SPATIOTEMPORAL ANALYSIS OF DENGUE CASES IN CEBU CITY FROM YEAR 2015 TO 2022

A. M. Rejuso*, S.C. Sampayan, K.V. Petallo, F.A. Pulaw, K.C. Rodriguez, Z.G. Rosales, M. Mumtaz, N.I. Saber, E.L. Salonga, A.R. Sente, A.B. Silvela, K.R. Krishna, Z.P. Pepito, M.C. Masalunga, A.L. Banaay

School of Medicine
Southwestern University PHINMA, Cebu City, Philippines - *armo.rejuso.swu@phinmaed.com, (salc.sampayan, kive.petallo, faas.pulaw, kaco.rodriguez, zygo.rosales, muha.mumtaz, noil.saber, ezle.salonga, anir.sente, arib.silvela, karn.krishna, mcmasalunga, albanaay).swu@phinmaed.com, zichrikerenpepito@gmail.com

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ABSTRACT:

Long-term climate changes, including increased temperature, shift in precipitation, wind patterns, and other climate factors, can disrupt the balance of nature and have significant implications in the transmission of dengue fever. This study investigated the spatial and temporal dynamics of dengue cases in Cebu City, a key metropolitan area in the Philippines characterized by a significant rate of urbanization in recent years. Climate Engine (CE), a cloud-based computing and visualization tool, was utilized in this study for database sources of Landsat 8 pre-processed satellite images. Time-series dataset of land surface temperatures (LST) and varying environmental indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI) were examined to investigate the effects of increased urban surface temperatures, expanding urban structures, and diminishing vegetation in Cebu City on dengue cases from 2015 to 2022. The spatial distribution of dengue cases was analyzed through GeoDA to identify hotspots within the city. The annual dengue cases in Cebu City exhibit a temporal trend with a peak in 2016 (4637 cases) and a lowest point in 2021 (399 cases), the year when the pandemic struck. Most dengue cases were recorded between June and December, exhibiting a strong seasonal pattern, and primarily concentrated within the wet season. Barangay Guadalupe topped the number of cases (1781) followed by Barangay Lahug (1219 cases), and Barangay Labangon (1128 cases) from 2015 to 2022. These three residential barangays are in proximity to each other, indicating a potential localized clustering of dengue cases in neighboring areas. The equation derived from the linear regression model serves as a predictive tool for estimating dengue cases in Cebu City and is expressed as *Dengue cases = -28.436 + 2.137 (LST) - 13.943 (NDVI) + 8.565 (NDWI) - 10.217 (NDBI)*. The findings of this study will have practical implications for urban planning and the development of local policies aimed at mitigating the rise in dengue cases.

1. INTRODUCTION

Long-term changes in climate patterns, including increase in temperature, changes in precipitation rate, and wind patterns, are constantly occurring over several decades. They are primarily caused by anthropogenic activities, specifically the burning of fossil fuels such as coal, oil, and natural gas, which releases greenhouse gases into the atmosphere resulting in a rise in the earth's temperature (Grossman, 2018). Climate change has drastically affected thousands of lives worldwide. Over time, warmer temperatures have altered weather patterns and disrupted the usual balance of nature (Ong et al., 2022). These changes have a possible significant impact on the transmission of vector-borne diseases, such as dengue fever.

Dengue is prevalent in many tropical regions. As the global climate continues to warm, there is an increased likelihood of increased dengue cases (Murray, Quam, Wilder-Smith, 2013). The constant alteration brought by climate change such as warming temperatures and unprecedented flooding have encouraged the spread of mosquitoes well beyond their traditional breeding grounds, bringing dengue fever to areas that were never before threatened by this debilitating illness (Houtman et al., 2022). Warmer temperatures also increase the lifespan of mosquitoes, shorten their incubation period, and increase their biting rate, all of which contribute to a higher incidence of dengue (Bellone and Failloux, 2020). Changing rainfall patterns may create more favorable breeding conditions for mosquitoes, leading to an increase in their population and the spread of the disease (Altoa and Bettinardi, 2013; Reinhold, Lazzari, and Lahondère, 2018). Globally, the incidence of dengue has grown dramatically in recent decades. It is estimated that 3.9 billion people are at risk of dengue infection and around 390 million are infected by the dengue virus per year. Despite a risk of infection existing in 129 countries, 70% of the actual burden is in Asia (World Health Organization, 2022).

The Philippines is characterized by a tropical climate, featuring relatively high temperatures, abundant rainfall, and high humidity levels. This ideal climate for mosquito species has contributed to its classification as one of the countries with the highest number of dengue cases globally (Bravo et al., 2014). Cebu City, a highly urbanized city in the Philippines, had one of the highest numbers of dengue cases for more than a decade (Edillo and Madarieta, 2012). Urbanization often results in the creation of artificial breeding grounds for mosquitoes, such as stagnant water in containers or discarded tires, which further exacerbates the dengue problem (Novaes et al., 2022; Ooi and Gubler, 2009). Moreover, climate changes resulting in increased temperature and rainfall, together with urbanization, may be associated with increased dengue incidence and outbreak risk (Ebi et al., 2016).

