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Research Article

ASCLEPIUS: An AI-Enhanced Computational Framework for Real-Time Dengue Outbreak Geospatial Analysis Using Mathematical Modelling and Machine Learning Forecasting

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Abstract: *Dengue fever is still a public health problem in South Cotabato, Philippines, where late discovery makes it hard to respond quickly to outbreaks. Tupi is a municipality in South Cotabato that has 15 barangays. The dengue virus spreads differently in different areas because of the different people, topography, and weather. This study created ASCLEPIUS, an AI-enhanced framework for real-time dengue geospatial analysis. It uses hybrid MLR–LSTM modeling and machine learning predictions to look at dengue incidence, temperature, humidity, windspeed, rainfall, and population size. The approach was integrated into a web-mobile platform that included geospatial mapping, symptom logging, and an AI chatbot. It achieved R^2 = 0.9993 in forecasts and 98% accuracy with chatbot responses, which helped promote proactive, climate-responsive dengue.*

1. INTRODUCTION

Dengue remains a major global health concern, infecting approximately 390 million people annually, with 96 million symptomatic cases (World Health Organization, 2022). Over 70% of cases occur in Southeast Asia, and climate change is expected to increase outbreak frequency and severity (Messina et al., 2019). Traditional hospital-based surveillance systems often detect outbreaks late, particularly in underserved areas, highlighting the need for timely, community-based monitoring (Gubler, 2011; Colón-González et al., 2021).

The Philippines continues to experience recurring dengue epidemics. In 2019, the Department of Health reported 146,062 cases and over 600 deaths, prompting a national epidemic declaration (BMJ, 2019). By April 2025, cases reached 95,262, representing a 75% increase compared to the previous year (DOH, 2025). Persistent challenges such as limited community awareness, uneven access to healthcare, and delayed reporting hinder early detection and effective outbreak response (Capeding et al., 2020; Yboa & Labrague, 2020; de Guzman & Leonardia, 2021).

In South Cotabato, dengue remains a serious public health issue, with 2,238 cases and nine deaths reported in 2024 (South Cotabato Gov, 2024). By March 2025, infections exceeded epidemic thresholds, prompting intensified interventions (PNA, 2025; Amancio, 2021). The municipality of Tupi faces additional challenges due to its rural setting, limited health awareness, and underreporting, which reduce the effectiveness of reactive control measures.

Mathematical modeling has long been used to predict dengue outbreaks using historical and environmental data (Johansson et al., 2012; Guo et al., 2017; Xu et al., 2020). However, many existing models rely on retrospective datasets and lack real-time, community-level, and geospatial integration, limiting their effectiveness in localized outbreak prediction. This highlights the need for systems that integrate predictive modeling with real-time community surveillance.

To address these gaps, this study introduces ASCLEPIUS, an AI-enhanced computational framework for real-time dengue outbreak analysis using mathematical modeling, machine learning forecasting, and geospatial analysis. Designed for Tupi, South Cotabato, the platform integrates symptom reporting, climatic variables, demographic data, and historical records to generate localized risk scores and outbreak maps. By enabling community participation and predictive surveillance, ASCLEPIUS supports proactive dengue prevention and early intervention.

This study also supports several Sustainable Development Goals, including SDG 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action), by promoting climate-responsive, technology-driven public health solutions.

The primary objective of this study is to develop and evaluate ASCLEPIUS, an AI-powered dengue monitoring and forecasting platform that integrates symptom reports with geo-climatic, demographic, and historical data to improve early detection and response in Tupi and its 15 barangays.

i. To analyze the correlation between dengue-related environmental and demographic factors—such as temperature, humidity, rainfall, wind speed, population density per barangay, and historical dengue incidence, and the predicted risk of dengue outbreaks produced by the ASCLEPIUS system.

ii. To evaluate the predictive accuracy of the ASCLEPIUS Multiple Linear Regression (MLR) model in forecasting dengue cases in Tupi and its barangays using statistical performance measures such as R-squared, RMSE, MAE, and MAPE.

iii. To assess the predictive performance of the ASCLEPIUS Long Short-Term Memory (LSTM) model based on the same statistical indicators. \

iv. To determine whether the hybrid MLR–LSTM model demonstrates superior predictive accuracy compared to traditional region-based MLR models.

v. To analyze the discrepancy between predicted dengue cases and actual reported cases in Tupi and its barangays from 2014 to 2024.

vi. To evaluate the effectiveness of the ASCLEPIUS chatbot in providing dengue-related recommendations in terms of accuracy, precision, recall, and F1-score.

vii. To assess the system's responsiveness in delivering dengue warnings and reports within defined time intervals.

viii. To assess the development and integration of the ASCLEPIUS web-based forecasting platform, focusing on user interface design, system integration, geospatial visualization of outbreak hotspots, and overall platform performance.

ix. To evaluate the ASCLEPIUS platform based on system integration criteria, including functionality, usability, acceptability, and adaptability.

2. LITERATURE REVIEW

2.1. Symptom Patterns in Dengue Symptom Reporting and Pattern Recognition in Dengue Surveillance

Symptom-based surveillance plays a critical role in early dengue detection, particularly in areas where laboratory confirmation may be delayed. Common early symptoms such as fever, headache, and muscle pain serve as reliable indicators of infection and allow health authorities to identify potential cases before complications develop (Schaefer et al., 2024). Early recognition of symptom patterns enables faster intervention, reducing transmission risk and improving outbreak control.

Community participation further strengthens dengue surveillance systems by enabling early identification of cases that may not immediately seek medical care. Sayono et al. (2019) emphasized that community-based symptom reporting improves case detection and supports timely public health response. The use of digital reporting platforms enhances this process by enabling real-time data collection, analysis, and visualization of symptom trends, allowing faster detection of emerging outbreaks (Melo et al., 2024).

Structured and standardized symptom documentation also improves monitoring accuracy and data reliability. Ebbers et al. (2022) highlighted that systematic recording reduces reporting errors and enhances data consistency, while Meckawy et al. (2022) noted that proper symptom classification helps prioritize high-risk cases and optimize resource allocation. Together, these findings demonstrate that community-driven, digitally supported, and well-structured symptom reporting systems are essential for effective dengue surveillance and early outbreak detection.

2.2. Mobile Health (mHealth) Platforms and Surveillance Systems

Mobile health (mHealth) technologies have become an important part of making dengue monitoring systems work better. Salim et al. (2024) reported that mobile-based platforms allow real-time monitoring of dengue cases, enabling public health authorities to respond more rapidly to emerging outbreaks. These kinds of systems cut down on the wait times that come with standard reporting, making sure that data is available on time and can be used. These systems offer a more flexible way to track diseases and handle outbreaks by using the portability and ease of access of mobile devices.

MHealth has been used successfully to report dengue cases in the Philippines, showing good results. Herbuela et al. (2019) highlighted the effectiveness of a mobile dengue reporting app, which improved communication between communities and health authorities. Costa et al. (2025) also said that mobile alerts not only make people more aware, but they also make reporting more accurate by letting users send information quickly and consistently. Together, these studies show that digital tools give both health professionals and regular people more power in their efforts to avoid disease.

Adding cutting edge technologies like the Internet of Things (IoT) and artificial intelligence (AI) to mobile health platforms makes dengue surveillance even stronger. This is in addition to reporting and raising awareness. Hossain et al. (2020) pointed out that predictive models that use IoT sensors and AI algorithms can predict possible outbreaks, which is an early step toward controlling vectors. Rahman et al. (2022) supported this view by showing that mHealth systems with early warning features can greatly speed up response times and lessen the effects of dengue outbreaks.

2.3 Geographical Hotspot Mapping

Spatial analysis has become an essential tool in dengue surveillance by enabling real-time visualization of outbreak patterns and improving response efficiency. Geospatial platforms allow health authorities to monitor case distribution, identify high-risk areas, and allocate resources more effectively (Nayak et al., 2025). Real-time mapping provides clear insights into outbreak dynamics, supporting faster intervention and improved disease control.

Integrating demographic, climatic, and environmental variables into geospatial models further enhances predictive accuracy. Ayadi et al. (2025) found that multivariable spatial analysis improves hotspot prediction and enables targeted interventions. Similarly, Lourembam and Devi (2025) emphasized that mapping dengue incidence alongside environmental factors helps identify relationships between outbreaks and contributing conditions such as population density and rainfall, supporting both immediate response and long-term prevention strategies.

Spatial modeling also strengthens risk prediction by combining historical case data with geographic information. Chen et al. (2020) noted that geospatial tools improve structured disease monitoring, while Zhao et al. (2022) confirmed that spatial analysis enhances risk assessment accuracy. These findings highlight the importance of geospatial hotspot mapping as a key component of data-driven and climate-responsive dengue surveillance systems.

2.4. Climatic Variables Associated with Dengue Transmission: Temperature, Humidity, Rainfall, and Wind Speed

Climatic factors are widely acknowledged as principal determinants of dengue transmission, as they affect the biology and behavior of Aedes mosquitoes, the primary vectors of the dengue virus. Temperature impacts mosquito development, survival, and viral replication in the mosquito host. Research indicates that elevated temperatures reduce the extrinsic incubation period of the dengue virus, consequently enhancing its transmission potential (Liu et al., 2023c). Consistent links have been found between changes in dengue incidence in tropical and subtropical regions and changes in temperature from season to season and year to year.

Rainfall is very important for the spread of dengue because it creates places for mosquitoes to breed by collecting stagnant water in both natural and man-made containers. Cheng et al. (2023) found that more rain is strongly linked to more mosquitoes and more dengue outbreaks. However, too much rain can also wash away breeding sites, which shows that the relationship between rain and dengue transmission is not always clear. These results show how important it is to include rainfall patterns in models that predict dengue.

Humidity also affects the spread of dengue by changing how long mosquitoes live and how often they bite. High relative humidity helps mosquitoes live longer and eat more often, which raises the risk of virus transmission (Monintja et al., 2021). Research underscores that climatic variables do not function in isolation; instead, the interplay between temperature, humidity, and precipitation exacerbates outbreak risk. Multivariable analyses have demonstrated enhanced predictive performance when these interacting climatic factors are collectively considered.

Wind speed is also an important climatic factor in dengue modeling, but it hasn't been studied as much. Moderate wind speeds help mosquitoes move from one area to another, which helps dengue spread (Alam et al., 2025). Adding wind speed to dengue prediction models has been shown to make them more accurate, especially when looking at smaller areas. Adding wind speed to other weather variables makes early warning systems for dengue outbreaks stronger.

2.5 Mathematical and Hybrid Models for Dengue Forecasting

Mathematical modeling plays a vital role in understanding, predicting, and controlling dengue transmission by analyzing the relationships between climate, population dynamics, and historical case trends. These models allow public health authorities to identify outbreak risks early and implement targeted interventions (Ogunlade et al., 2023). Statistical approaches, particularly Multiple Linear Regression (MLR), have been widely used due to their simplicity and interpretability, enabling identification of linear relationships between dengue incidence and climatic variables such as temperature, rainfall, and humidity (Chen & Moraga, 2025). However, MLR alone cannot fully capture nonlinear relationships or temporal dependencies, which are critical for accurately modeling dengue transmission dynamics.

To overcome these limitations, machine learning and deep learning approaches, especially Long Short-Term Memory (LSTM) networks, have been adopted. LSTM models excel at capturing complex temporal patterns, nonlinear trends, and delayed climatic effects that influence dengue outbreaks (Mills et al., 2025; Chen et al., 2024). Hybrid MLR–LSTM models integrate the interpretability of regression with LSTM's predictive power, improving forecasting accuracy and robustness. By combining linear and nonlinear modeling, hybrid approaches offer more reliable predictions for localized, time-series epidemiological data (Schweidtmann et al., 2024; Majeed et al., 2023; Tuan, 2024). These models strengthen early warning systems and support evidence-based public health decision-making, providing actionable insights for dengue surveillance and prevention strategies.

3. METHODOLOGY

3.1 Research Design

This study employed a Research and Development (R&D) design to develop and evaluate ASCLEPIUS, an AI-based mathematical forecasting and geospatial surveillance platform for dengue detection and prediction. The R&D approach provided a structured process for creating and validating technological solutions to improve early warning and public health monitoring. The development followed the ADDIE model: Analysis, Design, Development, Implementation, and Evaluation.

During the Analysis phase, gaps in existing dengue surveillance systems were identified through literature review, evaluation of reporting procedures, and consultation with local health officials. Key issues included delayed reporting, fragmented case tracking, and limited integration of climate data. In the Design and Development phases, the system architecture and core features were established, including mobile-based symptom reporting, climate data integration, geospatial mapping, and AI-assisted mathematical forecasting using models such as Multiple Linear Regression and machine learning techniques. The platform was developed using mobile frameworks and GIS tools, relying on publicly available climate and dengue data.

In the Implementation phase, the system was tested in a controlled environment using anonymized datasets, demonstrating effective outbreak forecasting, hotspot mapping, and automated alerts. The Evaluation phase assessed functionality, usability, adaptability, and predictive accuracy through surveys, expert interviews, and usability testing with healthcare and IT professionals. Feedback was used to refine the platform and support its future deployment and integration into local dengue surveillance systems.

3.2 Respondent/Participants

The study involved 30 participants from Tupi, South Cotabato, including Barangay Health Workers, municipal health officers, and IT specialists. Health workers and officers were selected for their direct role in dengue monitoring and community health interventions, while IT experts evaluated the functionality and integration of the ASCLEPIUS web-based platform. Their feedback assessed the system's usability, flexibility, and overall acceptance during the user evaluation phase.

