

Dengue Observatory: An Environment- and Weather-Driven Epidemiological Modelling Framework for Iloilo City

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Abstract

Dengue fever, a mosquito-borne viral infection, remains a significant public health threat in the Philippines. Iloilo City has been particularly vulnerable to recurring outbreaks due to its geographic and climatic conditions. This study presents a localized agent-based epidemiological modelling framework, the Dengue Observatory, which integrates real-time weather data and other environmental factors to simulate and visualize Dengue transmission dynamics in Iloilo City. The model incorporates weather variables and virulence factors to identify potential outbreak periods. Utilizing epidemiological records from the local government and meteorological data from 2020 to early 2025, the model highlights high-incidence zones across the city. It builds upon a more realistic SEIR model and explores refined parameterization strategies. Findings indicate a strong correlation between Dengue spikes and prolonged periods of rainfall and high humidity. Water-adjacent and low-lying areas consistently emerge as transmission hotspots. However, limitations include the difficulty in quantifying virulence levels and accurately mapping mosquito population densities. Despite these challenges, the model offers valuable insights that can support more targeted and data-driven public health interventions based on real-time environmental and spatial data.

1. Introduction

Dengue fever is a mosquito-borne viral infection that primarily spreads in tropical and subtropical regions. In recent years, it has become a significant public health concern in the Philippines. As of November 2024, the Department of Health (DOH) reported 340,680 Dengue cases nationwide, an alarming increase from the 188,574 cases recorded in 2023. This surge highlights the growing threat Dengue poses to the lives of Filipinos and the country's healthcare system.

Iloilo City, the capital of Iloilo province, has been notably affected. In August 2024, the local government declared a state of calamity, prompting emergency response measures and intensified vector control efforts. Between January and November 2024, the city recorded 1,810 cases and six deaths - figures that call for urgent action to prevent further outbreaks.

Aedes aegypti, the primary mosquito vector for Dengue, breeds in stagnant water found both indoors and outdoors. Iloilo City's proximity to rivers, ponds, and other bodies of water, combined with the Philippines' tropical climate, creates ideal breeding conditions for the species. Environmental factors such as rainfall, temperature, and humidity significantly influence Dengue transmission, as they shape mosquito reproduction and virus incubation rates (Teurlai et al., 2015). These environmental and geographical elements are thus critical to understanding the dynamics of Dengue spread.

Another underexplored aspect influencing disease severity is viral virulence. This refers to the varying levels of harm caused by various Dengue virus genotypes. While this factor may contribute to more severe or lethal infections, it is often excluded from predictive models due to the difficulty of obtaining clinical data. Assessing virulence requires laboratory analysis, and many infected individuals remain asymptomatic, complicating data collection (Bente and Rico-Hesse, 2006).

Given the vulnerability of Iloilo City, this study proposes the development of a Dengue Observatory, a localized, agent-based epidemiological modelling framework that integrates environmental variables and viral virulence to predict potential outbreaks. Early and accurate outbreak forecasts can help reduce transmission rates by enabling timely public health interventions (Chen et al., 2015). The model aims to support local authorities in resource planning, risk mitigation, and implementation of targeted vector control strategies (Medlock et al., 2009).

Several existing models attempt to forecast Dengue behavior, often using weather and population data. However, to be effective, models must be systematic, adaptable, and generalizable, incorporating environmental and demographic dynamics (Leung et al., 2023). Machine learning approaches such as neural networks, random forests, and support vector machines, have shown promise, though results vary. Some studies (Adde et al., 2016) demonstrate high accuracy when using climate data alone, but often omit spatial variables, which may limit predictive power. Others (Chang et al., 2015) suggest that combining entomological and meteorological factors yields better results. Mechanical models, which simulate disease transmission processes, may further enhance predictive accuracy by focusing on the dynamics underlying Dengue spread.

2. Exploratory Data Analysis

This study analyzed Dengue case data in Iloilo City from 2020 to 2024 to identify temporal and spatial patterns of disease incidence. Weekly case counts were collected at the level of barangays (small territorial and administrative districts forming the most local level of government in the Philippines). However, some gaps were observed due to incomplete reporting in certain barangays. The data were stratified by year, week, and location to model the temporal dynamics of Dengue transmission.