Numerous studies have analyzed the relationship between environmental variables and dengue (Sekarrini et al., 2022; Marti et al., 2020, Sarma et al., 2022). Remote sensing data from satellite imagery has a great capability in monitoring climate and environmental factors at both global and local scales. The data can be used to track changes in land use, vegetation cover, ocean currents, and atmospheric conditions (Guha and Govil, 2020). However, local research regarding the relationship between the number of dengue cases and environmental factors through the use of remote sensing data is quite limited. Satellite imagery, specifically from Landsat, can be used for the analysis of

* Corresponding author

environmental factors such as land surface temperature (LST), normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), and normalized difference water index (NDWI). Furthermore, Climate Engine (CE), an online cloud computing platform that pre-processes satellite imagery and climate data through machine learning algorithms, was utilized as the database source of the environmental factors analyzed in this study (Huntington et al., 2017; Rejuso et al., 2019).

This study focused on analyzing the spatiotemporal trends of environmental indices and changes in dengue incidence in Cebu City over the years, from 2015 to 2022. The objectives of the study were: 1) to analyze the spatial and temporal variations of dengue cases, LST, NDVI, NDWI, and NDBI in Cebu City; 2) to examine the relationships between the dengue cases with LST, NDVI, NDWI, and NDBI; 3) to identify and map the dengue hotspots within Cebu City; 4) to develop a linear regression model with dengue cases as the dependent variable and LST, NDVI, NDWI, and NDBI as predictors. This study could provide important insights into the underlying causes of the disease and inform strategies for prevention and control.

2. RESEARCH METHODOLOGY

2.1 Study Area and Research Population

Cebu City, located in the Philippines, is the capital of Cebu province and the regional center of the Central Visayas region. It is the central hub of Metro Cebu, an area encompassing various other fast-developing cities and municipalities (Cañete et al., 2019; Etemadi, 2000). It is situated in the eastern coastal plains of Cebu province located at 10° 17′ 34.8″ N, 123° 54′ 7.2″ E with an average elevation of 31.42 meters above sea level and spans an area of 330 square kilometers. It comprises 80 barangays, as displayed in Figure 1 and Table 1 in the Appendix. The majority of the population resides in 49 urban barangays that are situated along the coast, covering a mere 17% of the city's land area. Meanwhile, the remaining 12% live in 31 rural barangays located in upland areas beyond the coast, which account for 83% of the city's land area (Cañete et al., 2019; Etemadi, 2000).

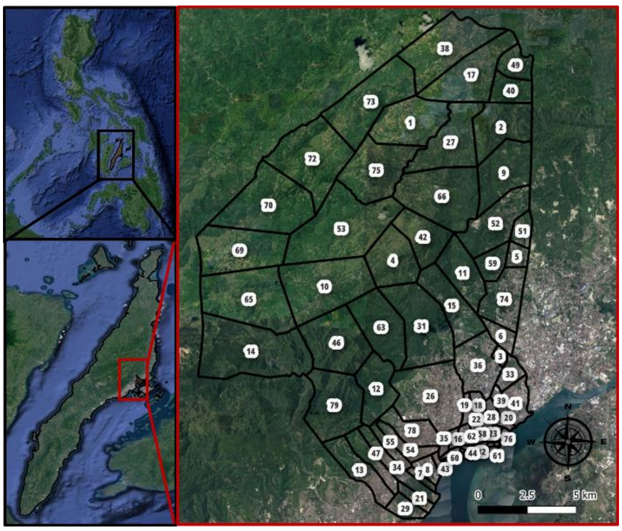

Figure 1. Map of Cebu City showing barangay boundaries with identification numbers

2.2 Study Design and Analysis Workflow

The methodology used in this research was adapted from a previous study, with modifications (Rejuso et al., 2019). Briefly, the study was done as follows:

1) Retrieving LST, NDVI, NDWI, SWIR, and NIR band layers from CE,
2) Generating the NDBI layer from SWIR and NIR band layers,
3) Computing the average values of LST and environmental indices per barangay,
4) Analyzing the correlations between LST, environmental indices, and dengue cases in Cebu City
5) Mapping of the dengue cases hotspots in Cebu City

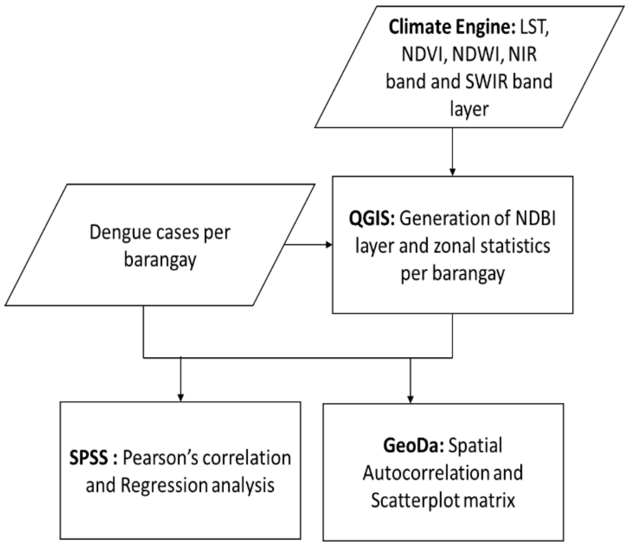

Figure 2. Workflow for investigating the relationship between environmental indices and dengue cases in Cebu City

2.3 Data Retrieval and Generation

Data on the dengue cases per barangay in Cebu City was provided by the Regional Epidemiology and Surveillance Unit (RSU 7) of the Department of Health - Central Visayas Center for Health Development (DOH-CVCHD). It was requested and accessed through the Electronic Freedom of Information website (e-FOI).