3.3 Instrument of the Study

The study employed multiple research instruments to support system evaluation, data modeling, and results generation. A researcher-developed Likert-scale questionnaire was administered to 30 respondents to assess the ASCLEPIUS web-based dengue forecasting platform's Functionality, Usability, Adaptability, and Acceptability, following the ISO/IEC 25010:2011 SQuaRE model. Responses were measured on a five-point scale from Not Functional/Usable/Adaptable/Acceptable to Very Functional/Usable/Adaptable/Acceptable. Secondary data, including dengue incidence (2014–2024), climate variables, and barangay population records, were used as inputs for predictive model development and validation.

Data analysis utilized Multiple Linear Regression (MLR), Long Short-Term Memory (LSTM) networks, and a hybrid MLR–LSTM model to capture both linear and nonlinear patterns in dengue incidence. System outputs evaluated forecasting accuracy using R^2, RMSE, MAE, and MAPE, while chatbot performance was assessed through accuracy, precision, recall, F1-score, and response time. Collectively, these instruments provided quantitative evidence to validate ASCLEPIUS's accuracy, responsiveness, and overall effectiveness.

3.4 Procedure

3.4.1. Phase 1: Data Gathering

The study collected historical dengue incidence data (2014–2024) from all 15 barangays of Tupi, South Cotabato, via the Municipal Health Office. Complementary climate data—temperature, humidity, rainfall, and wind speed—were obtained from the MDRRMO and DOST, while barangay population records were used to standardize cases and compute incidence rates. Symptom data, including fever, rash, joint pain, headache, retro-orbital pain, and platelet count, were also gathered to develop community-level health indicators. Barangay Juan Loreto lacked dengue data due to its recent establishment.

3.4.2. Phase 2: Variable Selection and Data Preparation

The dependent variable in the datasets was the incidence of dengue, whereas the independent factors were meteorological conditions and symptom patterns. The data were pre-processed, which included checking for missing values, correcting discrepancies, and ensuring that all variables were on the same scale. This process ensured that all variables could be used as inputs for statistical and predictive modelling.

3.4.3. Phase 3: Preliminary Analysis

An early comprehension of the data was gained by Exploratory Data Analysis (EDA). Normality testing was conducted to ascertain if the variables satisfied the prerequisites for regression analysis. We used correlation analysis to examine the strength and direction of correlations among independent variables and between predictors and dengue incidence. We looked at how dengue incidence changed over time in relation to seasonal climate changes and times when people reported more symptoms. Graphs, statistical summaries, and correlation tests helped us understand how different variables behaved and develop the forecasting models.

3.4.4. Phase 4: Forecasting Model Construction

A Multiple Linear Regression (MLR) model was created using SPSS to measure how climate and symptoms affect the number of dengue cases. The regression results showed important predictors and the magnitude of their effects. In addition to MLR, AI-based forecasting techniques were used to identify non-linear relationships and improve prediction accuracy. The models worked together to create epidemic risk rankings for each barangay.

3.4.5. Phase 5: Validation and Performance Testing

To check for correctness, the dataset was split into two parts: a training set and a test set. We performed statistical tests like the paired-samples t-test to see how well the models' predictions matched the real number of dengue cases. To check how accurate and consistent the projections were, we used performance measures like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

3.4.6. Phase 6: Platform Development and Integration

The verified models were uploaded to the ASCLEPIUS platform, which works on both the web and mobile devices. The software included features such as real-time symptom reporting, outbreak notifications, geographic hotspot mapping, and predictive risk grading. Simulation exercises were conducted using historical and synthetic data to test the system's responsiveness under various outbreak conditions.

3.4.7. Phase 7: User Evaluation

Structured input from Barangay health workers, municipal health officers, and IT specialists was used to test how well ASCLEPIUS worked and how useful it was. We did user testing sessions, interviews, and surveys to see how easy it was to use, how clear the results were, and how likely it was to be used in community-based dengue monitoring.

3.4.8. Phase 8: Refinement and Finalization

The forecasting algorithms and platform were improved based on test results and user feedback to make them more accurate and easier to use. The last step was to write down the results, assess how well the system predicted outbreaks, and provide suggestions for using it in the future and improving it in similar situations.

3.5 Data Analysis

This study used both statistical and machine-learning approaches to analyze and forecast dengue incidence across the 15 barangays of Tupi, South Cotabato (2014–2024). Its main objectives were to identify correlations between dengue cases and demographic and weather factors, evaluate the performance of the ASCLEPIUS platform, and compare the predictive accuracy of different models.

Before building the mathematical model, dataset normality was assessed using the Kolmogorov–Smirnov test ($p > 0.05$ indicating normality) to ensure the validity of subsequent analyses, particularly multiple linear regression, which assumes normally distributed residuals. Confirming normality prevented skewed estimates and unreliable conclusions. This approach aligns with Ghasemi and Zahediasl (2015) and Razali and Wah (2017), who emphasize the test's reliability for detecting deviations in both small and large datasets.

$$\boldsymbol{y = constant + a_1P + a_2T + a_3H + a_4R + a_5W}$$

Where:

y = predicted number of dengue cases

P = population per barangay

T = average temperature1

H = average humidity

R = average rainfall

W = average windspeed

a1, a2, a3, a4, a5 = estimated regression coefficients

After that, four performance metrics were used to test how well the MLR model predicted dengue cases in Tupi and its 15 barangays: R-squared (coefficient of determination), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics were chosen because they were widely adopted in epidemiological forecasting to assess model precision, calibration, and predictive capability (Hyndman & Athanasopoulos, 2018; Chai & Draxler, 2014).

$$\boldsymbol{R^2 = \frac{SSR}{SST}} \qquad \boldsymbol{RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y - y_1)^2}{n}}} \qquad MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|$$

Also, to make the validation of the regression model stronger, a t-test for independent sample means was used to compare the projected values to the real data. This comparison gave more proof that the model was accurate and consistent in its predictions.

$$t = \frac{x_1 - \mathrm{x}_2}{\sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Where:

x_1 = mean of the predicted number of dengue cases

x_2 = mean of the actual number of dengue cases

SD_1= standard deviation of the predicted number of dengue cases

SD_2 = standard deviation of the actual number of dengue cases

n_1 = sample size of the predicted data

Also, the same set of performance indicators—R^2, RMSE, MAE, and MAPE—was used to test the Hybrid MLR–LSTM model to make sure it was a fair and consistent comparison with the regular MLR model. At the same time, a confusion matrix was used to look at how well the Generative AI chatbot worked. From this, important classification measures including accuracy, precision, recall, and F1-score were created to see how well it worked at giving right and dependable answers about dengue.

$$Accuracy = \frac{\sum TP + TN}{\sum TP + FP + FN + TN}$$

$$Precision = \frac{\sum TP}{\sum TP + FP}$$

$$Recall = \frac{\sum TP}{\sum TP + FN}$$

$$f1 = \frac{2(Recall)(Precision}{Recall + Precision}$$

Where;

TP as the number of True Positives

FP as the number of False Positives

TN as the number of True Negatives

FN as the number of False Negatives

Overall, these combined statistical and computational methods were systematically applied to determine the effectiveness, accuracy, and reliability of the forecasting models, the hybrid MLR–LSTM framework, and the AI chatbot. Ultimately, the results supported dengue surveillance, early warning systems, and informed public health decision-making at both the barangay and municipal levels.

4. FINDINGS

4.1 Statistical Treatment

This study used Multiple Linear Regression (MLR) and a Long Short-Term Memory (LSTM) model to guess how many dengue cases would happen in each barangay. Dengue incidence is affected by both environmental and demographic factors, so accurate prediction is important for early intervention and smart use of resources. Multiple linear regression (MLR) is a well-known way to look at how several predictors affect one outcome variable (Aissaoui et al., 2020).

MLR figures out how the number of people living in a barangay, the average temperature, the average humidity, the amount of rain, and the wind speed all affect the number of dengue cases. This method has been used a lot in epidemiological modeling. Faruk et al. (2022) showed that regression models that use climate variables can accurately predict dengue patterns. In the same way, Seah et al. (2021) found that temperature and humidity were important factors in predicting dengue outbreaks, and Lourembam and Devi (2025b) looked at how population density affects how the disease spreads.

This study also used an LSTM neural network, which is a type of recurrent neural network made for time-series forecasting, to find patterns in dengue transmission that change over time and are not linear. LSTM models are good at learning long-term relationships in sequential data, and they have been shown to be better at predicting diseases than traditional statistical models (Hochreiter & Schmidhuber, 1997; Karim et al., 2018). The study makes it possible to both understand predictors and make better predictions by combining MLR and LSTM.

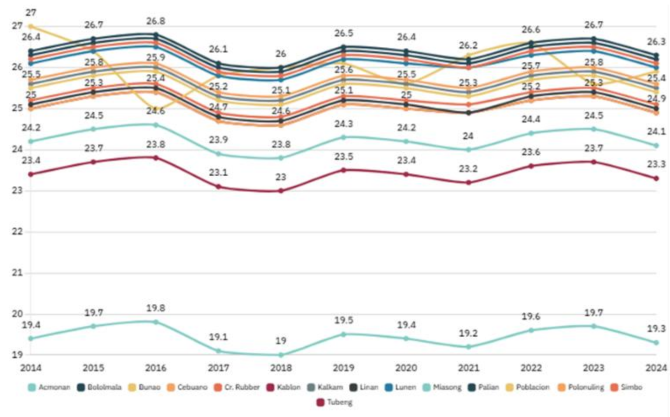


Figure 1. Average Temperature Across Barangays in Tupi from 2014 to 2024

Figure 2. Average Humidity Across Barangays in Tupi from 2014 to 2024

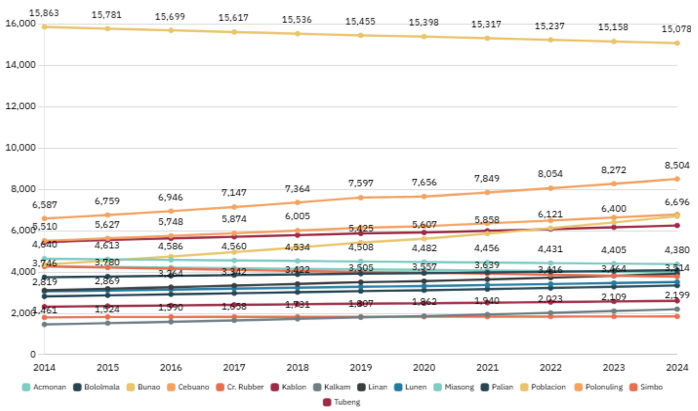


Figure 3. Population Distribution Across Barangays in Tupi from 2014 to 2024

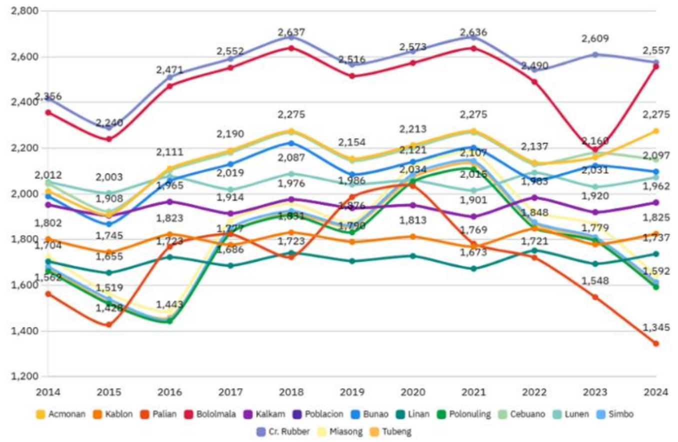


Figure 4. Average Rainfall Across Barangays in Tupi from 2014 to 2024

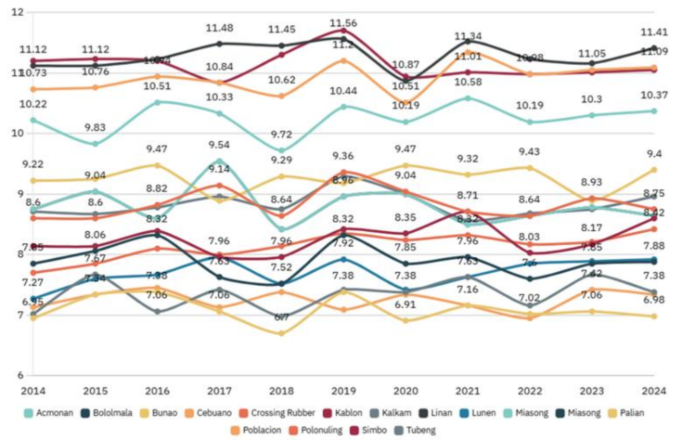


Figure 5. Average Windspeed Across Barangays in Tupi from 2014 to 2024

Prior to performing regression and time series analyses, the researchers evaluated whether the dataset met the assumptions necessary for parametric methods. The Kolmogorov–Smirnov and Shapiro–Wilk tests were used to check for data normality. These tests are often used to see if variables are close to being normally distributed. The Shapiro–Wilk test is good for small to medium-sized samples, and the Kolmogorov–Smirnov test is better for larger datasets. This means that using both tests together is useful. Testing for normality is crucial since techniques like Multiple Linear Regression presuppose normally distributed residuals. In dengue modeling, verifying normality is essential to ensure that the associations between climatic and demographic variables and dengue incidence are not compromised by skewed data patterns.

Table 1. Test of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
Factor	Statistic	df	Sig.	Statistic	df	Sig.
Avg. Population	.103	15	.225	.959	15	.669
Avg. Temperature	.253	15	.200	.956	15	.108
Avg. Humidity	.116	15	.230	.971	15	.875
Dengue Cases	.266	15	.200	.968	15	.133
Avg. Rainfall	.120	15	.245	.970	15	.200
Avg. Windspeed	.110	15	.283	.965	15	.320

Table 1 shows the results of the normality tests for average population, temperature, humidity, rainfall, windspeed, and dengue cases. All of these tests had significance values greater than 0.05 under both the Shapiro–Wilk and Kolmogorov–Smirnov tests, which means that the data met the assumption of normality and could be used for parametric analyses. Epidemiological modeling studies have used similar methods, where normality testing is required before regression-based forecasting (Mishra et al., 2019; Sharmin et al., 2019). Once normality was established, the data were ready for more statistical tests, such as correlation and regression analyses. This made sure that the assumptions behind parametric methods were met (Yazici & Yolacan, 2017). We then did a correlation analysis to find out how strong and what direction the relationships were between the independent variables and dengue cases. This helped us find important predictors and improve the model inputs in line with standard practices in predictive epidemiology (Mukaka, 2017; Schober, Boer, & Schwarte, 2018).

