RMSE) of 4.43, and Akaike Information Criterion (AIC) of 1354.82.

Although the MAE value of the model with external regressors (maximum temperature, vacant lot, and Aedes Index) was slightly higher than that of the SARIMA models (1,1,1) (0,1,1), the RMSE and AIC values were the lowest among all models. The p-value of the Ljung-Box test exceeded 0.05, indicating a lack of significant evidence to reject the null hypothesis. The residuals of the model exhibited an independent distribution, and no significant serial correlation was observed in the data. Additionally, the inclusion of these three external regressors has the potential to enhance the model.

The residual correlogram exhibited oscillations within the range of +10 to -10 during the early and middle months of 2018 and the initial months of 2021. Additionally, slight deviations surpassed these thresholds in both the positive and negative directions. The plot of the autocorrelation function (ACF) displays the residual data within the specified boundaries, with notable peaks observed at lags of 9, 38, 39, and 55. The residual value demonstrated a normal distribution, with a mean residual value of zero.

The figure presented in Fig.4 depicts the visualisation of the forecast for SARIMA models (1,1,1) (0,1,1) incorporating external regressors, such as maximum temperature, vacant lot, and Aedes Albopictus, along with the residual of the model. The observed line (red line) exhibited a consistent pattern of fluctuation, which was also observed in the prediction line (blue line) despite the latter being positioned at a higher level. The model demonstrated reliable