Figure 1 illustrates the weekly Dengue case counts from 2022 to 2024. The year 2024 recorded the highest incidence, with cases that started to rise in mid-June, peaked in early August, and tapered off by late October. This pattern corresponds with the Philippine rainy season. Notably, this seasonal spike in cases recurs annually, coincident with periods of increased rainfall and humidity.

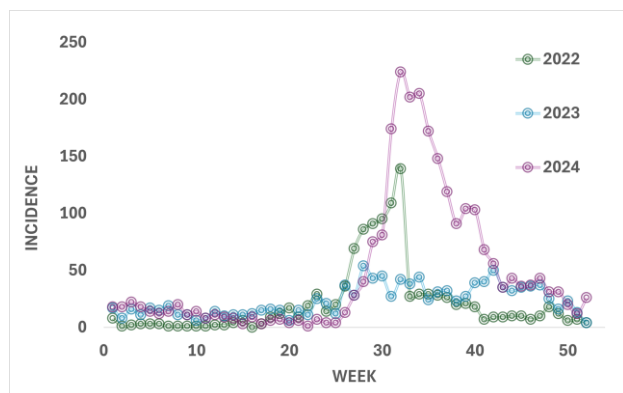


Figure 1. Weekly Dengue infection cases recorded from 2022 to 2024. Data was obtained from the office of DOH Iloilo.

Meteorological data were collected over the same time period to assess potential correlations with Dengue outbreaks. As shown in Figure 2, rainfall in Iloilo City generally increases in May, peaks in July, and declines in December. This trend closely mirrors the rise in Dengue cases, suggesting a positive correlation between rainfall and disease incidence. The inclusion of weather variables such as precipitation and humidity into the model is therefore justified.

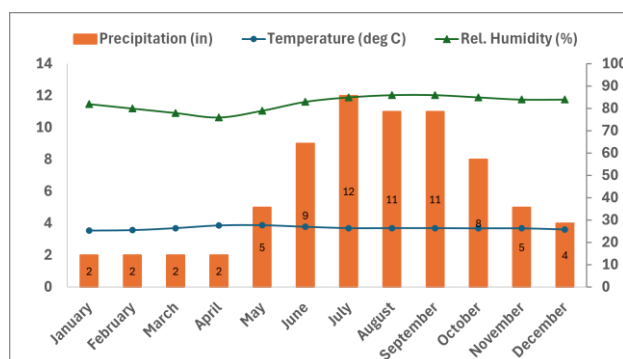


Figure 2. Monthly weather data averages from 2020 to 2024 from <https://www.weather25.com>.

Figure 3 shows the distribution of Dengue cases by district in Iloilo. Most of the cases are from Jaro District, with more than one fourth of the cases, followed by Molo and Mandurriao. Meanwhile, Figure 4 maps Iloilo City's water bodies, including the Iloilo River, which traverses multiple districts, as well as the Tigum and Batiano Rivers, fishponds, creeks, floodways, and coastal ports. *Aedes aegypti*, the primary Dengue vector, breeds in stagnant water; thus, proximity to water bodies likely contributes to high transmission risk. Jaro is situated near both the Tigum River and the Jaro Floodway, while Molo and Villa de Arevalo are adjacent to fishponds and the Batiano River. Districts with fewer cases, such as Mandurriao, Iloilo City Proper, and Lapuz, have less exposure to such water sources.

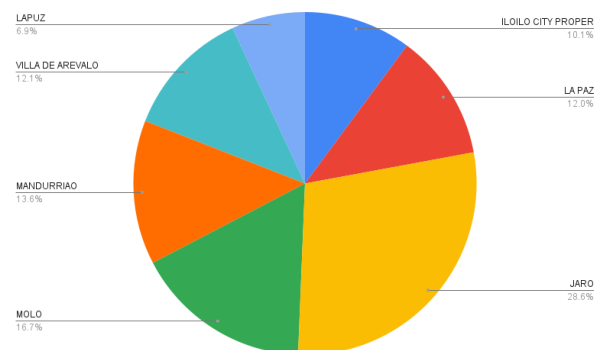


Figure 3. Distribution of Dengue incidence by district.