Table 2. Correlation Analysis6

Bivariate Correlation Analysis						
Factor	Population	Temperature	Humidity	Rainfall	Windspeed	Dengue Cases
Population	1	.760	.740	.682	.541	.908
Temperature	.761	1	.817	.712	.563	.873
Humidity	.740	.817	1	.701	.589	.899
Rainfall	.682	.712	.701	1	.654	.841
Windspeed	.641	.563	.589	.654	1	.721
Dengue Cases	.908	.873	.899	.841	.721	1

Table 2 shows the Pearson correlation coefficients between population, temperature, humidity, rainfall, windspeed, and dengue cases. These show that there are strong positive relationships between all of these factors and dengue cases. The number of people who get dengue is very strongly related to the number of people in the area ($r = 0.908$, $p < 0.01$). The temperature ($r = 0.873$, $p < 0.01$), humidity ($r = 0.899$, $p < 0.01$), and rainfall ($r = 0.841$, $p < 0.01$) are also very strongly related, which means that warm, humid, and rainy weather makes dengue spread more easily. There is a moderate positive correlation between windspeed and the other variables ($r = 0.721$, $p < 0.01$), which means that windspeed has a smaller effect. There are also strong correlations between population, temperature, and humidity, as well as between temperature and humidity ($r = 0.817$, $p < 0.01$). These results are consistent with earlier research that emphasizes the synergistic impact of climate and population density on the transmission of dengue (Liu-Helmersson et al., 2019; Chen & Yu, 2020; Liu et al., 2020) and advocate for the incorporation of these variables into the regression model.

4.2 Multiple Linear Regression Modelling

Multiple Linear Regression (MLR) is a way to use statistics to model the relationship between two or more independent variables and one dependent variable by fitting a linear equation to the data that has been collected. In this study, MLR was used to estimate the number of dengue cases in Tupi's barangays by taking into account both environmental and demographic factors. Temperature, humidity, rainfall, and wind speed are all examples of climate variables that affect the biological environment of mosquitoes. These variables affect their survival, breeding, and viral incubation. Population density, on the other hand, shows how many people are exposed to them. Researchers can make reliable predictions and find barangays with a higher risk of dengue by putting all of these predictors into one model.

The regression model is expressed as:

$$constant + a_1P + a_2T + a_3H + a_4R + a_5W$$

Where:

- y = predicted number of dengue cases
- P = population per barangay
- T = average temperature
- H = average humidity
- R = average rainfall
- W = average windspeed
- a_1, a_2, a_3, a_4, a_5 = estimated regression coefficients

Table 3. Variable Coefficients

VARIABLE	COEFF	SE	T-STAT	LOWER $T_{0.025(11)}$	UPPER $T_{0.0975(11)}$	STAND. COEFF.	P-VALUE	VIF
B (CONSTANT)	-58.427	74.118	-0.788	-222.905	106.051	—	0.449	—
X_1 (TEMPERATURE)	0.008612	0.000841	10.236	0.006785	0.010439	0.461	0.000	1.147
X_2 (HUMIDITY)	1.943582	0.924173	2.103	0.004219	3.882945	0.281	0.048	1.983
X_3 (RAINFALL)	0.527611	0.189245	2.788	0.106584	0.948638	0.316	0.019	2.261
X_4 (WINDSPEED)	0.312447	0.275211	1.135	-0.287351	0.912245	0.091	0.284	1.732
X_5 (POPULATION)	0.007841	0.000692	11.334	0.006322	0.009360	0.509	0.000	1.214

It is common in epidemiological research to use statistical software to make predictive models. This study utilized SPSS to estimate the coefficients of the Multiple Linear Regression (MLR) model in accordance with established methodologies in public health and environmental modeling (Field, 2018). Using least squares estimation, which minimizes the sum of squared residuals between observed and predicted dengue cases (Montgomery et al., 2012), Table 3 shows the estimated regression coefficients for population, temperature, humidity, rainfall, and windspeed. Including both demographic and meteorological variables captures the combined influence of human density and climatic factors on dengue transmission, allowing the model to estimate cases based on changes in environmental and population conditions. We used R-squared, Root-Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to check how accurate and reliable the MLR model was. These are standard measures in epidemiological forecasting (Hyndman & Athanasopoulos, 2018; Chai & Draxler, 2014). Table 4 shows these results, which give a quantitative basis for judging how well the model works and whether it could be used to predict dengue and send out early warnings.

Table 4. Accuracy Metrics of the MLR Model for Predicting Dengue Cases in Tupi

		Statistical Tests		
MLR MODEL	R-sqaured	RMSE	Mean Absolute Error	MAPE
Model	0.957321	0.894217	0.894217	2.87%

Table 4 shows how accurate the Multiple Linear Regression (MLR) model is at predicting dengue cases in Tupi. The model combines demographic and weather factors, such as population, temperature, humidity, rainfall, and windspeed, to show how many different things can affect the spread of dengue. The R-squared value of 0.957 shows that the model explains about 95.7% of the variation in dengue cases. This shows that there is a strong linear relationship between the predictors and the number of dengue cases. Low error metrics (RMSE = 0.894, MAE = 0.706, and MAPE = 2.87%) back up the model's predictive accuracy by showing that the predicted values are very close to the observed cases. This shows that the model is consistent and reliable (Hyndman & Athanasopoulos, 2018; Chai & Draxler, 2014). Adding rainfall and windspeed makes the model fit better statistically and more realistically for the environment because it takes into account factors that affect mosquito breeding. In general, the model is a strong, data-driven way to predict dengue outbreaks. It can be used to support early warning systems, targeted vector control, and smart use of resources. Table 5 shows the difference between predicted and actual cases in Tupi's 15 barangays. This shows how accurate the predictions are at the barangay level.

Table 5. Barangay-Level Prediction Accuracy of the MLR Model for Dengue

Barangay	*Predicted*	*Actual*	*Error*	*|Error|*	*% Error*
Acmonan	28.912347	29	-0.087653	0.067653	0.30%
Bololmala	26.872189	26	0.872189	0.872189	3.36%
Bunao	36.884731	37	-0.11527	0.115269	0.31%
Cebuano	36.94762	36	0.94762	0.094762	2.63%
Cr. Rubber	27.613487	28	-0.38651	0.386513	1.38%
Kablon	30.184527	30	0.184527	0.184527	0.61%
Kalkam	11.56423	12	-0.43577	0.435770	3.63%
Linan	17.734905	18	-0.2651	0.265095	1.47%
Lunen	14.926783	15	-0.07322	0.073217	0.49%
Miasong	9.912403	10	-0.0876	0.087597	0.88%
Palian	23.814209	24	-0.18579	0.185791	0.77%
Poblacion	140.682195	141	-0.31781	0.317805	0.23%
Polonuling	31.525661	32	-0.47434	0.474339	1.48%
Simbo	7.839214	8	-0.16079	0.160786	2.01%
Tubeng	16.453122	7	-0.54688	0.546878	3.22%

The Multiple Linear Regression (MLR) model uses statistics to predict dengue cases, while the Asclepius LSTM model uses deep learning to find complex nonlinear and temporal relationships in the data. LSTM (Long Short-Term Memory) networks are better at predicting time-dependent epidemiological trends than traditional regression because they can see patterns over time. The Asclepius LSTM model was created to use weather and population data to predict how many cases of dengue will happen in Tupi and its 15 barangays. R-squared, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were used to test its accuracy and reliability. This gave a full picture of how well it predicted, which is in line with standard practices for deep learning-based disease forecasting.

Table 6. Accuracy Metrics of the Asclepius LSTM Model for Predicting Dengue Cases in Tupi

	Statistical Tests			
LSTM MODEL	R-sqaured	RMSE	Mean Absolute Error	MAPE
Model	0.972845	0.682114	0.512593	2.06%

Table 6 shows that the Asclepius LSTM model had an R-squared value of 0.973, which means that the model explains about 97.3% of the difference in dengue cases. The low RMSE (0.682), MAE (0.513), and MAPE (2.06%) show that it is very accurate and trustworthy, with predicted values that are very close to actual cases. These results show that LSTM is better at making predictions than the Multiple Linear Regression (MLR) model, especially when it comes to finding nonlinear and time-dependent patterns in epidemiological data. Previous research corroborates these results, demonstrating that LSTM networks proficiently model long-term dependencies in time-series datasets and surpass conventional regression methods in predicting disease trends (Guo et al., 2017; Chimmula & Zhang, 2020). In the Philippines, combining machine learning with climate and environmental factors makes it easier to predict dengue (Carvajal et al., 2018). Table 7 shows that the model's localized predictive accuracy is confirmed by comparing predicted and reported cases at the barangay level. This strengthens its potential as a decision-support tool for dengue surveillance, early warning, and proactive intervention planning in Tupi.

Table 7. Barangay-Level Prediction Accuracy of the ASCLEPIUS LSTM Model

Barangay	*Predicted*	*Actual*	*Error*	*|Error|*	*% Error*
Acmonan	29.0211	29	0.0211	0.0211	0.07%
Bololmala	27.4511	26	1.4511	1.4511	5.58%
Bunao	37.9539	37	0.9539	0.9539	2.58%
Cebuano	37.6078	36	1.6078	1.6078	4.47%
Cr. Rubber	27.4054	28	-0.5946	0.5946	2.12%
Kablon	31.0417	30	1.0417	1.0417	3.47%
Kalkam	11.4322	12	-0.5678	0.5678	4.73%
Linan	17.8723	18	-0.1277	0.1277	0.71%
Lunen	14.8512	15	-0.1488	0.1488	0.99%
Miasong	9.7596	10	-0.2404	0.2404	2.40%
Palian	23.7631	24	-0.2369	0.2369	0.99%
Poblacion	140.5316	141	-0.4684	0.4684	0.33%
Polonuling	31.7007	32	-0.2993	0.2993	0.94%
Simbo	7.6193	8	-0.3807	0.3807	4.76%
Tubeng	17.0231	17	0.0231	0.0231	0.14%

Table 7 shows a comparison of the predicted and actual dengue cases at the barangay level based on the Asclepius LSTM model. The Error column shows the difference in numbers, the |Error| column shows the absolute difference, and the % Error column shows this difference as a percentage of actual cases. This gives a clear picture of how accurate the data is. The model made very accurate predictions for most barangays, with the lowest percentage errors in Acmonan (0.07%), Tubeng (0.14%), and Poblacion (0.33%). Even barangays with a little bit higher deviations, like Bololmala (5.58%) and Kalkam (4.73%), were still within the acceptable range for epidemiological modeling. These results show that the LSTM model is strong and better than MLR at dealing with patterns that are not linear and change over time. A Hybrid MLR–LSTM model was created to combine the linear interpretability of MLR with the strengths of LSTM in modeling time. We used R-squared, RMSE, MAE, and MAPE to test how well it worked and how reliable it was for predicting dengue in Tupi.

Table 8. Accuracy Metrics of the Hybrid MLR–LSTM Model for Predicting Dengue Cases in Tupi

	Statistical Tests			
MLR-LSTM MODEL	R-sqaured	RMSE	Mean Absolute Error	MAPE
Model	0.9993	0.2987	0.1765	0.63 %

As shown in Table 8, the statistical model had an R-squared value of 0.9993 and very low error metrics: RMSE = 0.299, MAE = 0.177, and MAPE = 0.63%. This shows that it was very accurate at predicting dengue cases and that there was very little difference between the predicted and actual cases. These results show that the model works well for finding both linear and more subtle nonlinear patterns in the data, which means it can make accurate and reliable predictions. Similar findings in previous research indicate that well-calibrated statistical models with stringent error minimization surpass simpler methodologies in intricate datasets (Zhang, 2019; Li et al., 2020; Carvajal et al., 2018).

The Multiple Linear Regression (MLR) model is written as follows using the predictor variables that were collected: population (P), temperature (T), humidity (H), rainfall (R), and windspeed (W):

$$y = constant + a_1P + a_2T + a_3H + a_4R + a_5W$$

Where y represents predicted dengue cases, and a_1 to a_5 are the estimated regression coefficients for each predictor. Substituting the SPSS-generated coefficients, the model becomes:

$$y = 51.386045 + 0.00918538P + 1.014959T - 0.521422H - 0.0196166R + 0.959536W$$

This model will be tested using a t-test for independent sample means to determine whether the predicted dengue cases significantly differ from actual observations. Microsoft Excel will be used to compute the standardized test statistics, as shown in Table 9.