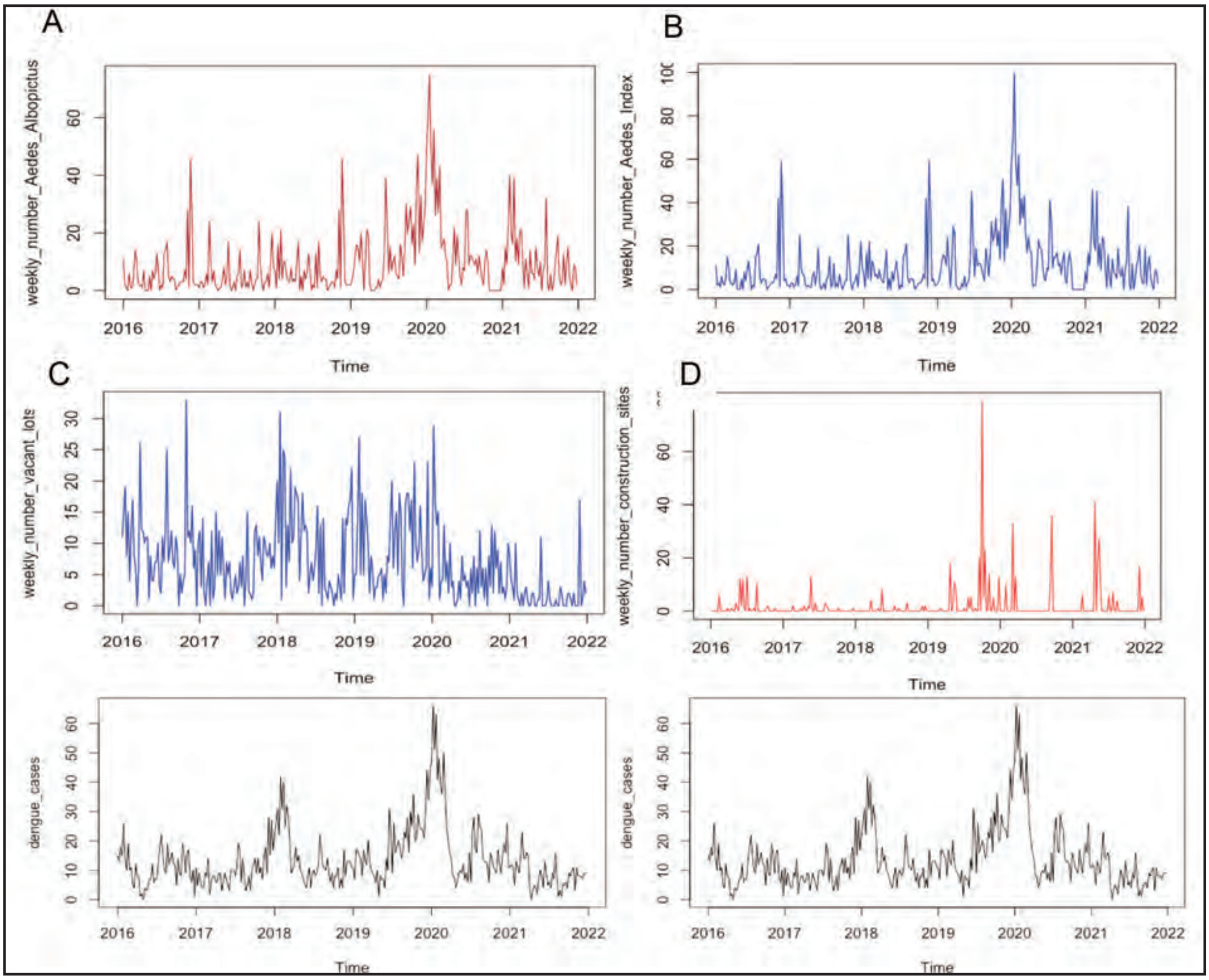

Fig. 3: Time Series of Dengue Cases in Kota Kinabalu Sabah years 2016 to 2021 and entomological variables A) weekly number of Aedes Albopictus (brown line); B) weekly number of Aedes Index (blue line); C) weekly number of vacant lot (blue line); D) weekly number of construction (red line)

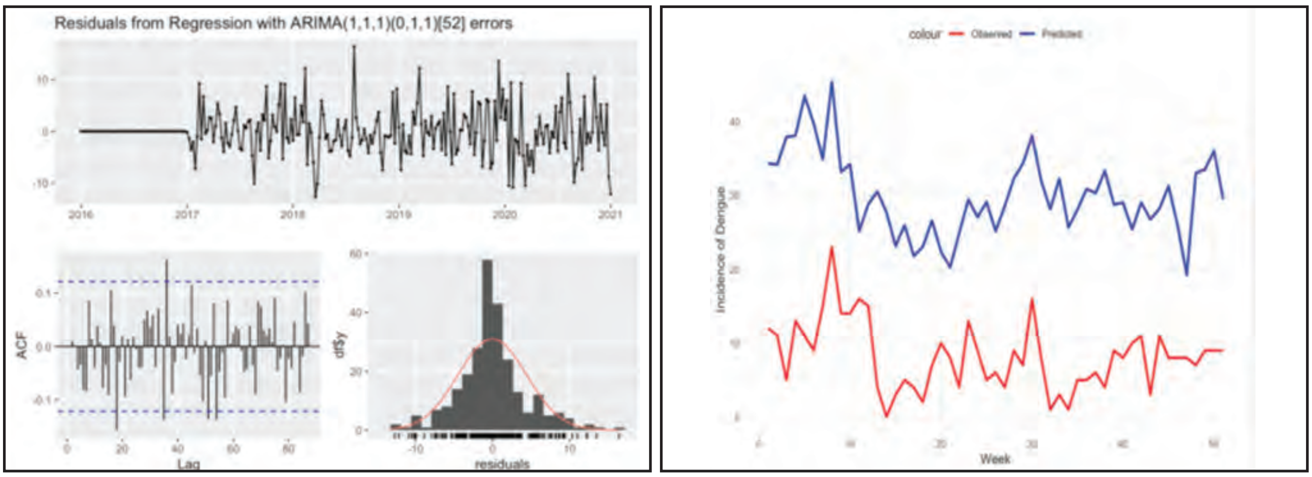

Fig. 4: Forecasting of the SARIMA model (1,1,1) (0,1,1) with external regressors of maximum temperature, vacant lot, and Aedes Albopictus and residual of the model

forecasting abilities, though it tended to slightly overestimate cases, likely due to the impact of COVID-19 on data patterns in 2021. Despite this, it showed potential as an early warning system for predicting dengue cases in Kota Kinabalu. Therefore, the SARIMA models (1,1,1) (0,1,1), which include external regressors such as maximum temperature, vacant lot, and Aedes albopictus, were found to be the most effective in predicting dengue incidence in Kota Kinabalu.

DISCUSSION

The optimal mean temperature range favourable for mosquito development is between 25°C and 27°C.[12] Despite this study, the mean temperature was 24–35 °C and exhibited an inverse correlation with dengue incidence. Higher temperatures in warm areas could potentially have detrimental impacts on the transmission range of viruses owing to reduced vector survival, reproduction, and immature habitats.[13]

Despite the mean minimal RH of 76% in this study, an interaction exists between humidity, temperature, and availability of water sources that facilitate the creation of suitable breeding conditions.[14] The influence of wind speed on dengue transmission in confined areas may not be substantial, as mosquitoes can locate appropriate breeding grounds and human hosts, even in the presence of moderate wind speeds 15 particularly in urban areas, such as Kota Kinabalu.

