Climate variability in the Philippines

Background

Climate Change has an indirect effect on the epidemiology of disease, but it directly affects environmental, sociological, and vector/pathogen dynamics (Chan *et al.*, 1999). Localized climate conditions need investigation because, although the country generally has a tropical climate, different regions have varying climate conditions that are more suitable for the survival of vectors/pathogens or compound existing diseases. The project implemented several studies to investigate the trends and patterns of diseases, including cholera, malaria, dengue, and other non-communicable diseases, as well as the impact of climate on the country. The investigation encompassed analyses at various levels of government to assess the relationship and impact of these environmental factors on disease incidence.

A Memorandum of Understanding was crafted with PAGASA to formalize a Joint Research Agreement and facilitate the sharing and use of high-resolution climate data. PAGASA officials are also collaborators and co-investigators in the study. The study examined the interaction of climate factors and analyzed them separately to identify the drivers strongly related to disease incidence. Average climate variables (temperature, relative humidity, and rainfall) were used to assess long-term changes from 1991 to 2020 and provide evidence of climate change in the country. In addition, to investigate the interplay between these variables, the occurrence of the El Niño-Southern Oscillation (ENSO) was also collected to identify short-term climate fluctuations and analyze their impact on the average climate variables. Furthermore, the frequency of extreme weather events and the lag effect of these events on disease incidence were also examined.

Understanding Climate Change in the Philippines

The study investigated the long-term change of climate parameters in the country from 1991 to 2020; these findings were correlated to diseases like dengue, cholera, malaria, and non-communicable diseases like hypertension and malnutrition.

Average Temperature Variables

Annual temperature shows an upward trend with an average increase of 0.026°C per year. In total, mean, minimum, and maximum temperatures increased by an average of 0.78°C from 1991 to 2020. The average maximum temperature (Tx) increased from 30.55°C to 31.32°C, temperature difference (ΔT) = 0.77°C, with the highest temperature recorded, Tx = 31.58°C in 1998. The mean temperature mean (Tm) increased from 26.26°C to 27.05°C (ΔT= 0.79°C), with the highest mean temperature, Tm =27.11°C recorded in 2016. The average minimum temperature (Tn) increased from 21.98°C to 22.77°C (ΔT= 0.79°C), with the highest minimum temperature recorded, Tn = 22.80°C in 2016 (Figure 2.1). The 0.8°C increase in mean temperature for 3 decades is close to the 0.9-1.9°C projection assuming a moderate emission scenario RCP4.5 (DOST-PAGASA, 2018).

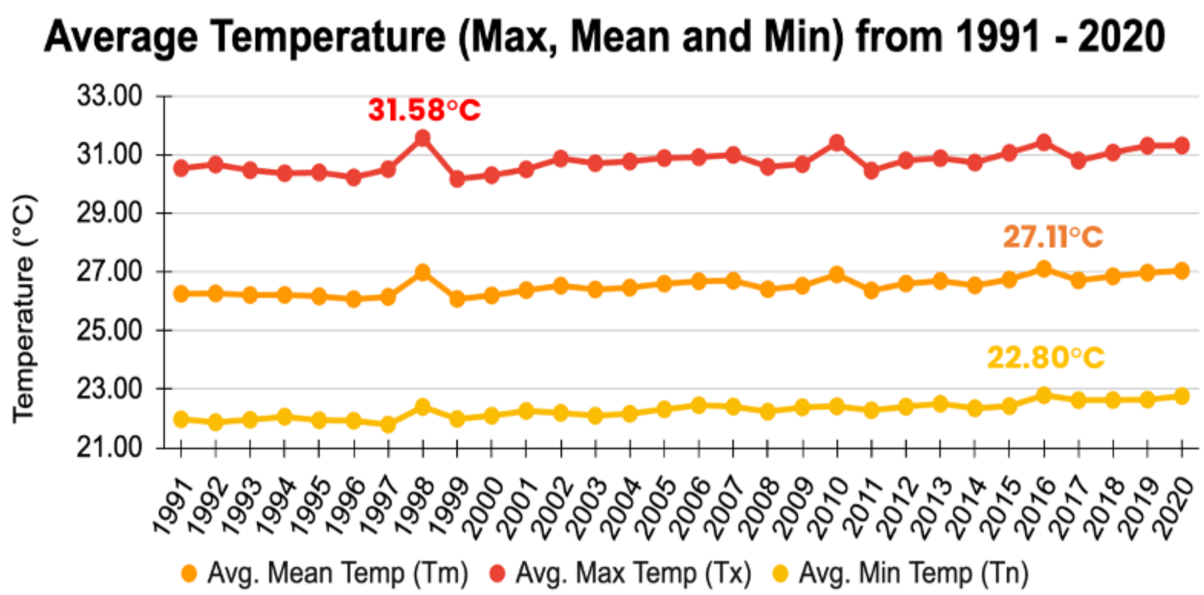

Figure 2.1 Average Temperature Variables from 1991 to 2020

Average Relative Humidity (RH)