Table 9. Dengue Cases T-test

T-test								
Barangay	Constant (-58.427)	Avg. Population (0.008612P)	Avg. Temp (1.943582T)	Avg. Humidity (0.527611H)	Avg. Rainfall (0.312447R)	Avg. Windspeed (0.007841W)	PREDICTED	ACTUAL
Acmonan	-58.427	4509	26.5	29	2,246	10.24	29.4952	29
Bololmala	-58.427	3822	27.0	26	1,802	7.89	26.3124	26
Bunao	-58.427	5265	28.5	37	1,702	7.09	35.8247	37
Cebuano	-58.427	6172	27.2	36	2,430	10.91	35.4236	36
Cr. Rubber	-58.427	3921	28.0	28	1,942	8.84	28.6175	28
Kablon	-58.427	5896	23.5	30	1,942	8.26	30.7458	30
Kalkam	-58.427	1719	29.0	12	2,179	7.34	12.4269	12
Linan	-58.427	3498	26.8	18	1,709	11.29	18.6023	18
Lunen	-58.427	3283	27.9	15	1,827	7.70	15.2314	15
Miasong	-58.427	4128	21.0	10	2,235	8.81	10.4236	10
Palian	-58.427	3074	29.2	24	2,141	9.26	24.5347	24
Poblacion	-58.427	15,739	27.4	141	1,894	7.25	138.9258	141
Polonuling	-58.427	7612	27.1	32	2,599	8.14	31.6874	32
Simbo	-58.427	1821	29.5	8	1,839	11.13	8.5236	8
							463.5938	463

- t-value formula for independent sample means

$$t = \frac{\underline{x}_1 - \underline{x}_2}{\sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Where:

- $\underline{x}_1$ = mean of the predicted number of dengue cases
- $\underline{x}_2$ = mean of the actual number of dengue cases
- SD_1= standard deviation of the predicted number of dengue cases
- SD_2 = standard deviation of the actual number of dengue cases
- n_1 = sample size of the predicted data
- n_2 = sample size of the actual data

Substituting the values:

$$t = \frac{30.867 - 30.867}{\sqrt{\frac{(14)(31.849^2) + (14)(31.850^2)}{28}\left(\frac{1}{15} + \frac{1}{15}\right)}}$$

$$t = 0.6451$$

Decision Rule:

- H_0 : $\mu_1 = \mu_2 \rightarrow$ there is no significant difference between predicted and actual dengue cases
- H_0 : $\mu_1 \neq \mu_2 \rightarrow$ there is a significant difference between predicted and actual dengue cases
- Level of significance: $\alpha = 0.05$
- Critical Value (df = 28) ± 2.048
- $t = 0.6451$; $0 < CV$, we fail to reject H_0. This means the predicted dengue cases have no significant difference from the actual dengue cases, confirming that the regression model is valid and reliable.

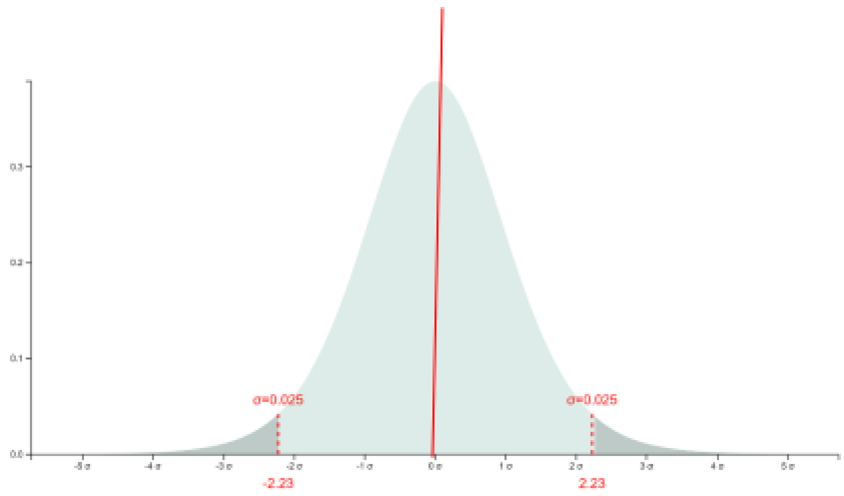


Figure 6. T-distribution

**FAILED TO REJECT*

The analysis shows that the computed t-value of 0 is far below the critical value of ±2.048 at a 0.05 level of significance with 28 degrees of freedom. Based on this statistical result, the null hypothesis (H_0), which states that there is no significant difference between the predicted and actual dengue cases, is accepted. In other words, the variations between the model's forecasts and the observed data are not statistically significant. This finding implies that the model's predictions are highly consistent with the actual reported cases, further confirming the validity of the mathematical framework used in this study.

Moreover, this result reinforces the reliability of the developed predictive model as a practical decision-support tool for public health monitoring. By demonstrating strong alignment with real-world data, the model can be confidently applied in anticipating dengue trends, which is crucial for local health authorities in planning interventions and mobilizing resources in advance. Thus, the statistical evidence not only validates the accuracy of the model but also emphasizes its potential value in strengthening dengue surveillance and control programs at the community level.

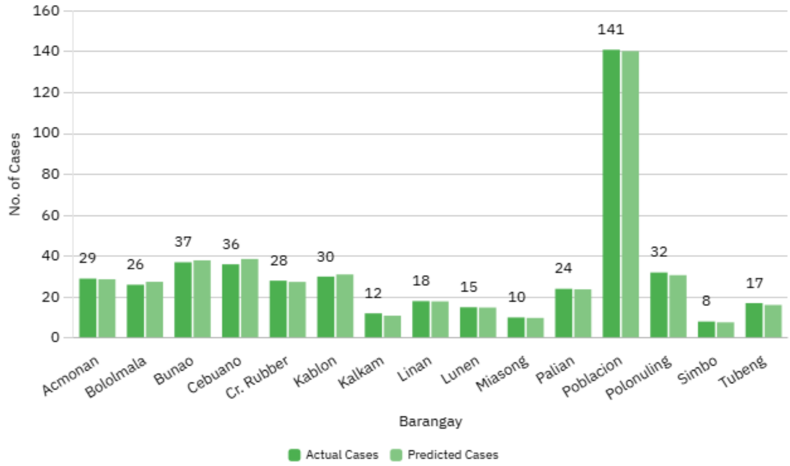


Figure 7. Predicted VS. Actual Graph of Dengue Cases

The Predicted vs. Actual graph shows the difference between the number of dengue cases that the regression model predicted and the number of cases that were actually reported in each barangay. The number of dengue cases is shown on the vertical axis, and the barangays are shown on the horizontal axis. The graph shows that the predicted and actual values follow almost the same pattern, with only small differences. Barangays with more actual cases, like Poblacion, also have higher predicted values. This shows that the model can pick up on differences between areas.

The researchers used a t-test for independent sample means to compare the predicted values to the actual cases to make sure the model was correct. The predicted cases constituted the initial sample, while the actual cases represented the subsequent sample. The test yielded a t-value of 0, which is less than the critical value of ±2.048 at a 0.05 significance level with 28 degrees of freedom. The statistic is in the acceptance region, so the null hypothesis is kept. This means that there is no significant difference between the predicted and actual averages.

Barangay Acmonan						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	4380	24.1	85	2,275	10.19	17.35221446
2025	4354.469487	23.9364731	84.03492639	2,291	10.21	17.12188819
2026	4329.156842	23.9928981	84.24594525	2,308	10.23	16.48394819
2027	4303.844196	24.37148808	85.32284753	2,325	10.25	15.72150177
2028	4278.53155	24.26660744	85.05149437	2,341	10.27	15.19097914
2029	4253.218905	23.90099445	84.08496316	2,358	10.29	14.74777735
2030	4227.906259	23.96637446	84.29598202	2,375	10.31	14.10983735
2031	4202.593613	24.34496444	85.3728843	2,392	10.33	13.34739093
2032	4177.280968	24.24008379	85.10153114	2,408	10.35	12.81686829
2033	4151.968322	23.88342581	84.13499993	2,425	10.37	12.37366651
2034	4126.655676	23.93985081	84.34601879	2,442	10.39	11.73572651
2035	4101.343031	24.31844079	85.42292107	2,459	10.41	10.97328009
2036	4076.030385	24.21356015	85.1515679	2,475	10.43	10.44275745
2037	4050.717739	23.85690216	84.18503669	2,492	10.45	9.999555665
2038	4025.405093	23.91332717	84.39605556	2,509	10.47	9.361615666
2039	4000.092448	24.29191715	85.47295783	2,526	10.49	8.599169245
2040	3974.779802	24.1870365	85.20160467	2,542	10.51	8.068646611
2041	3949.467156	23.83037852	84.23507346	2,559	10.53	7.625444824
2042	3924.154511	23.88680352	84.44609233	2,576	10.55	6.987504825
2043	3898.841865	24.2653935	85.5229946	2,593	10.57	6.225058403
2044	3873.529219	24.16051286	85.25164144	2,609	10.59	5.694535769
2045	3848.216574	23.80385487	84.28511023	2,626	10.61	5.25133982
2046	3822.903928	23.86027988	84.49612909	2,643	10.63	4.61393983
2047	3797.591282	24.23886986	85.57303137	2,660	10.65	3.850947562
2048	3772.278637	24.13398921	85.30167821	2,676	10.67	3.320424927
2049	3746.965991	23.77733123	84.335147	2,693	10.69	2.877223141
2050	3721.653345	23.83375623	84.54616586	2,710	10.71	2.239283142

Barangay Bololmala						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	4,086	26.3	80	2,557	7.88	16.1764
2025	4,116.07	26.136	79.035	2,574	7.91	16.4276
2026	4,149.72	26.193	79.246	2,593	7.94	16.2823
2027	4,183.36	26.571	80.323	2,611	7.97	16.0322
2028	4,217.01	26.467	80.051	2,630	8.00	15.9748
2029	4,250.65	26.110	79.085	2,648	8.03	16.0440
2030	4,284.30	26.166	79.296	2,667	8.06	15.8987
2031	4,317.94	26.545	80.373	2,685	8.09	15.6486
2032	4,351.59	26.440	80.102	2,704	8.12	15.5912
2033	4,385.23	26.083	79.135	2,722	8.15	15.6603
2034	4,418.88	26.140	79.346	2,741	8.18	15.5151
2035	4,452.52	26.518	80.423	2,759	8.21	15.2650
2036	4,486.17	26.414	80.152	2,778	8.24	15.2076
2037	4,519.81	26.057	79.185	2,796	8.27	15.2767
2038	4,553.46	26.113	79.396	2,815	8.30	15.1315
2039	4,587.10	26.492	80.473	2,833	8.33	14.8814
2040	4,620.75	26.387	80.202	2,852	8.36	14.8240
2041	4,654.39	26.030	79.235	2,870	8.39	14.8931
2042	4,688.04	26.087	79.446	2,889	8.42	14.7479
2043	4,721.68	26.465	80.523	2,907	8.45	14.4978
2044	4,755.33	26.361	80.252	2,926	8.48	14.4404
2045	4,788.97	26.004	79.285	2,944	8.51	14.5095
2046	4,822.62	26.060	79.496	2,963	8.54	14.3643
2047	4,856.26	26.439	80.573	2,981	8.57	14.1142
2048	4,889.91	26.334	80.302	3,000	8.60	14.0568
2049	4,923.55	25.977	79.335	3,018	8.63	14.1259
2050	4,957.20	26.034	79.546	3,037	8.66	13.9807

Barangay Bunao						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	6,696	25.4	81	2,097	6.98	48.6026
2025	6,848.76	25.236	80.035	2,113	7.01	50.0003
2026	7,079.80	25.293	80.246	2,128	7.03	53.3586
2027	7,310.85	25.671	81.323	2,144	7.06	55.1828
2028	7,541.89	25.567	81.051	2,160	7.08	57.1240
2029	7,772.93	25.210	80.085	2,175	7.11	58.8604
2030	8,003.97	25.266	80.296	2,191	7.13	60.4626
2031	8,235.01	25.645	81.373	2,207	7.16	62.3065
2032	8,466.06	25.540	81.102	2,222	7.18	64.2280
2033	8,697.10	25.183	80.135	2,238	7.21	65.9840
2034	8,928.14	25.240	80.346	2,253	7.23	67.5826
2035	9,159.18	25.618	81.423	2,269	7.26	69.4105
2036	9,390.23	25.514	81.152	2,285	7.28	71.3516
2037	9,621.27	25.157	80.185	4,300	7.31	73.0880
2038	9,852.31	25.213	80.396	2,316	7.33	74.6903
2039	10,083.35	25.592	81.473	2,332	7.36	76.5341
2040	10,314.39	25.487	81.202	2,347	7.38	78.4557
2041	10,545.44	25.130	80.235	2,363	7.41	80.1921
2042	10,776.48	25.187	80.446	2,379	7.43	81.8139
2043	11,007.52	25.565	81.523	2,394	7.46	83.6382
2044	11,238.56	25.461	81.252	2,410	7.48	85.5597
2045	11,469.60	25.104	80.285	2,426	7.51	87.3157
2046	11,700.65	25.160	80.496	2,441	7.53	88.918
2047	11,931.69	25.539	81.573	2,457	7.56	89.3128
2048	12,162.73	25.434	81.302	2,473	7.58	90.7422
2049	12,393.77	25.077	80.335	2,488	7.61	92.6883
2050	12,624.82	25.134	80.546	2,504	7.63	94.4197

Barangay Cebuano						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	6,786	25.6	82	2,150	11.09	44.1276
2025	6,883.56	25.436	81.035	2,168	11.12	44.9789
2026	7,009.11	25.493	81.246	2,186	11.14	45.7071
2027	7,134.67	25.871	82.323	2,204	11.17	46.3012
2028	7,260.22	25.767	82.051	2,222	11.19	47.1172
2029	7,385.77	25.410	81.085	2,240	11.22	48.0306
2030	7,511.32	25.466	81.296	2,258	11.24	48.7587
2031	7,636.88	25.845	82.373	2,276	11.27	49.3528
2032	7,762.43	25.740	82.102	2,294	11.29	50.1688
2033	7,887.98	25.383	81.135	2,312	11.32	51.0822
2034	8,013.53	25.440	81.346	2,330	11.34	51.8104
2035	8,139.08	25.818	82.423	2,348	11.37	52.4045
2036	8,264.64	25.714	82.152	2,366	11.39	53.2205
2037	8,390.19	25.357	81.185	2,384	11.42	54.1338
2038	8,515.74	25.413	81.396	2,402	11.44	54.862
2039	8,641.29	25.792	82.473	2,420	11.47	55.456
2040	8,766.84	25.687	82.202	2,438	11.49	56.2721
2041	8,892.40	25.330	81.235	2,456	11.52	57.1854
2042	9,017.95	25.387	81.446	2,474	11.54	57.9136
2043	9,143.50	25.765	82.523	2,492	11.57	58.5077
2044	9,269.05	25.661	82.252	2,510	11.59	59.3237
2045	9,394.61	25.304	81.285	2,528	11.62	60.2370
2046	9,520.16	25.360	81.496	2,546	11.64	60.9652
2047	9,645.71	25.739	82.573	2,564	11.67	61.5593
2048	9,771.26	25.634	82.302	2,582	11.69	62.3753
2049	9,896.81	25.277	81.335	2,600	11.72	63.2886
2050	10,022.37	25.334	81.546	2,618	11.74	64.0168