2.4 Environmental Indices

2.4.1 Land surface temperature (LST): LST refers to the temperature of the Earth's surface, including the rooftops, pavements, soil, and vegetation. It is calculated based on Equation 1 with the use of Satellite Brightness Temperature (BT), the wavelength of the emitted radiance (λ), ε is the land surface emissivity, and ρ is the product of Planck's constant (h), the speed of light (c), and the Boltzmann constant (σ) (Mustafah et al., 2020; Avdan et al., 2016). This calculation is already pre-processed in Climate Engine.

$$LST = \frac{BT}{1 + (\lambda(\mathrm{BT}) * \ln(\varepsilon)/\rho} \quad (1)$$

2.4.2 Normalized difference vegetation index (NDVI): NDVI based on the Near-Infrared (NIR) and Red bands, as demonstrated in Equation 2, is used in determining the vegetation cover in an area. The NDVI values have a range of -1 to +1, with values close to zero corresponding to built-up areas, while values close to +1 signify the maximum possible density of green vegetation (Isa, Wan Mohd, and Salleh, 2013; Liu and Zhang, 2011; Rejuso et al., 2019). This calculation is already pre-processed in Climate Engine.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

Where, NIR = near-infrared reflectance
RED = red reflectance

2.4.3 Normalized Difference Built-up Index (NDBI): NDBI is a frequently used indicator for identifying built-up areas in urban regions. The calculation of NDBI layers involves utilizing the Short-Wave Infrared 1 (SWIR 1) and Near-Infrared band layers, as presented in Equation 3. The NDBI values range between -1 to +1, where higher values of NDBI indicate a more highly built-up area (Za, Gao, and Ni, 2003; Rejuso et al., 2019). This calculation is processed in QGIS.

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \tag{3}$$

Where, SWIR1 = shortwave infrared 1 reflectance

2.4.4 Normalized Difference Water Index (NDWI): NDWI is used to detect the presence of water in the environment. It is calculated using the reflectance values in the Near-Infrared and Short-Wave Infrared 1 band layers as displayed in Equation 4. NDWI values range from -1 to +1. Higher NDWI values indicate a higher likelihood of water presence, while lower NDWI values indicate a lower likelihood of water presence (Gao, 1996; Rejuso et al., 2019).

$$NDWI = \frac{NIR - SWIR1}{NIR + SWIR1} \tag{4}$$

2.5 Data Analysis

2.5.1 Scatterplot Matrix and Correlation: A scatterplot matrix was utilized to assess and visualize the interrelationships between dengue cases, LST, NDBI, NDVI, and NDWI. Pearson's correlation was employed to determine the correlation among these variables. In this study, the strength of the correlation was dependent on the r-value, with a value above 0.7 or near 1 indicating a strong relationship, a value below 0.7 but above 0.5 indicating a moderate relationship, and a value below 0.5 indicating a weak relationship.

2.5.2 Linear Regression Model: A linear regression analysis was conducted to establish and develop a predictive model for dengue cases. The predictor variables used in the model are LST, NDVI, NDWI, and NDBI. Through this approach, the generated model can be used to forecast or predict the number of dengue cases based on the values of the predictor variables. The general equation of a linear regression model with multiple predictors can be written as displayed in Equation 5. The intercept term (β0) represents the estimated value of the dependent variable when all predictor variables are equal to zero. The regression coefficients (β1, β2, β3, ..., βn) associated with each predictor variable indicate the expected change in the number of dengue cases for a unit change in the corresponding predictor variable, assuming that all other variables remain constant. The predictor variables (X1, X2, X3...Xn) represent the measurements of LST, NDVI, NDWI, and NDBI, which are included in the model to predict the number of dengue cases. The error term (ε) accounts for the unexplained variability or random factors that may influence the relationship between the predictors and the dependent variable.

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta nXn + \varepsilon \tag{5}$$

3. RESULTS AND DISCUSSION

3.1 Dengue Cases

3.1.1 Annual variation: The annual dengue cases in Cebu City exhibit a temporal trend as depicted in Figure 3. The data highlights a peak in dengue cases, reaching its highest point in 2016 with a recorded count of 4637 cases. Conversely, the lowest number of dengue cases, totaling 399, was observed in 2021. There is a notable sudden drop in the reported cases during 2020 and 2021. Although the available data for the period of 2020 and 2021 globally are not comprehensive, there is a reduction in the total number of dengue cases reported to the World Health Organization compared to previous years (Khan et al., 2022; Sasmono and Santoso; 2022). During the start of 2020 and until 2021, the COVID-19 pandemic began to spread across the world that caused significant disruptions. The focus of public health authorities, medical professionals, and media coverage during that time primarily centered on the novel coronavirus and its impact on global health, especially on epidemiological data and surveillance systems (Olive et al., 2020). Thus, while there may not have been widespread reports of dengue cases during the COVID-19 pandemic and lockdown, it does not imply a complete absence of such cases.

A notable correlation between the societal disruption caused by the COVID-19 pandemic and a decrease in the risk of dengue after considering the climatic, host immunity, and other factors affecting dengue cycles was observed (Chen et al., 2022). Among the various factors, the strongest evidence of association with reduced dengue risk was observed in relation to school closures and decreased time spent in non-residential areas. These findings further support the notion that dengue transmission is facilitated through human movement, particularly in shared areas outside of homes (Chen et al., 2022; Stoddard et al., 2013).