The average relative humidity slightly decreased by 0.035% from 1991 to 2020. The range was 79.90% to 84.22% recorded in the years 2019 and 2000, respectively. The correlation analysis revealed a moderate to strong negative correlation between relative humidity and average maximum temperature ($r=-0.7457$, p-value <0.0001). This inverse relationship means that when there is an increase in temperature, there is a decrease in relative humidity (Figure 2.2).

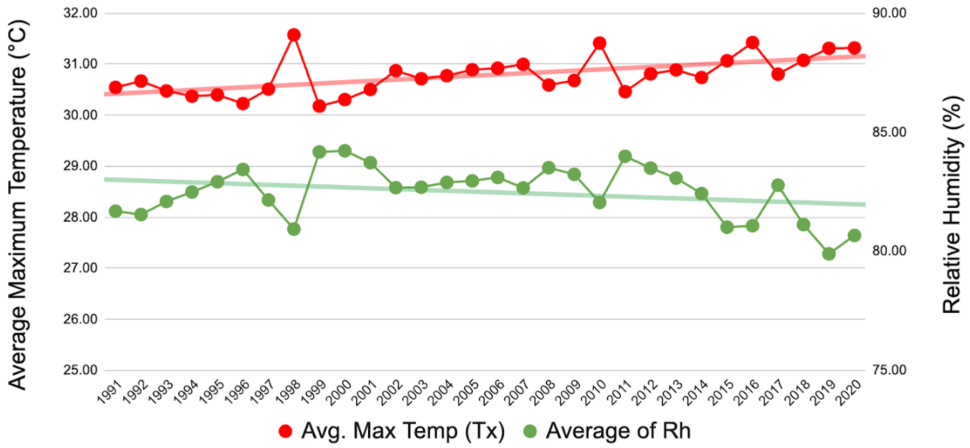

Figure 2.2 Average Maximum Temperature and Average Relative Humidity from 1991 to 2020

Average Rainfall (R)

The data on high-resolution rainfall obtained from DOST-PAGASA covered only the years 2001 to 2020 (20 years). Due to this limitation, the analysis on rainfall was conducted separately for long-term trend assessment. From 2001 to 2020, a decreasing trend of -0.084 was observed (Figure 2.3). The change in average rainfall varied across the regions, and seasonal rainfall changes were noted. The country is divided into different seasons: rainy season from June to November, the cool dry season from December to February, and the hot dry season from March to May (Figure 2.4).