Figure 4. Geographical map of Iloilo City including major water bodies that are potential breeding grounds for Dengue vectors.

Figure 5 shows a spatio-temporal visualization (red gradient) of the cumulative incidence of Dengue overlaying the geographical map of the barangays in Iloilo. Darker red implies higher incidence levels. The southern districts (Villa de Arevalo and Molo) and the northern district (Jaro) contain multiple purple and black barangays. Although some of these are near natural water sources, others may suggest alternative breeding grounds such as roof gutters, pots, tires, and air-conditioning runoff. This emphasizes the importance of including both natural and artificial breeding sites in the spatial component of the model.

In Figure 6, we show the total incidence of Dengue from 2020 to 2024 against the population of the districts based on the 2020 National Census. The Jaro district, which recorded the highest number of Dengue cases, also has the largest population. In contrast, Lapuz, which had the fewest cases, is also the least populated district. This observation suggests that population contributes to the number of Dengue cases, alongside geographic proximity to potential breeding grounds for mosquitoes. This is confirmed with a high correlation coefficient of $R^2 = 0.913$.

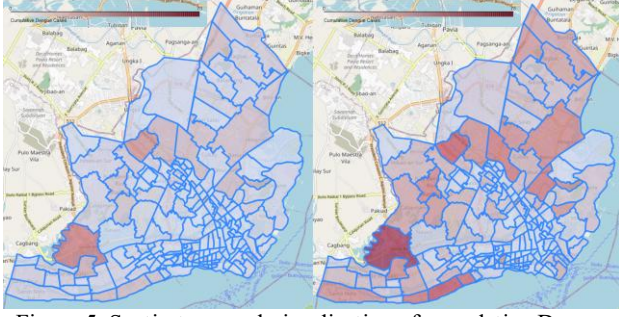


Figure 5. Spatio-temporal visualization of cumulative Dengue incidence by district overlaid with the geographical map. Left: July (start of outbreak), Right: December (end of year).

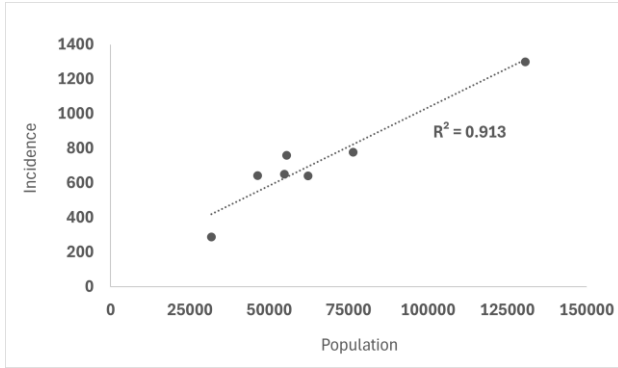


Figure 6. Total Dengue incidence from 2022 to 2024 versus population based on 2020 National Census (<https://openstat.psa.gov.ph>).

In general, this analysis helps to understand the interaction between population distribution and environmental factors in the transmission of Dengue in Iloilo City. The derived spatial insights support the estimation of a location index for each district, which can be used in the modelling framework to simulate transmission risk. Areas with high cases and geographic vulnerability may warrant prioritized monitoring and targeted vector control strategies.

3. Methodology

3.1 Epidemiological Model

An agent-based model (ABM) was developed for Dengue infection in Iloilo City to simulate the localized spread of the disease under varying environmental conditions. Agent-based models are computational tools that simulate the actions and interactions of autonomous agents, each following defined behavioral rules. This model builds upon the classical SEIR-SI epidemiological framework, adapted from (Islam et al., 2024) and is governed by a set of differential equations.