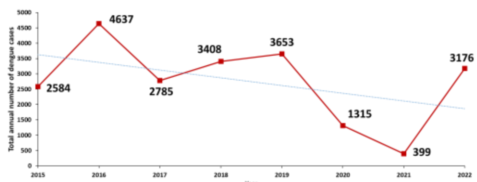

Figure 3. Total number of dengue cases in Cebu City annually from 2015 to 2022

3.1.2 Monthly variation: The monthly dengue cases in Cebu City are illustrated in Figure 4. Fluctuations and varying dengue incidences were observed. The majority of dengue cases in Cebu City recorded a remarkable increase between June and December which corresponds to the literature. The occurrence of dengue outbreaks in the Philippines exhibits a strong seasonal pattern, primarily concentrated within the wet season from June to February (Undurraga et al., 2017). The highest number of recorded dengue cases occurred in November 2016 (819 cases), followed by October 2016 (774 cases), and finally June 2022 (680 cases). These could be attributed to the change in

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environmental conditions during the wet and dry seasons in the Philippines. These alternating seasons can significantly impact the breeding and transmission of dengue-carrying mosquitoes. The wet season, characterized by increased rainfall and higher humidity, provides favorable conditions for mosquito breeding and dengue transmission (Edillo et al., 2022; Iguchi, Seposo, and Honda, 2018,).

In contrast, Cebu City experienced a significant decline in the number of dengue cases, marking a period of low incidence, from March to April. The occurrence of low dengue cases during the dry season can be attributed to several factors. The dry season is characterized by a decrease in rainfall, leading to a reduction in the availability of breeding sites for mosquitoes. The absence of stagnant water reduces the chances of mosquito reproduction and limits their population growth. The instances of lowest number of recorded dengue cases were observed in July 2020 (8 cases), followed by October 2020 (11 cases), and finally May 2020 (12 cases). It is important to note that these remarkably low figures may be attributed to the disruptive effects of the COVID-19 pandemic on epidemiological data collection and surveillance systems. The implementation of measures such as lockdowns, travel restrictions, and physical distancing measures significantly influenced the healthcare system's capacity to detect, diagnose, and report dengue cases accurately (Khan et al., 2022; Olive et al., 2020; Plasencia-Dueñas, Failoc-Rojas, and Rodriguez-Morales, 2022).

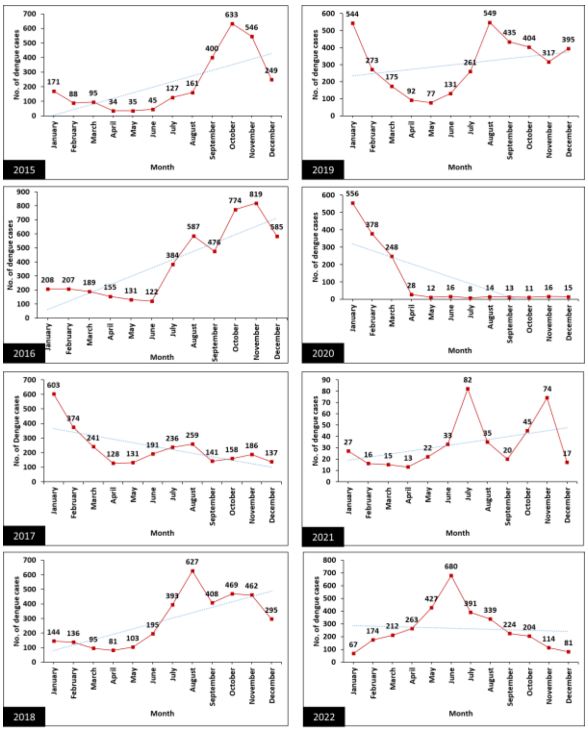

Figure 4. Monthly dengue cases in Cebu City during 2015 – 2022

3.1.3 Spatial Distribution and Hotspot Determination: A barangay-level map with the total dengue cases in Cebu City from 2015 to 2022 is shown in Figure 5. Barangay Guadalupe (ID no. 26) with 1781 cases, Barangay Lahug (ID no. 36) with 1219 cases, and Barangay Labangon (ID no. 35) with 1128 cases have recorded the highest total number of dengue cases from 2015 to 2022. A discernible pattern is observed which indicates that high dengue cases are observed within the residential and commercial barangays rather than on the mountain barangays in Cebu City. Studies have indicated that environmental factors play a crucial role in the transmission of vector-borne diseases. Areas designated for residential purposes are more susceptible to dengue transmission (Garcia, and De las Llagas, 2011; Gurevitz, Antman, Laneri, and Morales, 2021; Seidahmed, Lu, Chong, and Eltahir, 2018).

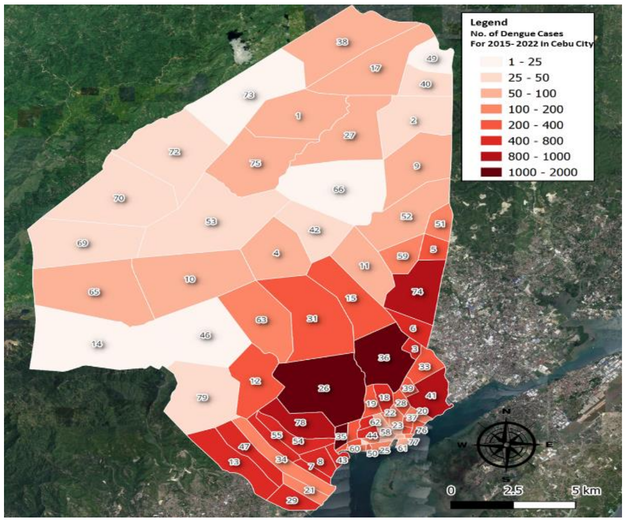

Figure 5. Barangay-level total dengue cases in Cebu City during 2015- 2022

The annual barangay-level map with the total dengue cases per year in Cebu City is shown in Figure 6, where values at the bottom-right corner indicate the highest number of dengue cases in the entire city. Barangay Guadalupe, Barangay Lahug, and Barangay Labangon recorded the highest total number of dengue cases from 2015 to 2022 as displayed in Figure 6. These three residential barangays are near each other, indicating a potential localized clustering of dengue cases in neighboring areas. This might be due to the possible similarity in environmental conditions, which could facilitate faster breeding and proliferation of dengue-carrying mosquitoes.