An elevated Aedes index typically correlates with a heightened probability of dengue occurrence. The same was observed in Sri Lanka and Vietnam.[16,17] The Aedes Index has a significant and strong relationship with dengue cases. The species Aedes Aegypti was the most captured because it exhibited endophilic behaviour, while Aedes Albopictus was predominantly exophilic and found in outdoor vegetation.[18] As a result, the health inspector found it easier to collect larvae outside the premises than indoors, where permission was required to conduct an inspection within the house.

Many construction sites have implemented mosquito prevention methods, and construction workers and site managers have often destroyed or controlled mosquito breeding grounds. Consistent monitoring, proper drainage, sealing or eliminating sources of standing water, and application of larvicidal treatments. These steps reduce the risk of dengue and reduce mosquito density.[19] The optimal microenvironments for A. aegypti growth can be identified by minimising exposure to sunlight, increasing and closer proximity to vegetation, and shaded and vegetated surroundings, which are frequently found in vacant lots.[20]

The SARIMA model (1,1,1) (0,1,1) with an external regressor was developed using the weekly maximal temperature, vacant lot, and A. albopictus, which provided the best-suited model in this study. These findings contradict those of previous studies conducted in various countries, where temperature and humidity have been consistently identified as strong predictors of the magnitude of dengue incidence.[21] These findings were dissimilar to the findings in Bangkok. The multivariate Poisson regression model for time series data indicates that a 1% increase in rainfall is associated with a corresponding increase of 3.3% in the incidence of dengue cases in Bangkok.[22] However, in this study, rainfall was not a significant predictor. This finding was like that of a study in Makassar, which stated humidity as a strong predictor.[23]

The accuracy of SARIMA models for forecasting in 2007 improved with the inclusion of climatic variables as external regressors. Temperature significantly influenced the model's ability to forecast dengue incidence.[24,25] However, humidity did not have a notable impact in the West Indies region.[24,26]

The differences in time-series forecasting findings between different studies can be attributed to several factors, including the choice of forecasting methods from simple statistical models such as ARIMA to more advanced approaches such as exponential smoothing methods, machine learning algorithms, and deep learning models such as Long Short-Term Memory (LSTM) networks.[27] The selection of the forecasting method can significantly affect the accuracy and performance of the predictions.

Time series data can exhibit diverse characteristics such as trends, seasonality, irregular fluctuations, or long-term dependencies. The presence or absence of these patterns can influence the choice and effectiveness of the forecasting models. For example, some models may perform well for data with clear patterns, whereas others may excel at capturing complex dependencies or handling irregular fluctuations. In addition, the size and quality of the datasets used for the analysis can affect the performance of the forecasting models.[28]

During this study, the COVID-19 pandemic introduced numerous challenges, including movement control orders (MCO) imposed throughout 2020. These disruptions likely affected individuals' access to hospitals and clinics, impacting the quality of collected samples, particularly for dengue notifications within the eDengue system. Furthermore, surveillance data may have been underestimated, affecting the accuracy of model predictions. The model's training on pre-COVID data may have contributed to deviations in forecast accuracy due to changes in data patterns during the pandemic. Future analyses should include an evaluation of model performance with post-COVID data as an additional sensitivity test to improve reliability.

CONCLUSION

The incidence of dengue is expected to increase in Kota Kinabalu. Hence, it is necessary for governmental authorities, non-governmental organisations, and policymakers to implement nationwide initiatives in conjunction with current policies to address the impending challenges arising from the prevalence of dengue. Therefore, community education campaigns should be conducted to enhance public awareness. These forecasting results provide valuable insights into the number of individuals who may contract dengue in the future. This information can be used to aid public health policymakers in predicting dengue outbreaks and implementing preventive measures. Additionally, these data can inform the development of appropriate policies and strategies to effectively manage and control future dengue outbreaks in Kota Kinabalu. The findings showed that temperature, entomological parameters, and number of vacant lots were correlated with the incidence of dengue in Kota Kinabalu. In this study, two Seasonal ARIMA models (1,1,1) (0,1,1)52 with external regressors with maximal temperature, vacant lots, and Aedes albopictus were the best-suited model to predict the future incidence of dengue fever cases in the forthcoming year, which is useful for health care administrators for better preparedness.

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ETHICAL STATEMENT

The study was approved by the Ethics Committee of University Malaysia Sabah also with approval code JKEtika 1/23 (30) and National Malaysian Research Registry (NMRR ID -23-00058- LZV(IIR)

CONFLICT OF INTEREST

The authors declare they have no conflicts of interest.

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