The human compartment of the model follows an SEIR model:

$$\frac{dS_H}{dt} = \Lambda_H - \beta_H(t)S_H I_H - \mu_H S_H \quad (1)$$

$$\frac{dE_H}{dt} = \beta_H(t)S_H I_H - (\alpha + \mu_H)E_H \quad (2)$$

$$\frac{dI_H}{dt} = \alpha E_H - (\gamma(v) + \mu_H + \sigma(v))I_H \quad (3)$$

$$\frac{dR_H}{dt} = \gamma(v)I_H - \mu_H R_H \quad (4)$$

On the other hand, the vector compartment follows an SI model:

$$\frac{dS_M}{dt} = \Lambda_M(p, h, r, L) - \beta_M(t)S_M I_H - \mu_M S_M \quad (5)$$

$$\frac{dI_M}{dt} = \beta_M(t)S_M I_H - \mu_M I_M \quad (6)$$

From the model, S_H , E_H , I_H , R_H respectively represent the susceptible, exposed, infectious and removed compartments for humans, while S_M and I_M represent the susceptible and infectious compartments, respectively, for mosquitoes (Figure 7). Transmission occurs when a susceptible human is bitten by an infectious mosquito, transitioning to the exposed state at a time-dependent transmission rate $\beta_H(t)$. The exposed individual becomes infectious at an infection rate $\gamma(v)$, which is influenced by virulence v and eventually moves to the removed compartment. Similarly, mosquitoes become infectious at a virulence-dependent transmission rate $\beta_M(v)$ and die at a rate μ_M .

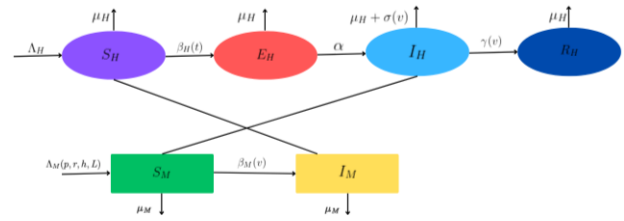


Figure 7. Flow diagram of the SEIR-SI model of Dengue infection.

While many parameters were adapted from prior studies, this model introduces new variables to account for virulence and weather-related factors. Below is an overview of key components:

Virulence-dependent transmission rate in mosquito population, $\beta_M(v)$

Virulence, representing the lethality or harmfulness of Dengue, affects mosquito transmission rates. More virulent strains of Dengue tend to spread less efficiently, reflecting an inverse relationship between transmission and virulence, integrated mathematically into $\beta_M(v)$.

Time-dependent transmission rate for humans, $\beta_H(t)$

The human transmission rate follows a sinusoidal function over the calendar year to reflect seasonal variation. Dengue cases typically rise in mid-June and decline by late October. Adjustment in magnitude A reflects peak transmission intensity while adjustment in the phase shift ϕ and period T (adjusted to 25 and 43 respectively), aligns with epidemiological timing. This allows environmental factors like weather to modulate transmission risk over time.

Virulence-dependent infectious individuals recover, $\gamma(v)$

As virulence increases, the likelihood of recovery decreases. This relationship is modelled so that more virulent strains reduce the probability of recovery, thereby influencing the dynamics of the infected population.

Virulence-dependent death rate of human by the disease, $\sigma(v)$

Similarly, virulence increases the probability of death from Dengue, with higher virulence associated with greater lethality in infected humans.

Parameter	Description	Value	Reference
$\beta_M(v)$	Virulence-dependent transmission rate for mosquitoes	$\beta_M(v) = \frac{1}{v} \times 0.3$	Sun (2018)
$\beta_H(t)$	Time-dependent transmission rate for humans	$\beta_H(t) = \begin{cases} 0, & 0 \leq t \leq 24 \\ A \sin\left(\frac{2\pi(t-\varphi)}{T}\right), & 25 \leq t \leq 43 \\ 0, & 44 \leq t \leq 52 \end{cases}$	Assumed
α	Transition rate from exposed to infectious (1 / latent period)	$\frac{1}{3}$	Sun (2018)
$\gamma(v)$	Recovery rate (virulence-dependent, 1 / infectious period)	$\gamma(v) = v \times \frac{1}{4}$	Hamdan (2020)
A	Amplitude of seasonal transmission variation	[0.1, 0.5]	Assumed
φ	Phase shift for seasonal variation	25	Assumed
T	Period of seasonal variation	43	Assumed
μ_H	Natural death rate of humans	0.001	Hamdan (2020)
$\sigma(v)$	Disease-induced death rate in humans (virulence-dependent)	$\sigma(v) = v \times 0.001$	Assumed
Λ_H	Human birth rate	10^{-6}	Assumed
$\Lambda_M(p, r, h, L)$	Weather- and location-dependent mosquito birth rate	$\Lambda_M(p, r, h, L) = \frac{p}{27.6} \cdot \frac{h}{81.3} \cdot \frac{r}{6.4} \cdot L \cdot 10^{-3}$	Assumed
μ_M	Mosquito death rate	10^{-5}	Assumed
p	Temperature	Varies	Average Temp (°C)
h	Humidity	Varies	Relative Humidity (%)
r	Rain	Varies	Precipitation (inches)
v	Virulence	1.33	Deaths / Cases
L	Location index	Varies	Assumed