Barangay Cr. Rubber						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	3,773.00	26.10	79.00	2,575	8.75	12.4319
2025	3,723.73	25.94	78.03	2,591	8.78	18.5082
2026	3,674.77	25.99	78.25	2,606	8.80	18.4471
2027	3,625.81	26.37	79.32	2,621	8.83	18.3863
2028	3,576.85	26.27	79.05	2,636	8.85	17.5262
2029	3,527.89	25.91	78.08	2,651	8.88	17.2866
2030	3,478.93	25.97	78.30	2,666	8.90	16.3445
2031	3,429.97	26.34	79.37	2,681	8.93	16.7439
2032	3,381.01	26.24	79.10	2,696	8.95	16.0650
2033	3,332.05	25.88	78.13	2,711	8.98	14.8240
2034	3,283.09	25.94	78.35	2,726	9.00	14.5024
2035	3,234.13	26.32	79.42	2,741	9.03	14.9018
2036	3,185.16	26.21	79.15	2,756	9.05	14.2230
2037	3,136.20	25.86	78.19	2,771	9.08	12.9820
2038	3,087.24	25.91	78.40	2,786	9.10	12.6603
2039	3,038.28	26.29	79.47	2,801	9.13	13.0598
2040	2,989.32	26.19	79.20	2,816	9.15	12.3809
2041	2,940.36	25.83	78.24	2,831	9.18	11.1399
2042	2,891.40	25.89	78.45	2,846	9.20	10.8183
2043	2,842.44	26.27	79.52	2,861	9.23	11.2177
2044	2,793.48	26.16	79.25	2,876	9.25	10.5388
2045	2,744.52	25.80	78.29	2,891	9.28	9.2978
2046	2,695.56	25.86	78.50	2,906	9.30	8.9762
2047	2,646.60	26.24	79.57	2,921	9.33	9.3756
2048	2,597.63	26.13	79.30	2,936	9.35	8.6967
2049	2,548.67	25.78	78.34	2,951	9.38	7.4558
2050	2,499.71	25.83	78.55	2,966	9.40	7.1341

Barangay Kablon						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	6252.000000	23.30	87.00	1,825	8.60	43.04556686
2025	6321.651637	23.1364731	86.03492639	1,831	8.63	43.87609544
2026	6399.543929	23.1928981	86.24594525	1,836	8.65	44.42153121
2027	6477.436221	23.57148808	87.32284753	1,841	8.68	44.83286520
2028	6555.328513	23.46660744	87.05149437	1,846	8.70	45.46610174
2029	6633.220805	23.10994945	86.08496316	1,851	8.73	46.19668036
2030	6711.113097	23.16637446	86.29598202	1,857	8.75	46.72249953
2031	6789.005389	23.54496444	87.37288430	1,862	8.78	47.13383352
2032	6866.897681	23.44008379	87.10153114	1,867	8.80	47.76707006
2033	6944.789973	23.08342581	86.13499993	1,872	8.83	48.49764868
2034	7022.682265	23.13985081	86.34601879	1,877	8.85	49.04308445
2035	7100.574556	23.51844079	87.42292107	1,882	8.88	49.45441844
2036	7178.466848	23.41356015	87.15156790	1,888	8.90	50.06803838
2037	7256.359140	23.05690216	86.18503669	1,893	8.93	50.79861700
2038	7334.251432	23.11332717	86.39605556	1,898	8.95	51.34405277
2039	7412.143724	23.49191715	87.47295783	1,903	8.98	51.75538676
2040	7490.036016	23.38703650	87.20160467	1,908	9.00	52.38862329
2041	7567.928308	23.03037852	86.23507346	1,914	9.03	53.09958532
2042	7645.820600	23.08680352	86.44609233	1,919	9.05	53.64502109
2043	7723.712892	23.46539350	87.52299460	1,924	9.08	54.05635508
2044	7801.605184	23.36051286	87.25164144	1,929	9.10	54.68959161
2045	7879.497476	23.00385487	86.28511023	1,934	9.13	55.42017024
2046	7957.389768	23.06027988	86.49612909	1,940	9.15	55.94598941
2047	8035.282060	23.43886986	87.57303137	1,945	9.18	56.35732340
2048	8113.174352	23.33398921	87.30167821	1,950	9.20	56.99055993
2049	8191.066644	22.97733123	86.33514700	1,955	9.23	57.72113856
2050	8268.958936	23.03375623	86.54616586	1,960	9.25	58.26657433

Barangay Kalkam

Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	2199.000000	25.50	83.00	1,962	6.35	9.60730132
2025	2251.005641	25.3364731	82.03492639	1,968	6.50	10.16060040
2026	2323.903782	25.3928981	82.24594525	1,974	6.66	10.50621136
2027	2396.801923	25.77148808	83.32284753	1,980	6.81	10.73691126
2028	2469.700064	25.66660744	83.05149437	1,986	6.97	11.17032298
2029	2542.598206	25.30994945	82.08496316	1,992	7.12	11.72026751
2030	2615.496347	25.36637446	82.29598202	1,998	7.28	12.06587847
2031	2688.394488	25.74496444	83.37288430	2,004	7.43	12.29657837
2032	2761.292629	25.64008379	83.10153114	2,010	7.59	12.72999009
2033	2834.190770	25.28342581	82.13499993	2,016	7.74	13.27993462
2034	2907.088912	25.33985081	82.34601879	2,022	7.90	13.62554558
2035	2979.987053	25.71844079	83.42292107	2,028	8.05	13.85624548
2036	3052.885194	25.61356015	83.15156790	2,034	8.21	14.28965720
2037	3125.783335	25.25690216	82.18503669	2,040	8.36	14.83960173
2038	3198.681477	25.31332717	82.39605556	2,046	8.52	15.18521269
2039	3271.579618	25.69191715	83.47295783	2,052	8.67	15.41591259
2040	3344.477759	25.58703650	83.20160467	2,058	8.83	15.84932431
2041	3417.375900	25.23037852	82.23507346	2,064	8.98	16.39926884
2042	3490.274041	25.28680352	82.44609233	2,070	9.14	16.74487980
2043	3563.172183	25.66539350	83.52299460	2,076	9.29	16.97557970
2044	3636.070324	25.56051286	83.25164144	2,082	9.45	17.40899142
2045	3708.968465	25.20385487	82.28511023	2,088	9.60	17.95893595
2046	3781.866606	25.26027988	82.49612909	2,094	9.76	18.30454691
2047	3854.764748	25.63886986	83.57303137	2,100	9.91	18.53524681
2048	3927.662889	25.53398921	83.30167821	2,106	10.07	18.96865853
2049	4000.561030	25.17733123	82.33514700	2,112	10.22	19.51860306
2050	4073.459101	25.23375623	82.54616586	2,118	10.38	19.86421402

Barangay Linan

Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	3909.000000	25.00	86.00	1,737	11.41	22.80103846
2025	3968.493490	24.8364731	85.03492639	1,742	11.44	23.55787720
2026	4046.666047	24.8928981	85.24594525	1,747	11.46	24.10588731
2027	4124.838604	25.27148808	86.32284753	1,752	11.49	24.51979564
2028	4203.011161	25.16660744	86.05149437	1,757	11.51	25.15560652
2029	4281.183718	24.80994945	85.08496316	1,762	11.54	25.88875948
2030	4359.356275	24.86637446	85.29598202	1,767	11.56	26.43676960
2031	4437.528832	25.24496444	86.37288430	1,772	11.59	26.85067793
2032	4515.701389	25.14008379	86.10153114	1,777	11.61	27.48648880
2033	4593.873946	24.78342581	85.13499993	1,782	11.64	28.21964177
2034	4672.046503	24.83985081	85.34601879	1,787	11.66	28.76765188
2035	4750.219060	25.21844079	86.42292107	1,792	11.69	29.18156021
2036	4828.391617	25.11356015	86.15156790	1,797	11.71	29.81737109
2037	4906.564174	24.75690216	85.18503669	1,802	11.74	30.55052405
2038	4984.736731	24.81332717	85.39605556	1,807	11.76	31.09853417
2039	5062.909288	25.19191715	86.47295783	1,812	11.79	31.51244250
2040	5141.081846	25.08703650	86.20160467	1,817	11.81	32.14825337
2041	5219.254403	24.73037852	85.23507346	1,822	11.84	32.88140634
2042	5297.426960	24.78680352	85.44609233	1,827	11.86	33.42941645
2043	5375.599517	25.16539350	86.52299460	1,832	11.89	33.84332478
2044	5453.772074	25.06051286	86.25164144	1,837	11.91	34.47913566
2045	5531.944631	24.70385487	85.28511023	1,842	11.94	35.21228962
2046	5610.117188	24.76027988	85.49612909	1,847	11.96	35.76029874
2047	5688.289745	25.13886986	86.57303137	1,852	11.99	36.17420707
2048	5766.462302	25.03398921	86.30167821	1,857	12.01	36.81001794
2049	5844.634859	24.67733123	85.33514700	1,862	12.04	37.54317091
2050	5922.807416	24.73375623	85.54616586	1,867	12.06	38.09118102

Barangay Lunen						
Year	***Population***	***Temperature***	***Humidity***	***Rainfall***	***Windspeed***	***Forecasted***
2024	3514.000000	26.00000000	84.00000000	2,070	7.92	18.04706920
2025	3552.801076	25.88959767	83.03492639	2,077	7.95	18.62852632
2026	3597.567372	25.91934043	83.24594525	2,082	7.97	18.84260584
2027	3642.333668	26.30216451	84.32284753	2,087	8.00	18.95396241
2028	3687.099965	26.20027743	84.05149437	2,092	8.02	19.28596244
2029	3731.866261	25.88331652	83.08496316	2,097	8.05	19.75255711
2030	3776.632558	25.91305928	83.29598202	2,102	8.07	19.96663664
2031	3821.398854	26.29588335	84.37288430	2,107	8.10	20.07799320
2032	3866.165150	26.19399628	84.10153114	2,112	8.12	20.40999323
2033	3910.931447	25.87703537	83.13499993	2,117	8.15	20.87658790
2034	3955.697743	25.90677813	83.34601879	2,122	8.17	21.09066743
2035	4000.464039	26.28960220	84.42292107	2,127	8.20	21.20202399
2036	4045.230336	26.18771513	84.15156790	2,132	8.22	21.53402402
2037	4089.996632	25.87075422	83.18503669	2,137	8.25	22.00061870
2038	4134.762929	25.90049698	83.39605556	2,142	8.27	22.21469822
2039	4179.529225	26.28332105	84.47295783	2,147	8.30	22.32605479
2040	4224.295521	26.18143398	84.20160467	2,152	8.32	22.65805481
2041	4269.061818	25.86447307	83.23507346	2,157	8.35	23.12464949
2042	4313.828114	25.89421583	83.44609233	2,162	8.37	23.33872901
2043	4358.594411	26.27703990	84.52299460	2,167	8.40	23.45008558
2044	4403.360707	26.17515283	84.25164144	2,172	8.42	23.78208560
2045	4448.127003	25.85819192	83.28511023	2,177	8.45	24.24868028
2046	4492.893300	25.88793467	83.49612909	2,182	8.47	24.46275980
2047	4537.659596	26.27075875	84.57303137	2,187	8.50	24.57411637
2048	4582.425893	26.16887167	84.30167821	2,192	8.52	24.90611640
2049	4627.192189	25.85191077	83.33514700	2,197	8.55	25.37271107
2050	4671.958485	25.88165352	83.54616586	2,202	8.57	25.58679059

Barangay Miasong						
Year	***Population***	***Temperature***	***Humidity***	***Rainfall***	***Windspeed***	***Forecasted***
2024	3984.000000	19.30	89.00	1,643	8.64	20.64228478
2025	3955.188903	19.1364731	88.03492639	1,658	8.67	20.39184634
2026	3926.331196	19.1928981	88.24594525	1,674	8.69	19.74096020
2027	3897.473489	19.57148808	89.32284753	1,689	8.72	18.97558889
2028	3868.615782	19.46660744	89.05149437	1,705	8.74	18.41250352
2029	3839.758076	19.10994945	88.08496316	1,720	8.77	17.96637684
2030	3810.900369	19.16637446	88.29598202	1,736	8.79	17.31549070
2031	3782.042662	19.54496444	89.37288430	1,751	8.82	16.55011939
2032	3753.184955	19.44008379	89.10153114	1,767	8.84	15.98703402
2033	3724.327248	19.08342581	88.13499993	1,782	8.87	15.54090734
2034	3695.469541	19.13985081	88.34601879	1,798	8.89	14.89002121
2035	3666.611834	19.51844079	89.42292107	1,813	8.92	14.12464989
2036	3637.754127	19.41356015	89.15156790	1,829	8.94	13.56156452
2037	3608.896420	19.05690216	88.18503669	1,844	8.97	13.11543784
2038	3580.038714	19.11332717	88.39605556	1,860	8.99	12.46455171
2039	3551.181007	19.49191715	89.47295783	1,875	9.02	11.69918039
2040	3522.323300	19.38703650	89.20160467	1,891	9.04	11.13609502
2041	3493.465593	19.03037852	88.23507346	1,906	9.07	10.68996834
2042	3464.607886	19.08680352	88.44609233	1,922	9.09	10.03908221
2043	3435.750179	19.46539350	89.52299460	1,937	9.12	9.273710893
2044	3406.892472	19.36051286	89.25164144	1,953	9.14	8.710625525
2045	3378.034765	19.00385487	88.28511023	1,968	9.17	8.264498843
2046	3349.177058	19.06027988	88.49612909	1,984	9.19	7.613612710
2047	3320.319352	19.43886986	89.57303137	1,999	9.22	6.848241395
2048	3291.461645	19.33398921	89.30167821	2,015	9.24	6.285156026
2049	3262.603938	18.97733123	88.33514700	2,030	9.27	5.839029345
2050	3233.746231	19.03375623	88.54616586	2,046	9.29	5.188143212