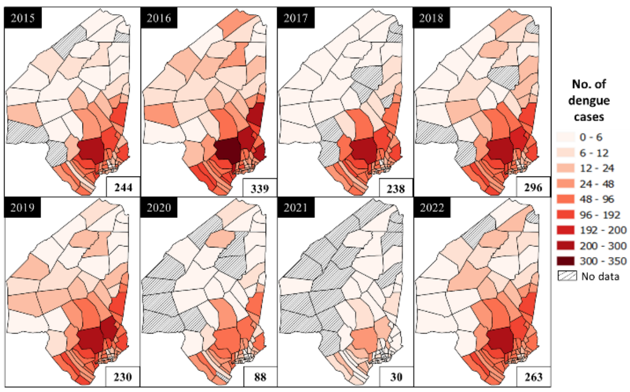

Figure 6. Barangay-level dengue maps in Cebu City from 2015 to 2022

3.2 Relationship between dengue cases between LST, NDVI, NDWI, and NDBI

3.2.1 Cebu City: Scatterplots showing the relationship of dengue cases with LST, NDVI, NDWI, and NDBI are presented in Figure 7. The slopes of the linear fit lines are also included in Figure 7, with significance levels indicated by two asterisks (**) denoting a p-value less than 0.01, while significance levels without asterisks denote a p-value greater than 0.05. The results indicate a weak positive correlation between dengue cases and two predictor variables, LST and NDBI. The slope of 0.240 for LST and 0.144 for NDBI ($p < 0.01$) indicates that there is a small increase in dengue cases with increased values of LST and NDBI. For every unit increase in LST, there is an estimated increase of 0.240 in dengue cases. Similarly, for every unit increase in NDBI, there is an estimated increase of 0.144 in dengue cases. These results indicate that land surface temperature and built-up areas may have a modest impact on dengue cases. Conversely, a weak negative relationship was identified between dengue cases and NDVI, with a slope of -0.141 ($p < 0.01$). This finding suggests that as NDVI values increase, there is a decrease in dengue cases. The negative association indicates that areas with higher vegetation density, as indicated by higher NDVI values, may be associated with lower dengue transmission. Moreover, a weak negative relationship was identified between dengue cases and NDWI, with a slope of -0.175 ($p < 0.01$). This implies that areas characterized by a higher amount of moisture, as indicated by higher NDWI values, are associated with lower dengue cases. The negative correlation suggests that the presence of water bodies or moist environments may hinder mosquito breeding and subsequently reduce dengue transmission.

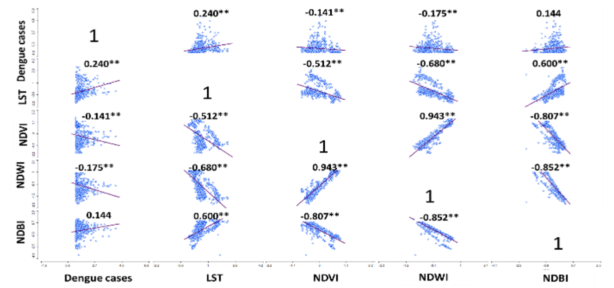

Figure 7. Relationship between dengue cases, LST, and other indices with its corresponding slope of linear fit in Cebu City

3.2.2 Barangay Guadalupe, Cebu City: Figure 8 illustrates the scatterplots depicting the relationship between the variables in Barangay Guadalupe, Cebu City. The results indicate a direct relationship between the dengue cases and LST. The slope of 0.474 ($p > 0.05$) for LST and dengue cases suggests a moderate positive correlation between these variables. This means that as LST increases, there tends to be an increase in dengue cases. Furthermore, there is a weak positive relationship between dengue cases and NDVI with a slope of 0.238 ($p > 0.05$). This means that as NDVI increases, there is a slight increase in dengue cases. On the other hand, dengue cases have a negative association with NDWI. A moderate negative correlation between dengue cases and NDWI with a slope of -0.486 ($p > 0.05$) implies that as NDWI values increase, there is a tendency for dengue cases to decrease. Moreover, a very weak negative relationship was identified between dengue cases and NDBI, with a slope of - 0.058 ($p > 0.05$). This suggests that as NDBI values increase, there is a slight tendency for dengue cases to decrease.

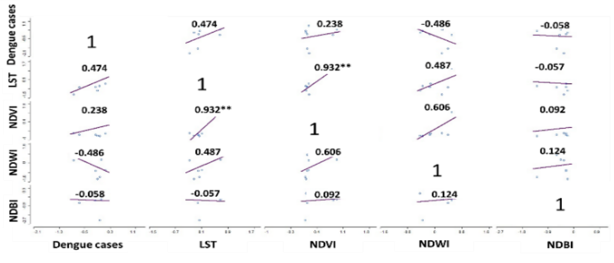

Figure 8. Relationship between dengue cases, LST, and other indices with its corresponding slope of linear fit in Barangay Guadalupe, Cebu City