Table 1. Description of the parameters of the modified SEIR-SI model

Weather and Geographic-dependent birth rate of mosquito, $\Lambda_M(p, r, h, L)$

The mosquito birth rate is influenced by environmental variables such as precipitation p , temperature r , and humidity h , along with a location index L . Favorable weather condition, particularly increased rainfall, enhances mosquito breeding. The model uses average meteorological values and spatial proximity from breeding sites to modulate mosquito population dynamics.

Virulence, v

Virulence values were derived by dividing the number of Dengue-related deaths by the total number of reported cases in Iloilo City. This estimation was deemed necessary due to limited direct data.

Location Index, L

The location index assigns a district's relative risk based on incidence data. Although this ought to be related to their proximity to breeding sites of the Dengue vector, influencing mosquito abundance and transmission potential across districts, the location index is basically a ranking of the districts based on Dengue incidence data, i.e., districts with high incidence are assigned high location index.

District	Location Index
Iloilo City	2
La Paz	2
Jaro	5
Molo	4
Mandurriao	2
Villa de Arevalo	4
Lapuz	1

Table 2. Location index assignment of the different districts.

3.2 Agent-Based Simulation

Building on the SEIR-SI model, an agent-based model was implemented to simulate Dengue spread at the individual level. ABMs are particularly suited for modelling vector-borne diseases in complex urban settings due to their ability to capture heterogeneous interactions among agents and their

environments. The simulation includes three agent classes, namely (i) *PersonAgent* (humans), (ii) *MosquitoAgent* (mosquitoes), and (iii) *DistrictAgent* (geographical zones). Each *PersonAgent* includes attributes such as a unique ID, state (susceptible, exposed, infected, recovered), and district of residence. *MosquitoAgent* includes similar fields, with additional flags: *bitten* indicates a bite from an infectious mosquito, *bite* marks when the mosquito has fed on an infected human. The agents are randomly initialized across the seven districts of Iloilo City. The number of agents per district is proportional to the 2020 population of the districts. The simulation employs GIS data to bind agents to real-world spatial boundaries. The states of the agents are visualized using colored markers: Green (Susceptible), Yellow (Exposed), Red (Infected), Grey (Recovered), and Black (Mosquito) as shown in Figure 8.

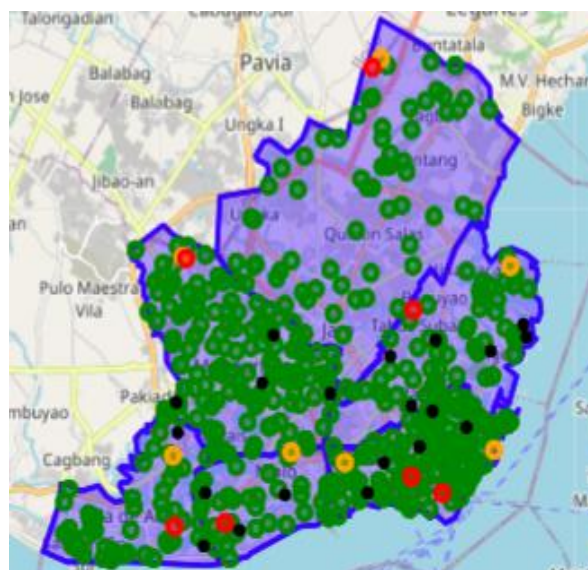


Figure 8. Agent-based simulation of SEIR-SI model using MesaGeo platform. Susceptible individuals (green) bitten by Dengue vectors (black) becomes exposed (yellow) and could eventually become infected (red).