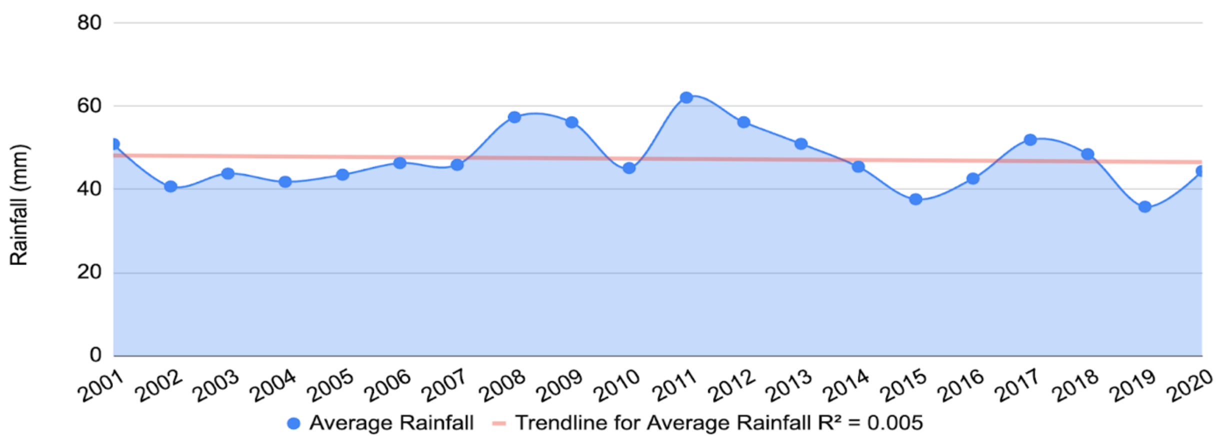

Figure 2.3. Average Rainfall from 2001 to 2020

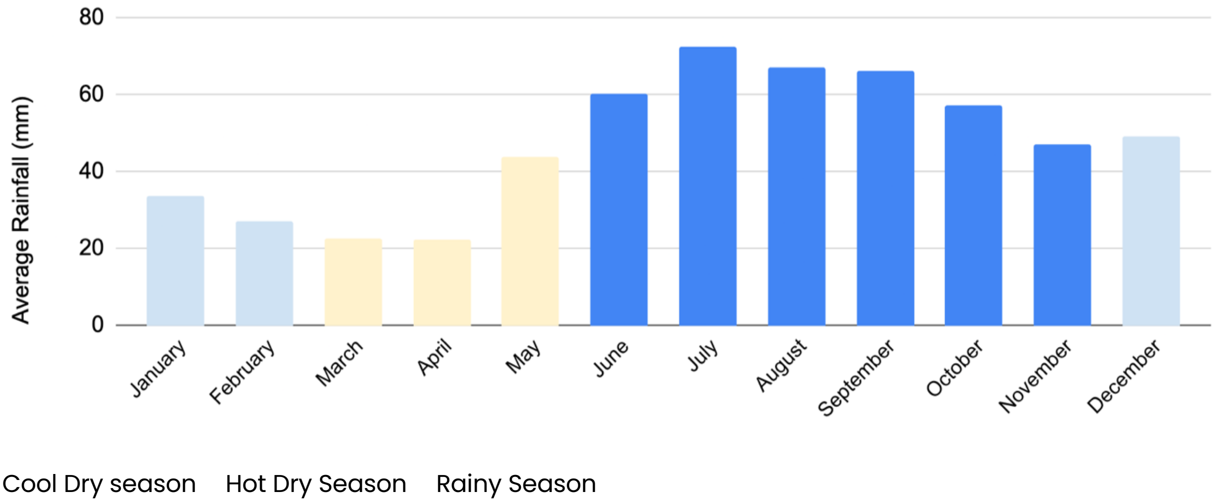

Figure 2.4. Average Rainfall per month from 2001 to 2020

Climate Type

The different climate types per region were also assessed. The Köppen–Geiger (KG) climate classification is a widely used system that divides the world into five main climate types based on long-term temperature and precipitation patterns: Tropical (A), Arid (B), Temperate (C), Continental (D), and Polar (E). These categories are further subdivided according to seasonality, precipitation distribution, and temperature variations (Peel, Finlayson and McMahon, 2007). Based on this, the Philippines is classified into five KG categories: Tropical Rainforest (Af), Tropical Monsoon (Am), Tropical Savanna (Aw/As), Temperate Subtropical Highland (Cfb), and Temperate Dry-winter Subtropical Highland (Cwb), each representing distinct climate conditions (Figure 2.5). Identifying the climate type provides insight into the baseline climate of each region. It helps explain how meteorological variables —short-term atmospheric conditions such as daily temperature, rainfall, and humidity—eventually contribute to long-term climate variability. In contrast, climate variables are defined as the statistical averages and patterns of meteorological data measured over decades (World Meteorological Organization, 2022). Since not all regions experience the same climate conditions, such distinctions are important. The most common climate types were a combination of Af and Am in Regions VI, VII, and IX, followed by Af and Cfb in Regions X, XI, and XII. The least common was Region IV-B, which contains all identified climate types (Af, Am, As, Cwb, and Cfb) (Beck *et al.*, 2023). This study, therefore, examined the significance of climate types and parameters across regions (Table 2.1).