3.3 Linear regression analysis

3.3.1 Cebu City: A linear regression model equation:

$$\textit{Dengue cases} = -28.436 + 2.137(LST) - 13.943(NDVI) + 8.565(NDWI) - 10.217(NDBI) \tag{6}$$

was generated for predicting dengue cases using all the predictor variables LST, NDVI, NDWI, and NDBI for Cebu City. Using this equation, an increase of 1 unit in LST is associated with an estimated increase of 2.137 dengue cases, while an increase of 1 unit in NDVI is associated with an estimated decrease of 13.943 dengue cases. Similarly, an increase of 1 unit in NDWI is associated with an estimated increase of 8.565 dengue cases, and an increase of 1 unit in NDBI is associated with an estimated decrease of 10.217 dengue cases. The correlation coefficient, r, for this linear regression model equation, is only 0.243, suggesting a weak positive linear relationship between the predictor variables and dengue cases. However, the coefficient of determination (r-squared) is 0.059, indicating that only 5.9% of the variation in dengue cases can be explained by the linear regression model using LST, NDVI, NDWI, and NDBI as predictors. The adjusted R-squared value, which considers the number of predictor variables and the sample size, is 0.052. This indicates that when accounting for model complexity and sample size, only 5.2% of the variation in dengue cases is genuinely explained by the selected predictors. The low correlation coefficient, r-squared, and adjusted r-squared suggest that the model may not capture the full complexity of the factors influencing dengue cases.

3.3.2 Barangay Guadalupe, Cebu City: The linear regression model equation,

$$\textit{Dengue cases} = -233.370 + 45.038(LST) - 1524.228(NDVI) - 5260.832(NDWI) + 325.038(NDBI) \tag{7}$$

was generated for predicting dengue cases using the all predictor variables LST, NDVI, NDWI, and NDBI specifically for Barangay Guadalupe, Cebu. Similar to the first equation, the coefficients in the equation indicate the estimated impact of each predictor variable on dengue cases. The correlation coefficient (r) is 0.986, indicating a strong positive linear relationship between the predictor variables and dengue cases. The coefficient of determination (r-squared) is 0.973, suggesting that approximately 97.3% of the variation in dengue cases can be explained by the linear regression model using LST, NDVI, NDWI, and NDBI as predictors. The adjusted R-squared value is 0.937. This suggests that when considering model complexity and sample size, approximately 93.7% of the variation in dengue cases is explained by the selected predictors. These results indicate a strong relationship between the predictor variables and dengue cases, with the model accounting for a significant portion of the variation in dengue cases. The high adjusted R-squared value suggests that the selected predictors have substantial predictive power for dengue cases in Barangay Guadalupe.

4. CONCLUSION

Through spatial and temporal analysis of dengue cases, the study showed that Barangays Guadalupe, Labangon, and Lahug are the prominent dengue hotspots within Cebu City. The comparative analysis of dengue cases and other indices indicated a weak positive linear relationship between dengue cases, LST, and NDBI, while weak inverse relationships were observed between dengue cases and the NDVI as well as NDWI. Through a focused comparative analysis of dengue cases in Barangay Guadalupe, Cebu City, the relationship between dengue cases and the aforementioned indices was identified. Dengue cases exhibited a moderate positive relationship with LST, a weak positive relationship with NDVI, and a weak negative relationship with NDWI. The results of this study yield valuable insights into the relationship between dengue cases and key environmental factors such as LST, NDVI, NDWI, and NDBI. While there is a weak correlation between dengue and these indices when the entirety of Cebu City is considered, at the level of Barangay Guadalupe, the generated linear regression equation may be valuable for policy-makers in addressing the number of dengue cases per year in their area.

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REFERENCES

Alto, B.W., Bettinardi, D., 2013. Temperature and dengue virus infection in mosquitoes: independent effects on the immature and adult stages. *Am J Trop Med Hyg.*, 88(3), 497-505. doi.org/10.4269/ajtmh.12-0421.

Avdan, U., Kaplan, G., 2016. Algorithm for Automated Mapping of Land Surface Temperature Using LANDSAT 8 Satellite Data. *Journal of Sensors*, 1-8. doi.org/10.1155/2016/1480307.

Bellone, R., Failloux, A., 2020. The Role of Temperature in Shaping Mosquito-Borne Viruses Transmission. *Front Microbiol.*, 11, 584846. doi.org/10.3389/fmicb.2020.584846.

Bravo, L., Roque, V. G., Brett, J., Dizon, R., L'Azou, M., 2014. Epidemiology of dengue disease in the Philippines (2000-2011): a systematic literature review. *PLoS neglected tropical diseases*, *8*(11), e3027. doi.org/10.1371/journal.pntd.0003027

Canete, S.F., Schaap, L.L., Andales, R., Otadoy, R.E.S., Blanco, A., Babaan, J., Cruz, C., 2019. Analysis of the impact of vegetation distribution, urbanization, and solar radiation on the seasonal variation of the urban heat island effect in Cebu city using landsat and global horizontal irradiance data. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.* XLII-4/W19, 93-100. doi.org/10.5194/isprs-archives-XLII-4-W19-93-2019.