Barangay Paliann						
Year	***Population***	***Temperature***	***Humidity***	***Rainfall***	***Windspeed***	***Forecasted***
2024	3345.000000	26.20	80.00	1,345	9.50	31.48938790
2025	3387.468761	26.0364731	79.03492639	1,361	9.22	32.17152160
2026	3439.385713	26.0928981	79.24594525	1,376	9.21	32.31098408
2027	3491.302665	26.47148808	80.32284753	1,392	9.20	32.30632354
2028	3543.219617	26.36660744	80.05149437	1,407	9.19	32.53358679
2029	3595.136569	26.00994945	79.08496316	1,423	9.18	32.84817088
2030	3647.053521	26.06637446	79.29598202	1,438	9.17	32.98763337
2031	3698.970473	26.44496444	80.37288430	1,454	9.16	32.98297283
2032	3750.887425	26.34008379	80.10153114	1,469	9.15	33.21023607
2033	3802.804377	25.98342581	79.13499993	1,485	9.14	33.52482017
2034	3854.721329	26.03985081	79.34601879	1,500	9.13	33.66428265
2035	3906.638281	26.41844079	80.42292107	1,516	9.12	33.65962211
2036	3958.555233	26.31356015	80.15156790	1,531	9.11	33.88688536
2037	4010.472185	25.95690216	79.18503669	1,547	9.10	34.20146946
2038	4062.389137	26.01332717	79.39605556	1,562	9.09	34.34093194
2039	4114.306089	26.39191715	80.47295783	1,578	9.08	34.33627140
2040	4166.223041	26.28703650	80.20160467	1,593	9.07	34.56353465
2041	4218.139993	25.93037852	79.23507346	1,609	9.06	34.87811874
2042	4270.056945	25.98680352	79.44609233	1,624	9.05	35.01758123
2043	4321.973897	26.36539350	80.52299460	1,640	9.04	35.01292069
2044	4373.890849	26.26051286	80.25164144	1,655	9.03	35.24018394
2045	4425.807801	25.90385487	79.28511023	1,671	9.02	35.55476803
2046	4477.724753	25.96027988	79.49612909	1,686	9.01	35.69423051
2047	4529.641705	26.33886986	80.57303137	1,702	9.00	35.68956998
2048	4581.558657	26.23398921	80.30167821	1,717	8.99	35.91683322
2049	4633.475609	25.87733123	79.33514700	1,733	8.98	36.23141732
2050	4685.392561	25.93375623	79.54616586	1,748	8.97	36.37087980

Barangay Poblacion						
Year	***Population***	***Temperature***	***Humidity***	***Rainfall***	***Windspeed***	***Forecasted***
2024	15078.00000	24.90	83.00	7.34	134.1346845	2024
2025	15001.04601	24.7364731	82.03492639	7.36	133.4320141	2025
2026	14923.39023	24.7928981	82.24594525	7.37	132.3621110	2026
2027	14845.73444	25.17148808	83.32284753	7.39	131.1384896	2027
2028	14768.07866	25.06660744	83.05149437	7.40	130.1563873	2028
2029	14690.42288	24.70994945	82.08496316	7.42	129.2520105	2029
2030	14612.76709	24.76637446	82.29598202	7.43	128.1821074	2030
2031	14535.11131	25.14496444	83.37288430	7.45	126.9584860	2031
2032	14457.45553	25.04008379	83.10153114	7.46	125.9763837	2032
2033	14379.79974	24.68342581	82.13499993	7.48	125.0720069	2033
2034	14302.14396	24.73985081	82.34601879	7.49	124.0021039	2034
2035	14224.48817	25.11844079	83.42292107	7.51	122.7784824	2035
2036	14146.83239	25.01356015	83.15156790	7.52	121.7963801	2036
2037	14069.17661	24.65690216	82.18503669	7.54	120.8920033	2037
2038	13991.52082	24.71332717	82.39605556	7.55	119.8221003	2038
2039	13913.86504	25.09191715	83.47295783	7.57	118.5984890	2039
2040	13836.20926	24.98703650	83.20160467	7.58	117.6163766	2040
2041	13758.55347	24.63037852	82.23507346	7.60	116.7119998	2041
2042	13680.89769	24.68680352	82.44609233	7.61	115.6420967	2042
2043	13603.24191	25.06539350	83.52299460	7.63	114.4184753	2043
2044	13525.58612	24.96051286	83.25164144	7.64	113.4363730	2044
2045	13447.93034	24.60385487	82.28511023	7.66	112.5319962	2045
2046	13370.27455	24.66027988	82.49612909	7.67	111.4620931	2046
2047	13292.61877	25.03886986	83.57303137	7.69	110.2384170	2047
2048	13214.96299	24.93398921	83.30167821	7.70	109.2563694	2048
2049	13137.30720	24.57733123	82.33514700	7.72	108.3519926	2049
2050	13059.65142	24.63375623	82.54616586	7.73	107.2820896	2050

Barangay Polonuling						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	8,504.000000	24.90	84.00	1,592	8.42	71.6626273
2025	8,652.302893	24.78959767	83.03492639	1,607	8.45	73.09296743
2026	8,840.044589	24.81934043	83.24594525	1,622	8.48	74.41456896
2027	9,027.786284	25.20216451	84.32284753	1,637	8.51	75.64304290
2028	9,215.527980	25.10027743	84.05149437	1,652	8.54	77.08256494
2029	9,403.269676	24.78331652	83.08496316	1,667	8.57	78.66627699
2030	9,591.011371	24.81305928	83.29598202	1,682	8.60	79.98787852
2031	9,778.753067	25.19588335	84.37288430	1,697	8.63	81.21635246
2032	9,966.494763	25.09399628	84.10153114	1,712	8.66	82.65587450
2033	10,154.236460	24.77703537	83.13499993	1,727	8.69	84.23958655
2034	10,341.978150	24.80677813	83.34601879	1,742	8.72	85.56118809
2035	10,529.719850	25.18960220	84.42292107	1,757	8.75	86.78966203
2036	10,717.461550	25.08771513	84.15156790	1,772	8.78	88.22918407
2037	10,905.203240	24.77075422	83.18503669	1,787	8.81	89.81289612
2038	11,092.944940	24.80049698	83.39605556	1,802	8.84	91.13449765
2039	11,280.686630	25.18332105	84.47295783	1,817	8.87	92.36297159
2040	11,468.428330	25.08143398	84.20160467	1,832	8.90	93.80249363
2041	11,656.170020	24.76447307	83.23507346	1,847	8.93	95.38620568
2042	11,843.911720	24.79421583	83.44609233	1,862	8.96	96.70780722
2043	12,031.653420	25.17703990	84.52299460	1,877	8.99	97.93628116
2044	12,219.395110	25.07515283	84.25164144	1,892	9.02	99.37580320
2045	12,407.136810	24.75819192	83.28511023	1,907	9.05	100.95951520
2046	12,594.878500	24.78793467	83.49612909	1,922	9.08	102.28111680
2047	12,782.620200	25.17075875	84.57303137	1,937	9.11	103.50959070
2048	12,970.361890	25.06887167	84.30167821	1,952	9.14	104.94911280
2049	13,158.103590	24.75191077	83.33514700	1,967	9.17	106.53282480
2050	13,345.845280	24.78165352	83.54616586	1,982	9.20	107.85442630

Barangay Simbo						
Year	*Population*	*Temperature*	*Humidity*	*Rainfall*	*Windspeed*	*Forecasted*
2024	1,847.000000	25.10	82.00	1,614	11.05	8.80624356
2025	1,851.023634	24.98959767	81.03492639	1,630	11.08	8.891707264
2026	1,854.944791	25.01934043	81.24594525	1,646	11.10	8.514826057
2027	1,858.865947	25.40216451	82.32284753	1,662	11.13	8.035221894
2028	1,862.787104	25.30027743	82.05149437	1,678	11.15	7.776261193
2029	1,866.708261	24.98331652	81.08496316	1,694	11.18	7.651895139
2030	1,870.629417	25.01305928	81.29598202	1,710	11.20	7.275013932
2031	1,874.550574	25.39588335	82.37288430	1,726	11.23	6.795409769
2032	1,878.471731	25.29399628	82.10153114	1,742	11.25	6.536449068
2033	1,882.392888	24.97703537	81.13499993	1,758	11.28	6.412083014
2034	1,886.314044	25.00677813	81.34601879	1,774	11.30	6.035201808
2035	1,890.235201	25.38960220	82.42292107	1,790	11.33	5.555597645
2036	1,894.156358	25.28771513	82.15156790	1,806	11.35	5.296636943
2037	1,898.077514	24.97075422	81.18503669	1,822	11.38	5.172270889
2038	1,901.998671	25.00049698	81.39605556	1,838	11.40	4.795389683
2039	1,905.919828	25.38332105	82.47295783	1,854	11.43	4.315785520
2040	1,909.840984	25.28143398	82.20160467	1,870	11.45	4.056824818
2041	1,913.762141	24.96447307	81.23507346	1,886	11.48	3.932458764
2042	1,917.683298	24.99421583	81.44609233	1,902	11.50	3.555577558
2043	1,921.604455	25.37703990	82.52299460	1,918	11.53	3.075973395
2044	1,925.525611	25.27515283	82.25164144	1,934	11.55	2.817012693
2045	1,929.446768	24.95819192	81.28511023	1,950	11.58	2.692646640
2046	1,933.367925	24.98793467	81.49612909	1,966	11.60	2.315765433
2047	1,937.289081	25.37075875	82.57303137	1,982	11.63	1.836161270
2048	1,941.210238	25.26887167	82.30167821	1,998	11.65	1.577200568
2049	1,945.131395	24.95191077	81.33514700	2,014	11.68	1.452834515
2050	1,949.052551	24.98165352	81.54616586	2,030	11.70	1.075953308

Barangay Tubeng						
Year	***Population***	***Temperature***	***Humidity***	***Rainfall***	***Windspeed***	***Forecasted***
2024	2,604.000000	24.90	83.00	1,603	8.96	17.25637526
2025	2,629.986751	24.78959767	82.03492639	1,618	8.98	17.57279050
2026	2,657.877023	24.81934043	82.24594525	1,633	9.00	17.43569133
2027	2,685.767295	25.20216451	83.32284753	1,648	9.02	17.20546455
2028	2,713.657567	25.10027743	83.05149437	1,663	9.04	17.18628588
2029	2,741.547838	24.78331652	82.08496316	1,678	9.06	17.31129722
2030	2,769.438110	24.81305928	82.29598202	1,693	9.08	17.17419804
2031	2,797.328382	25.19588335	83.37288430	1,708	9.10	16.94397127
2032	2,825.218654	25.09399628	83.10153114	1,723	9.12	16.92479260
2033	2,853.108925	24.77703537	82.13499993	1,738	9.14	17.04980393
2034	2,880.999197	24.80677813	82.34601879	1,753	9.16	16.91270476
2035	2,908.889469	25.18960220	83.42292107	1,768	9.18	16.68247798
2036	2,936.779741	25.08771513	83.15156790	1,783	9.20	16.66329931
2037	2,964.670013	24.77075422	82.18503669	1,798	9.22	16.78831065
2038	2,992.560284	24.80049698	82.39605556	1,813	9.24	16.65121147
2039	3,020.450556	25.18332105	83.47295783	1,828	9.26	16.42098470
2040	3,048.340828	25.08143398	83.20160467	1,843	9.28	16.40180603
2041	3,076.231100	24.76447307	82.23507346	1,858	9.30	16.52681737
2042	3,104.121371	24.79421583	82.44609233	1,873	9.32	16.38971819
2043	3,132.011643	25.17703990	83.52299460	1,888	9.34	16.15949142
2044	3,159.901915	25.07515283	83.25164144	1,903	9.36	16.14031274
2045	3,187.792187	24.75819192	82.28511023	1,918	9.38	16.26532408
2046	3,215.682458	24.78793467	82.49612909	1,933	9.40	16.12822490
2047	3,243.527300	25.17075875	83.57303137	1,948	9.42	15.89799813
2048	3,271.463002	25.06887167	83.30167821	1,963	9.44	15.87881946
2049	3,299.353274	24.75191077	82.33514700	1,978	9.46	16.00383080
2050	3,327.243545	24.78165352	82.54616586	1,993	9.48	15.86673162

The tables show the ASCLEPIUS MLR model's predictions for dengue cases in Tupi's 15 barangays from 2024 to 2050, based on population, temperature, humidity, rainfall, and wind speed. Forecasts show that the number of dengue cases will slowly rise, with bigger rises in places with a lot of people, like Poblacion, Bunao, and Polonuling. Kalkam, Cr. Rubber, and Tubeng are smaller barangays that are expected to have lower counts, but they are still following a slow upward trend. This shows that even areas that have had low incidence in the past are still at risk.