Agents interact based on probabilistic rules governed by the model parameters. Environmental variables such as rainfall, temperature, and location index are normalized and probabilistically integrated to influence mosquito birth rates and spatial distributions. The simulation was implemented in Python, using the Mesa library (Masad et al., 2015) and MesaGeo (Corvince, 2018) libraries for geospatial features. The rendered map of Iloilo City serves as the base for simulating agent interactions. Graphs were incorporated to track state transitions and population dynamics on a weekly basis.

4. Results and Discussion

Simulations were conducted to generate two key insights into the dynamics of Dengue transmission in Iloilo City. The first objective was to assess the model's accuracy by comparing simulated weekly Dengue infection data against the actual 2024 records. The second was to forecast potential Dengue trends for 2026 using the projected meteorological data from www.weather25.com.

Figure 9 illustrates the simulated weekly Dengue cases for 2024 under varying amplitude values, ranging from $A=0.1$ to $A=0.5$. Among these, the $A=0.4$ simulation produced the highest number of Dengue cases. Notably, simulations with lower A values ($0.1 - 0.3$), showed peaks in late July and broader high infection period. On the other hand, higher values of A (0.4 and 0.5) resulted in an earlier peak in early July but less broad period of high infection. However, when juxtaposed with the 2024 Dengue incidence data (Figure 10), $A=0.2$ simulation turns out to give the lowest average relative error (0.8862) and RMSE (0.8375) with respect to the normalized values (normalization was done by dividing with respect to the maximum total incidence). Moreover, the actual and simulated incidence data have a high correlation coefficient of 0.9240. The simulation closely mirrored real trends especially the time at peak infection (Figure 11) and transient infection of the disease in the early part of the year.

Following validation, the model was also used to demonstrate forecasting of Dengue cases in 2026 using projected rainfall and temperature data from the same data source. Humidity was held constant based on 2024 values. Based on our proposed model, the forecast results (Figure 12) suggest that exposure to Dengue starts at Week 22, and an outbreak starts in the following weeks. The projected peak in Dengue cases is around early August but around the same time, exposure steadily declines. These observations align with the seasonal increase in rainfall and underscores the importance of initiating vector control and public health interventions in the month July to reduce the impact of a potential Dengue outbreak.

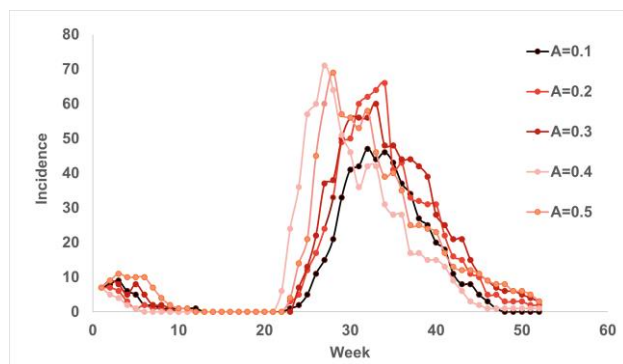


Figure 9. Simulated Dengue incidence using 2024 data at varying values of the transmission amplitude A .

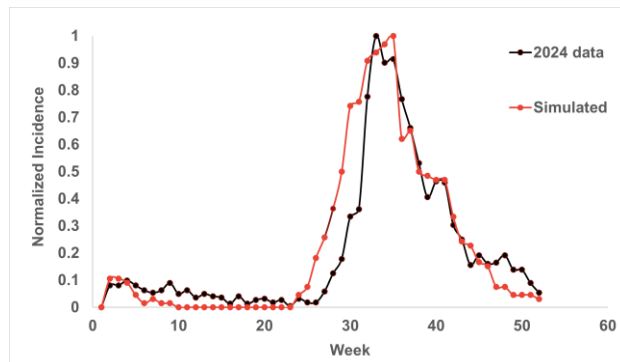


Figure 10. The 2024 Dengue incidence data (normalized) is closest to the agent-based SEIR simulation using $A=0.2$.