Chen, Y., Li, N., Lourenço, J., Wang, L., Cazelles, B., Dong, L., Li, B., Liu, Y., Jit, M., Bosse, N. I., Abbott, S., Velayudhan, R., Wilder-Smith, A., Tian, H., Brady, O. J., CMMID COVID-19 Working Group, 2022). Measuring the effects of COVID-19-related disruption on dengue transmission in Southeast Asia and Latin America: a statistical modelling study. *The Lancet. Infectious diseases*, 22(5), 657–667. doi.org/10.1016/S1473-3099 (22)00025-1

Ebi, K. L., Nealon, J., 2016. Dengue in a changing climate. *Environmental research*, 151, 115–123. doi.org/10.1016/j.envres.2016.07.026

Edillo, F. E., Halasa, Y. A., Largo, F. M., Erasmo, J. N. V., Amoin, N. B., Alera, M. T. P., Yoon, I. K., Alcantara, A. C., Shepard, D. S., 2015. Economic cost and burden of dengue in the Philippines. *The American journal of tropical medicine and hygiene*, 92(2), 360–366. doi.org/10.4269/ajtmh.14-0139

Edillo, F. and S. Madarieta. 2012. Trends of dengue infections (1997–2008) in Cebu Province, Philippines. *Dengue Bull.*, 36, 1–13.

Etemadi, F.U., 2000. Civil society participation in city governance in Cebu City. *Environment and Urbanization*, 12(1), 57–72. doi.org/10.1177/095624780001200105

Garcia, F. B., De las Llagas, L. A., 2011.An examination of the spatial factors of dengue cases in Quezon City, Philippines: a geographic information system (GIS)-based approach, 2005-2008. *Acta Medica Philippina*, 45(1), 53-62

Grossman, M., 2018. Climate Change and the Individual, *The American Journal of Comparative Law*, 66(1), 345–378, doi.org/10.1093/ajcl/avy018

Guha, S, Govil, H., 2020. Land surface temperature and normalized difference vegetation index relationship: a seasonal study on a tropical city. *SN Appl. Sci.* 2, 1661. doi.org/10.1007/s42452-020-03458-8

Gurevitz, J.M., Antman, J.G., Laneri, K., Morales, J.M., 2021. Temperature, traveling, slums, and housing drive dengue transmission in a non-endemic metropolis. *PLOS Neglected Tropical Diseases* 15(6), e0009465. doi.org/10.1371/journal.pntd.0009465

Ong, E., Obeles, A., Ong, B., Tantengco, O, 2022. Perspectives and lessons from the Philippines' decades-long battle with dengue. *The Lancet regional health.* 24, 100505. doi.org/10.1016/j.lanwpc.2022.100505

Murray, N., Quam, M., Wilder-Smith A., 2013. Epidemiology of dengue: past, present and future prospects. *Clin Epidemiol*. 5, 299-309. doi.org/10.2147/CLEP.S34440.

Reinhold, J.M., Lazzari, C.R., Lahondère, C., 2018. Effects of the Environmental Temperature on Aedes aegypti and Aedes albopictus Mosquitoes: A Review. *Insects.* 9(4), 158. doi.org/10.3390/insects9040158.

Huntington, J. L., Hegewisch, K. C., Daudert, B., Morton, C. G., Abatzoglou, J. T., McEvoy, D. J., Erickson, T., 2017. Climate engine: Cloud computing and visualization of climate and remote sensing data for advanced natural resource monitoring and process understanding. *Bulletin of the American Meteorological Society*, 98(11), 2397–2409. doi.org/10.1175/BAMS-D-15-00324.1

Iguchi, J.A., Seposo, X.T., Honda, Y., 2018. Meteorological factors affecting dengue incidence in Davao, Philippines. *BMC Public Health* 18, 629. doi.org/10.1186/s12889-018-5532-4

Isa, N. A., Wan Mohd, W. M. N., Salleh, S. A., 2013. The effects of built-up and green areas on the land surface temperature of the Kuala Lumpur City. *International Archives of the*

Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, XLII-4/W5, 107–112. doi.org/10.5194/isprs-archives-XLII-4-W5-107-2017

Khan, S., Akbar, S. M. F., Yahiro, T., Mahtab, M. A., Kimitsuki, K., Hashimoto, T., Nishizono, A., 2022. Dengue Infections during COVID-19 Period: Reflection of Reality or Elusive Data Due to Effect of Pandemic. *International journal of environmental research and public health*, 19(17), 10768. doi.org/10.3390/ijerph191710768

Kitron, U., Scott, T. W., 2013. House-to-house human movement drives dengue virus transmission. *Proceedings of the National Academy of Sciences of the United States of America*, 110(3), 994–999. doi.org/10.1073/pnas.1213349110

Liu, L., Zhang, Y. 2011. Urban heat island analysis using the landsat TM data and ASTER Data: A case study in Hong Kong. *Remote Sensing*, 3(7), 1535–1552. doi.org/10.3390/rs3071535

Marti, R., Li, Z., Catry, T., Roux, E., Mangeas, M., Handschumacher, P., Gaudart, J., Tran, A., Demagistri, L., Faure, J., Carvajal, J.J., Drumond, B., Xu, L., Herbreteau, V., Gurgel, H., Dessay , N., Gong, P.,2020. A Mapping Review on Urban Landscape Factors of Dengue Retrieved from Earth Observation Data, GIS Techniques, and Survey Questionnaires. *Remote Sensing*, 12(6), 932. doi.org/10.3390/rs12060932

Mustafa, E., Guoxiang, L., Yun-Gang, C., Mosbeh, K., Ashraf, B., Fawzi, Z., 2020. Study for Predicting Land Surface Temperature (LST) Using Landsat Data: A Comparison of Four Algorithms. *Advances in Civil Engineering*. doi.org/10.1155/2020/7363546.