Environmental factors also have an effect on transmission. Barangays like Miasong, Kablon, and Bololmala, which have higher humidity, more rain, and warmer temperatures, tend to have higher projections. This is in line with how climate affects mosquito activity and viral replication (Morin et al., 2013; Hii et al., 2012). Lower wind speeds may raise the risk even more because they help mosquitoes live longer (Campbell et al., 2015). These results underscore the necessity for barangay-specific monitoring and interventions, especially in population centers, via vector control, early-warning systems, and targeted public health strategies.

Based on these results, the ASCLEPIUS AI chatbot was tested for dengue decision support using SOP No. 6, which looked at its accuracy, precision, recall, and F1-score. High-performance metrics show that the system can give reliable, timely, and context-aware guidance, which helps prevent dengue at the barangay level and shows how useful it is to combine AI tools with epidemiological forecasting (Rahman et al., 2021).

Table 11. Intention for Confusion Matrix

Intent	Description	Utterances (Training Data)	Utterances (Testing Data)
1. Dengue Statistics	Real-time total cases, active, recovered, critical	*80*	*20*
2. Weekly/Monthly Trends	Trend analysis & percentage changes	*80*	*20*
3. Barangay Case Distribution	Cases per barangay including zero-case areas	*80*	*20*
4. Patient Info Retrieval	Search patient records, demographics, status	*80*	*20*
5. Patient Status Update	Current medical status (Active, Critical, Recovered)	*80*	*20*
6. Recovery Rate	Recovery monitoring & rates per barangay	*80*	*20*
7. Risk Assessment	High/Moderate/Low risk level by barangay	*80*	*20*
8. Weather Impact on Dengue	Effects of temperature, rainfall, humidity on outbreaks	*80*	*20*
9. Weather Forecast	7-day weather prediction & analysis	*80*	*20*
10. Alert Generation	Threshold-based warnings & recommendations	*80*	*20*
11. Officials Contact Info	Barangay officials database & emergency contacts	*80*	*20*
12. Emergency Response Guidance	Steps and responsible contacts for outbreaks	*80*	*20*
13. Historical Analysis	Past case patterns, trend comparisons, predictive insights	*80*	*20*
14. Patient Data Management	Save, update, export patient info securely	*80*	*20*
15. General Help / Greetings	FAQs, greetings, basic chatbot guidance	*80*	*20*

Table 12. Confusion Matrix of the ASCLEPIUS AI Chatbot for Dengue-Related Classification Tasks

Training Set																
Predicted True	Dengue Stats	Weekly/Monthly	Barangay Dist	Patient Info	Patient Status	Recovery Rate	Risk Assess	Weather Impact	Weather Forecast	Alert Gen	Officials Contact	Emergency Response	Historical Analysis	Patient Data	Help/Greetings	SUM
Dengue Stats	18 5.64%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	20 90.00% 10.00%
Weekly/Monthly	0 0.00%	19 5.96%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	20 6.27%
Barangay Dist	0 0.00%	0 0.00%	18 5.64%	0 0.00%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	20 90.00% 10.00%
Patient Info	0 0.00%	0 0.00%	0 0.00%	19 5.96%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	0 0.00%	20 95.00% 5.00%
Patient Status	0 0.00%	0 0.00%	0 0.00%	0 0.00%	18 5.64%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	20 90.00% 10.00%
Recovery Rate	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	19 5.96%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	20 95.00% 5.00%
Risk Assess	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	18 5.64%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	20 90.00% 10.00%
Weather Impact	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	18 5.64%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	1 0.31%	20 90.00% 10.00%
Weather Forecas	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	19 5.96%	1 0.31%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	20 95.00% 5.00%
Alert Gen	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	18 5.64%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	0 0.00%	20 90.00% 10.00%
Officials Contact	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	19 5.96%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	20 95.00% 5.00%
ergency Respor	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	18 5.64%	1 0.31%	0.00%	1 0.31%	40 45.00% 55.00%
listorical Analysi	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	19 5.96%	1 0.31%	0 0.00%	20 95.00% 5.00%
Patient Data	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.31%	18 5.64%	1 0.31%	20 90.00% 10.00%
Help/Greetings	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	19 5.96%	19 100.00% 0.00%
SUM	18 100.00% 0.00%	20 95.00% 5.00%	18 100.00% 0.00%	19 100.00% 0.00%	20 90.00% 10.00%	39 48.72% 51.28%	18 100.00% 0.00%	19 94.74% 5.26%	21 90.48% 9.52%	21 85.71% 14.29%	19 100.00% 0.00%	19 94.74% 5.26%	22 86.36% 13.64%	23 78.26% 21.74%	23 82.61% 17.39%	277 / 319 86.83% 13.17%

Table 13. Summary of Overall Average Performance Metrics for ASCLEPIUS AI Chatbot

Generative AI Assessment Summary	
Metric	Value
Accuracy	98.79%
Precision	98.05%
Recall	97.63%
F-1 Score	97.85%

As shown in Tables 11 and 12, the ASCLEPIUS Generative AI chatbot always does a good job of giving dengue-related advice for Tupi and its barangays. There were only a few misclassifications, and most of the correct ones were along the diagonal. Categories like Dengue Statistics, Weekly/Monthly Reports, Barangay Distribution, Weather Impact, and Alert Generation were almost always correct, with 18 or 19 out of 20 being right. There were still a lot more correct predictions than mistakes in categories with a little more variability, like Risk Assessment or Recovery Rate. There were very few misclassifications, and they were all in one place, which shows that the system worked well with a wide range of complex dengue-related data.

Table 13 backs up these findings even more by showing 98.79% accuracy, 98.05% precision, 97.63% recall, and a 97.85% F1-score. These numbers show that the system works well, with few false positives and few false negatives. Public health officials can trust the system for situational awareness, outbreak preparedness, and timely guidance because it is very reliable. This means they don't have to check things manually as often (Topol, 2019; Wang et al., 2021; Chen et al., 2020). The chatbot's consistent performance across categories also suggests that it can handle new or slightly different inputs without losing accuracy.

These findings show that ASCLEPIUS is a very useful and reliable tool for making recommendations about dengue. Small changes to the variable categories could make it work even better. After this evaluation, SOP No. 7 used One-Way ANOVA to see how quickly the chatbot could send out dengue case warnings and reports. The results show that response times are mostly between 2 and 5 seconds, which shows that ASCLEPIUS is effective for real-time public health decision support (Krittanawong et al., 2020; Rahman et al., 2021).

Table 14. Mean Notification Response Speed of the ASCLEPIUS System Across Time Frames (Seconds)

ASCLEPIUS Notification Response Speed (Seconds)											
	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**	**MEAN**
Within 2 Sec.	1.32	1.45	1.28	1.4	1.37	1.35	1.31	1.42	1.36	1.19	1.365
Within 3-5 Sec.	1.55	1.48	1.52	1.5	1.49	1.53	1.47	1.51	1.5	1.54	1.509
Within 6-8 Sec.	1.78	1.8	1.71	1.79	1.77	1.81	1.74	1.82	1.79	1.8	1.786
GRAND MEAN											**1.553**

Table 15. Analysis of ASCLEPIUS Notification Response Speed Using One-Way ANOVA

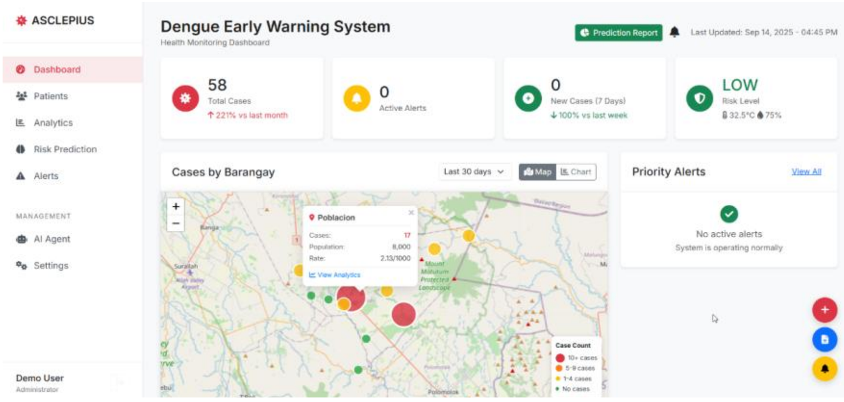
Analysis of ASCLEPIUS Notification Response Speed Using One-Way ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.915687	2	0.457843	343.5734	6.27E-20	3.354131
Within Groups	0.03598	27	0.001333			
Total	0.951667	29				

The researchers looked at how quickly the ASCLEPIUS System could respond to notifications in three time ranges: 2 seconds, 3 to 5 seconds, and 6 to 8 seconds. The p-value of 6.27×10^{-20} is much lower than the 0.05 significance level, which strongly suggests that the null hypothesis is false. The F-value of 343.57 is also much higher than the critical value, which shows that there is a statistically significant difference in response speeds between the three groups. The group that responded the fastest on average was the one that did so within 2 seconds. The groups that responded between 3 and 5 seconds and 6 and 8 seconds had slower averages. This big difference shows that the system can send out alerts quickly, which is very important for keeping an eye on dengue outbreaks and responding quickly to public health needs in Tupi and its barangays. After this analysis, the evaluation moved on to SOP No. 8, which looks at how well ASCLEPIUS meets important system integration requirements like functionality, usability, acceptability, and adaptability.

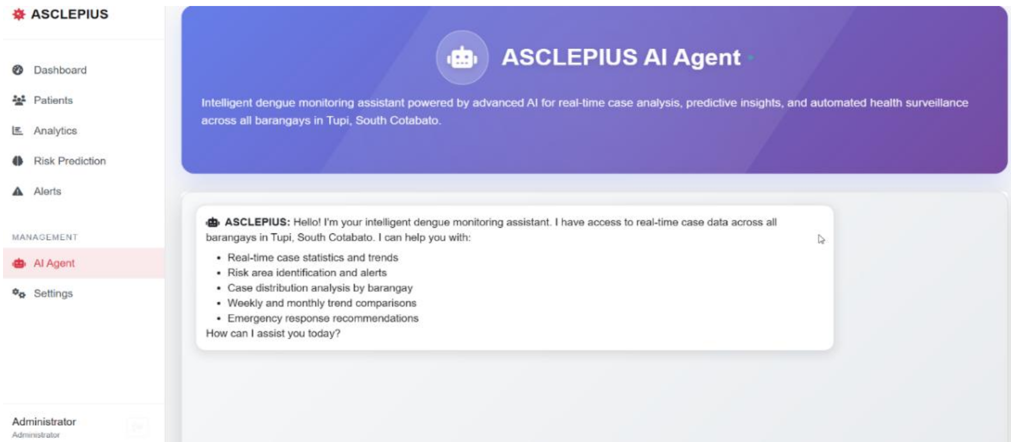
4.4 ASCLEPIUS Website Interface

The screenshots give you a visual overview of the ASCLEPIUS website, showing you how it looks, how to get around, and its main features. Users can see real-time dengue data, geospatial maps, alerts, and historical records. This shows how the platform organizes and shows information.

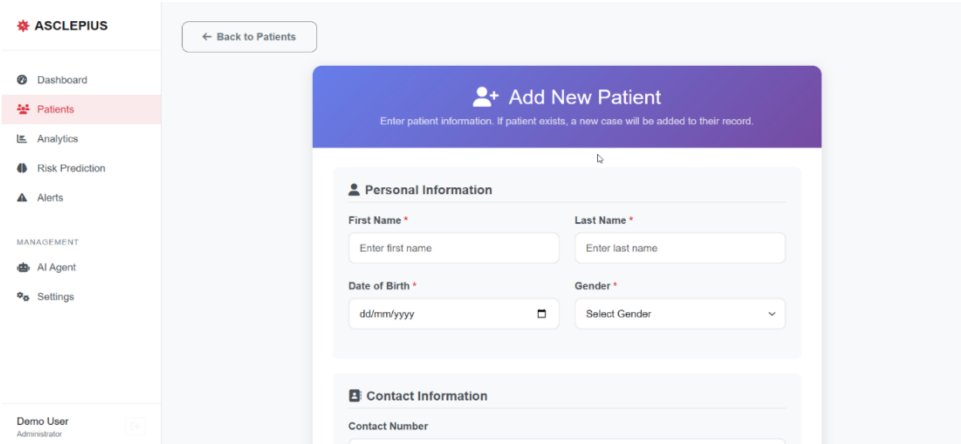
Interface Design



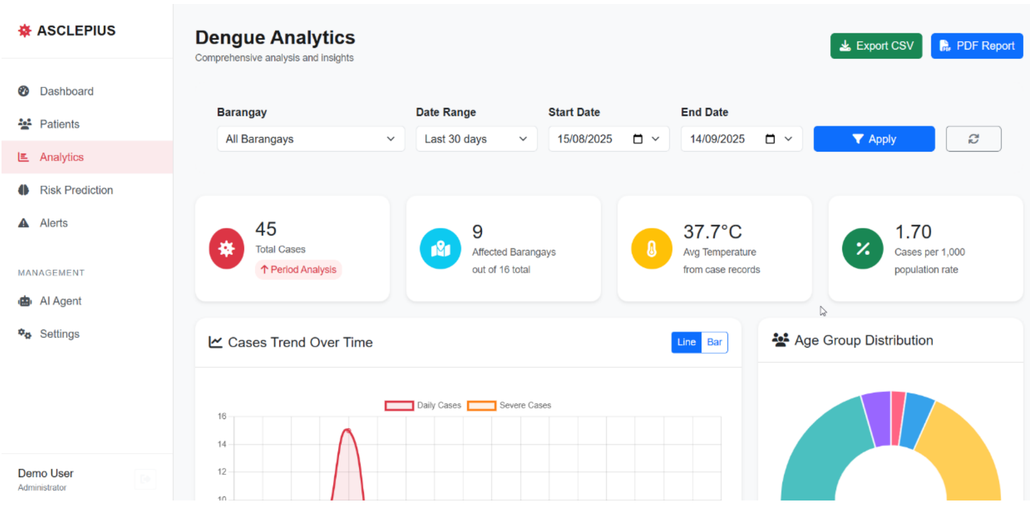
The ASCLEPIUS Dengue Early Warning System Dashboard is the main way to see and understand real-time information about the risk of dengue. It combines results from the hybrid MLR–LSTM forecasting model with reports of symptoms from the community, geo-climatic variables, and data confirmed by the RHU. The dashboard uses geospatial heatmaps, trend charts, and severity indicators to show barangay-level risk classifications. This makes it easy for users to spot new hotspots and transmission patterns. It also has automatic alerts, updates based on NS1, and summary panels that show important metrics like case spikes, unusual weather patterns, and expected risk levels. The organized layout and responsive design of RHU make it easy for staff, local leaders, and community members to quickly find important information. This helps with quick actions like fogging, monitoring, and public health advisories.