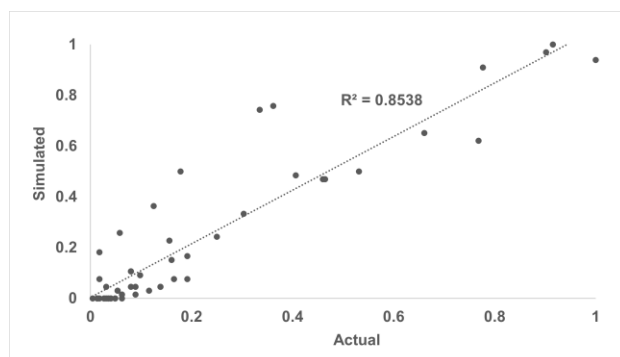


Figure 11. Simulated versus actual data are highly correlated especially at peak infection.

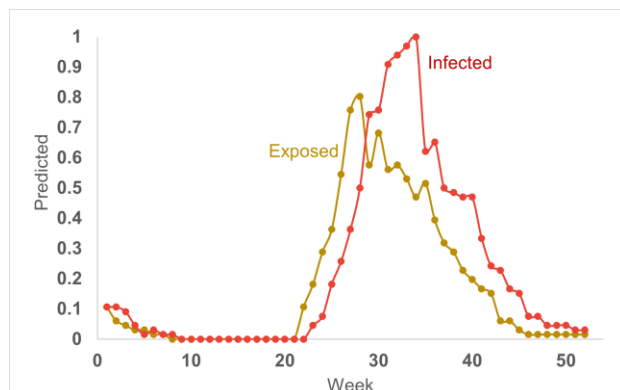


Figure 12. Simulated Dengue cases for 2026 using projected weather data. Times at rising exposure and peak infection can be used by local government units to create informed policies.

While the model provides valuable insights into the dynamics of Dengue disease spread and control, several sources of uncertainty should be acknowledged. One key area of uncertainty lies in the estimation of virulence, often inferred from observed deaths and confirmed cases. These data can be influenced by underreporting, delays in diagnosis, testing availability, and changing case definitions over time. Additionally, the infection fatality rate and case fatality rate may vary significantly across populations, depending on demographic factors, healthcare capacity, and intervention timing. In our current model, virulence-related parameters were estimated under simplifying assumptions. Future iterations will incorporate more rigorous methods of uncertainty quantification, such as probabilistic modelling or sensitivity analysis, to evaluate how these assumptions influence model outcomes (Kenney, 2023; Sorci et al. 2022). Acknowledging and addressing these uncertainties is essential for drawing

robust conclusions and guiding evidence-based decision-making.

A technical limitation of this study is the reduced number of agents used in the simulation due to hardware constraints. This prevented a full-scale representation of Iloilo City's population. In the future, we plan to explore cloud-based or high-performance computing solutions to improve scalability and generalizability of the proposed model, showing how it could be adapted to other urban contexts or scaled up to regional applications, with appropriate modifications to input data and model calibration.

5. Conclusion and Future Works

This study developed a localized SEIR-SIR model to simulate Dengue transmission in Iloilo City, incorporating environmental and virulence factors. Utilizing GeoMesa for spatial and temporal analysis, the model successfully predicted the timing of Dengue outbreaks, identifying consistent surges in cases toward the end of July. Simulations also indicated that higher amplitudes in rainfall and humidity could trigger earlier outbreaks, with projections suggesting a potential upsurge in July to August 2026.

These findings highlight the model's potential as a decision-support tool for public health planning. With advance knowledge of high-risk periods, government and health officials can implement timely interventions such as intensified mosquito surveillance, targeted insecticide application, and community awareness campaigns. The model thus contributes to building an early warning system for Dengue outbreaks in Iloilo City. Further modifications can still be made with the model to capture more realistic weather and environmental effects. Different mobility models can also be integrated into the agent-based simulation of the SEIR-SI Dengue infection model (Lessani et al., 2023) including crossing boundaries between districts. Spatiotemporal mobility patterns derived from data (Zhang et al., 2023) such as opening and closing of school year or district festivities, may also shed light into understanding the spatiotemporal patterns of infection.

Moreover, the framework could be integrated into citizen science initiatives, e.g. AI4PEP project (AI4PEP, 2025), enabling the public to explore Dengue dynamics by adjusting key parameters in the model. This collaboration would foster greater community engagement and awareness, empowering individuals to better understand how environmental conditions and public health strategies affect disease spread.

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