Novaes, C., Silva Pinto, F., Marques, R., 2022. Aedes Aegypti-Insights on the Impact of Water Services. *GeoHealth*, 6(11), e2022GH000653. doi.org/10.1029/2022GH000653

Olive, M. M., Baldet, T., Devillers, J., Fite, J., Paty, M. C., Paupy, C., Quénel, P., Quillery, E., Raude, J., Stahl, J. P., Thiann-Bo-Morel, M., Roiz, D., 2020. The COVID-19 pandemic should not jeopardize dengue control. *PLoS neglected tropical diseases*, 14(9), e0008716. doi.org/10.1371/journal.pntd.0008716

Ooi, E., Gubler, D. J., 2009. Dengue in Southeast Asia: epidemiological characteristics and strategic challenges in disease prevention. *Cadernos de saude publica*, 25(1), S115–S124. doi.org/10.1590/s0102-311x2009001300011

Plasencia-Dueñas, R., Failoc-Rojas, V. E., Rodriguez-Morales, A. J., 2022. Impact of the COVID-19 pandemic on the incidence of dengue fever in Peru. *Journal of medical virology,* 94(1), 393–398. doi.org/10.1002/jmv.27298

Rejuso, A.J, Cortes, .A, Blanco, A., Cruz, C., Babaan, J., 2019. Spatio-temporal analysis of urban heat island in Mandaue City, Cebu. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.* XLII-4/W19. 361-367. doi.org/10.5194/isprs-archives-XLII-4-W19-361-2019.

Sarma, D.K., Kumar, M., Balabaskaran Nina, P., Balasubramani, K., Pramanik, M., Kutum, R., Shubham, S., Das, D., Kumawat, M., Verma, V., Dhurve, J., George, S.L., Balasundreshwaran, A., Prakash, A., Tiwari, R., 2022. An assessment of remotely sensed environmental variables on Dengue epidemiology in Central India. *PLOS Neglected Tropical Diseases* 16(10): e0010859. doi.org/10.1371/journal.pntd.0010859

Sasmono, R.T., Santoso, M.S., 2022. Movement dynamics: reduced dengue cases during the COVID-19 pandemic. The Lancet. *Infectious diseases,* 22(5), 570–571. doi.org/10.1016/S1473-3099 (22)00062-7

Seidahmed, O. M. E., Lu, D., Chong, C. S., Ng, L. C., Eltahir, E. A. B., 2018. Patterns of Urban Housing Shape Dengue Distribution in Singapore at Neighborhood and Country Scales. *GeoHealth*, 2(1), 54–67. doi.org/10.1002/2017GH000080

Stoddard, S. T., Forshey, B. M., Morrison, A. C., Paz-Soldan, V. A., Vazquez-Prokopec, G. M., Astete, H., Reiner, R. C., Jr, Vilcarromero, S., Elder, J. P., Halsey, E. S., Kochel, T. J., Undurraga, E. A., Edillo, F. E., Erasmo, J. N. V., Alera, M. T. P., Yoon, I. K., Largo, F. M., Shepard, D. S., 2017. Disease Burden of Dengue in the Philippines: Adjusting for Underreporting by Comparing Active and Passive Dengue Surveillance in Punta Princesa, Cebu City. *The American journal of tropical medicine and hygiene,* 96(4), 887–898. doi.org/10.4269/ajtmh.16-0488

Undurraga, E. A., Edillo, F. E., Erasmo, J. N. V., Alera, M. T. P., Yoon, I. K., Largo, F. M., Shepard, D. S., 2017. Disease Burden of Dengue in the Philippines: Adjusting for Underreporting by Comparing Active and Passive Dengue Surveillance in Punta Princesa, Cebu City. *The American journal of tropical medicine and hygiene*, 96(4), 887–898. doi.org/10.4269/ajtmh.16-0488

Zha, Y., Gao, J., Ni, S., 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24(3), 583–594. doi.org/10.1080/01431160304987

World Health Organization, 2022. Dengue and Severe dengue. who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue (20 May 2023)

APPENDIX

Table 1. Identification numbers and barangay names in Cebu City

ID no.	Barangay	ID no.	Barangay
1	Adlaon	41	Mabolo
2	Agsungot	42	Malubog
3	Apas	43	Mambaling
4	Babag	44	Pahina Central
5	Bacayan	45	Pahina San Nicolas
6	Banilad	46	Pamutan
7	Basak Pardo	47	Pardo
8	Basak San Nicolas	48	Pari-An
9	Binaliw	49	Paril
10	Bonbon	50	Pasil
11	Budla-An	51	Pit-Os
12	Buhisan	52	Pulangbato
13	Bulacao	53	Pung-Ol-Sibugay
14	Buot-Taup Pardo	54	Punta Princesa
15	Busay	55	Quiot Pardo
16	Calamba	56	Sambag I
17	Cambinocot	57	Sambag II
18	Camputhaw	58	San Antonio
19	Capitol Site	59	San Jose
20	Carreta	60	San Nicolas Central
21	Cogon Pardo	61	San Roque
22	Cogon Ramos	62	Santa Cruz
23	Day-As	63	Sapangdaku
24	Duljo	64	Sawang Calero
25	Ermita	65	Sinsin
26	Guadalupe	66	Sirao
27	Guba	67	Sr Santo Nino
28	Hippodromo	68	Suba Poblacion
29	Inayawan	69	Sudlon I
30	Kalubihan	70	Sudlon II
31	Kalunasan	71	T. Padilla
32	Kamagayan	72	Tabunan
33	Kasambagan	73	Tagbao
34	Kinasang-An Pardo	74	Talamban
35	Labangon	75	Taptap
36	Lahug	76	Tejero
37	Lorega	77	Tinago
38	Lusaran	78	Tisa
39	Luz	79	To-Ong Pardo
40	Mabini	80	Zapatera

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