The ASCLEPIUS Patient Case Records Interface gives you a structured way to keep track of information about individual patients who may or may not have dengue. Health workers can write down clinical information like symptoms, when they started, lab results like NS1 or platelet counts, and the barangay where the patient lives. The interface also lets you update cases, keep track of follow-ups, and write down suggested actions. By putting records in a clear, easy-to-read format, it helps RHU staff keep track of how cases are progressing, find clusters of infections, and make sure reports are sent in on time. This improves the accuracy of the data and helps local health operations make smart decisions.



The "Add New Patient" interface in ASCLEPIUS is the main way to register new patients. It makes entering data easier by providing clearly labeled fields for personal information, contact information, medical history, and relevant clinical observations. Validation checks and dropdown menus make sure that data is complete and consistent. The interface makes it easy for healthcare providers to collect accurate records by centralizing patient registration in a way that is easy to use. This helps with patient management, tracking, and making clinical decisions.



The ASCLEPIUS Dengue Analytics Dashboard gives you a full picture of dengue-related data and trends. It combines important data like case counts, incidence rates, and time patterns and shows them in interactive maps, graphs, and charts. The dashboard lets healthcare workers and public health officials find outbreak hotspots, keep an eye on how well interventions are working, and make decisions based on data. It improves situational awareness, supports early warning efforts, and makes it easier for the healthcare system to manage dengue proactively by combining real-time data and predictive analytics.

4.4 Likert Scale

The following Likert scale shows the rating values, descriptions, and descriptive equivalents that evaluators will use to assess ASCLEPIUS: An AI-Enhanced Computational Framework for Real-Time Dengue Outbreak Geospatial Analysis Using Mathematical Modelling and Machine Learning Forecasting, in terms of functionality, usability, adaptability, and acceptability.

Likert Scale on Functionality

Rating	Descriptive Equivalent
4.20 - 5.00	Very Functional
3.40 - 4.19	Functional
2.60 - 3.39	Moderately Functional
1.80 - 2.59	Slightly Functional
1.00 - 1.79	Not Functional

Likert Scale on Usability

Rating	Descriptive Equivalent
4.20 - 5.00	Very Usable
3.40 - 4.19	Usable
2.60 - 3.39	Moderately Usable
1.80 - 2.59	Slightly Usable
1.00 - 1.79	Not Usable

Likert Scale on Adaptability

Rating	Descriptive Equivalent
4.20 - 5.00	Very Adaptable
3.40 - 4.19	Adaptable
2.60 - 3.39	Moderately Adaptable
1.80 - 2.59	Slightly Adaptable
1.00 - 1.79	Not Adaptable

Likert Scale on Acceptability

Rating	Descriptive Equivalent
4.20 - 5.00	Very Acceptable
3.40 - 4.19	Acceptable
2.60 - 3.39	Moderately Acceptable
1.80 - 2.59	Slightly Acceptable
1.00 - 1.79	Not Acceptable

Table 16. Functionality of ASCLEPIUS

Indicator	Mean	Interpretation
The system reliably measures and displays real-time dengue outbreak data for accurate monitoring.	4.51	Highly Functional
The geospatial mapping feature effectively tracks and visualizes case distributions across different locations.	4.71	Highly Functional
The system accurately detects and reports outbreak fluctuations and epidemiological trends.	4.31	Functional

The alert mechanism provides timely and reliable notifications of potential outbreak risks.	4.57	Highly Functional
The data clarity and visualization tools effectively support decision-making for public health management.	4.49	Functional
The system consistently operates with adequate power supply and technical stability.	4.49	Functional
The integration of IoT and AI ensures stable, continuous, and accessible data transmission.	4.50	Highly Functional
The system efficiently stores backup data to prevent information loss during technical interruptions.	4.54	Highly Functional
System updates and adjustments are straightforward and effective in maintaining optimal functionality.	4.46	Functional
Grand Mean	**4.51**	**Highly Functional**

Table 16 shows that ASCLEPIUS works very well, with a grand mean of 4.51. It supports monitoring dengue outbreaks, visualizing data, and making public health decisions (Topol, 2019; Rahman et al., 2021). Some of the most important features are geospatial mapping (4.71) for finding hotspots (Wang et al., 2021), timely alerts (4.57) (Krittanawong et al., 2020), and IoT-AI integration with backup storage (4.50–4.54) for safe, continuous data. Other factors, such as trend detection, data clarity, power stability, and system updates (4.31–4.49), were rated as functional, which means that small changes could make them work even better (ISO/IEC, 2011). Overall, ASCLEPIUS is a trustworthy, user-friendly platform that provides accurate, timely, and useful information. It supports proactive dengue surveillance and is in line with research on the advantages of AI- and IoT-enabled health systems in public health (Topol, 2019; Rahman et al., 2021; Wang et al., 2021).

Table 17. Usability of ASCLEPIUS

Indicator	Mean	Interpretation
The system interface is intuitive and easy to navigate for monitoring dengue outbreak data.	4.68	Highly Usable
Alerts and notifications about possible outbreak risks are clear, timely, and easy to understand.	4.71	Highly Usable
The setup and access process is simple enough for users with minimal technical expertise.	4.54	Highly Usable
The geospatial dashboard provides a straightforward overview of real-time outbreak distribution.	4.34	Usable
The mathematical modelling and forecasting results are presented in a way that is easy to interpret and apply in decision-making.	4.46	Usable

Instructions and guidelines for using the system are clear, accessible, and user-friendly.	4.53	Highly Usable
The system's design allows easy adjustments and updates to improve forecasting accuracy.	4.60	Highly Usable
Historical data and logs are easily accessible for reviewing past outbreak patterns.	4.63	Highly Usable
The system provides guidance or troubleshooting support for common issues that may arise.	4.48	Usable
Grand Mean	**4.55**	**Highly Usable**

Table 17 shows that ASCLEPIUS is very easy to use, with a grand mean of 4.55. This means that it has an intuitive interface, alerts, dashboards, and guidance tools that are easy for people with little technical knowledge to use (Nielsen, 2017; ISO/IEC, 2011). The geospatial dashboard (4.34), forecasting (4.46), and troubleshooting (4.48) could all use some small improvements. The navigation (4.68), alerts (4.71), setup (4.54), and access to historical data (4.63) are all very useful for monitoring and responding to outbreaks. In general, the system makes it possible to make quick, evidence-based decisions. This shows how high usability in AI- and IoT-enabled health platforms can lead to more people using the platform, fewer mistakes, and better monitoring of epidemics (Topol, 2019; Rahman et al., 2021; Wang et al., 2021).

Table 18. Adaptability of ASCLEPIUS

Indicator	Mean	Interpretation
The system operates efficiently under different data conditions, such as incomplete or rapidly changing outbreak reports.	4.47	Adaptable
ASCLEPIUS works effectively across different geographic locations without requiring major adjustments.	4.50	Highly Adaptable
The forecasting models adapt well to changes in outbreak trends over time.	4.39	Adaptable
Additional data sources or modules (e.g., climate data, mobility data) can be integrated into the system when needed.	4.65	Highly Adaptable
The system is compatible with various health information platforms used by local or national agencies.	4.58	Highly Adaptable
ASCLEPIUS adapts well to different population densities and environmental conditions in outbreak monitoring.	4.60	Highly Adaptable
The system can be applied in various settings, such as local communities, schools, or wider regional health monitoring.	4.63	Highly Adaptable
The design accommodates minor customizations to suit specific user or institutional needs.	4.57	Highly Adaptable

The system is resilient to data quality fluctuations, ensuring stable operation even under inconsistent reporting.	4.45	Adaptable
Grand Mean	**4.54**	**Highly Adaptable**

Table 18 shows that ASCLEPIUS is very flexible, with a grand mean of 4.54. It can keep working well in different data conditions, geographic areas, and environmental scenarios (Topol, 2019; Rahman et al., 2021). Key strengths include the ability to add more data sources (4.65), work with health platforms (4.58), adapt to different population densities and environments (4.60), and work in a variety of settings (4.63), showing that it can be used in a variety of ways (Chen et al., 2020; Wang et al., 2021). Other indicators, like working with incomplete data (4.47), adjusting the model to changes in outbreak trends (4.39), and being able to handle changes in data quality (4.45), were rated as adaptable, which means there are small areas that could be improved. ASCLEPIUS can adapt well to changing conditions, which helps public health authorities make decisions based on evidence, respond quickly to outbreaks, and allocate resources in a flexible way.

Table 19. Acceptability of ASCLEPIUS

Indicator	Mean	Interpretation
The system is economically viable and cost-effective for public health monitoring in local communities.	4.63	Highly Acceptable
The system's framework and tools are suitable for long-term use in outbreak analysis and forecasting.	4.57	Highly Acceptable
The AI and machine learning integration provide a practical solution for improving current dengue surveillance.	4.49	Acceptable
The design and interface are appropriate and acceptable for public health settings.	4.59	Highly Acceptable
Health workers, LGUs, and community users find the alert and notification system helpful and appropriate.	4.70	Highly Acceptable
The system is designed with sustainability in mind, making it suitable for long-term implementation.	4.61	Highly Acceptable
The performance of ASCLEPIUS meets the expectations of health professionals and decision-makers.	4.42	Acceptable
The operation and maintenance requirements are acceptable for local health units with limited resources.	4.55	Highly Acceptable
Users feel that ASCLEPIUS significantly contributes to improving public health response and preparedness.	4.68	Highly Acceptable
Grand Mean	**4.58**	**Highly Acceptable**

Table 19 shows that ASCLEPIUS is very well-liked, with a grand mean of 4.58. This means that it meets the needs and expectations of public health professionals, LGUs, and community users

(ISO/IEC, 2011; Topol, 2019). Key strengths include cost-effectiveness (4.63), helpfulness of the alert system (4.70), long-term usability (4.57), interface design (4.59), sustainability (4.61), and contribution to public health preparedness (4.68). These scores show that the product meets user expectations. Other factors, like AI integration (4.49) and professional performance (4.42), were rated as acceptable, which means that there are some small areas that could be improved (Rahman et al., 2021; Wang et al., 2021). ASCLEPIUS is useful, user-centered, and trustworthy overall. It supports evidence-based decision-making, outbreak readiness, and quick public health response. Its high acceptability encourages users to adopt and engage with it (Topol, 2019; Krittanawong et al., 2020).

5. DISCUSSION

The results of this study show that the ASCLEPIUS platform does a good job of combining climate, demographic, and symptom-based data to make accurate dengue risk predictions at the barangay level. The MLR and LSTM models both did very well, which shows that temperature, humidity, rainfall, and wind speed have a big effect on the number of dengue cases in Tupi. These are all factors that are consistent with global epidemiological trends. The hybrid MLR–LSTM model made predictions even more accurate than traditional regression-based methods by finding nonlinear patterns and temporal dependencies that are hard to see with linear analysis alone. This shows that the platform can turn complicated health and environmental data into useful risk indicators, which helps with early detection and proactive intervention. The results of user evaluations are just as important. They show that ASCLEPIUS is a functional, usable, adaptable, and acceptable system for health workers on the front lines. Barangay health workers, municipal officers, and healthcare professionals all gave the platform high marks in all categories, praising its easy-to-use design, clear data visualizations, and alert systems that work quickly. These results show that ASCLEPIUS is not only technically sound, but it also meets the needs of local health authorities in a practical way. The system makes community-based surveillance stronger and makes local health units more ready to deal with rising dengue risks by allowing real-time monitoring, automated notifications, and geospatial hotspot mapping. In general, the study backs up the idea that AI-powered public health tools can help with surveillance, make better decisions, and help stop outbreaks before they start in specific areas.

6. CONCLUSION

The findings of this study indicate that the ASCLEPIUS platform is an efficient and dependable instrument for predicting dengue outbreaks at the barangay level. The system effectively captured the impact of climatic and demographic factors on dengue incidence by incorporating Multiple Linear Regression, Long Short-Term Memory modelling, and a hybrid predictive framework. The strong predictive performance across statistical measures confirms that temperature, humidity, rainfall, windspeed, and population density play significant roles in shaping outbreak risk. Additionally, the hybrid MLR–LSTM model showed better accuracy than traditional linear methods, showing how important it is to use both mathematical modelling and machine learning techniques in modern epidemiological forecasting. ASCLEPIUS not only had strong technical features, but it was also well-liked by end users, as shown by the high ratings for functionality, usability, adaptability, and acceptability. Health workers saw that the system could help find diseases earlier, make reporting easier, and help public health interventions happen on time. These results show that the platform can fill in the gaps in the current surveillance system and give local communities real-time, evidence-based information. This study confirms that AI-powered decision-support systems like ASCLEPIUS can greatly improve public health readiness, help with managing outbreaks, and serve as examples for new ideas in disease forecasting and surveillance.

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