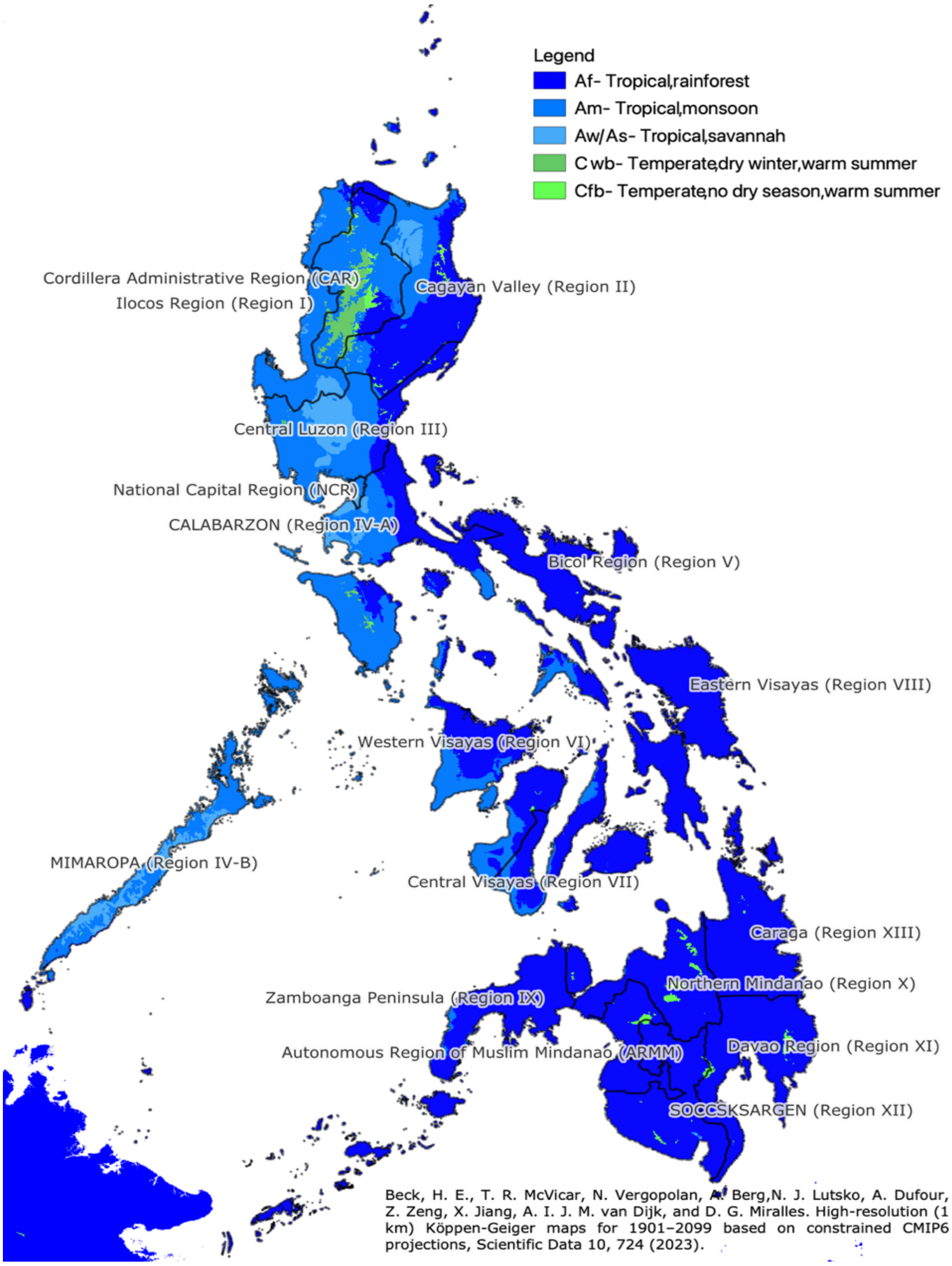

Figure 2.5. Köppen-Geiger Climate Classification Map of the Philippines

Table 2.1. Köppen-Geiger Climate Classification and climate normal per region

Main Island	Regions	KGC	Tn °C	Tx °C	Tm °C	R (mm)	AccR (mm)	Max R
Luzon	CAR	Af, Am, Cwb, Cfb	19.5	29.6	24.6	7	2,556	147
	National Capital Region	Am, As	23.1	30.4	26.8	8	2,988	131
	Region I	Am, As, Cwb	19.9	29.9	24.9	7	2,597	139
	Region II	Af, Am, As, Cfb	19.8	29.8	24.8	7	2,590	141
	Region III	Af, Am, As, Cfb	21.6	30.7	26.2	8	2,868	121
	Region IV-A	Af, Am, As	23.5	30.5	27.0	8	2,977	102
	Region IV-B	Af, Am, As, Cwb, Cfb	23.0	30.9	26.9	7	2,642	53
	Region V	Af, Am	23.6	30.4	27.0	7	2,556	147
Visayas	Region VI	Af, Am	23.8	31.5	27.6	7	2,469	72
	Region VII	Af, Am	23.7	31.2	27.5	6	2,335	66
	Region VIII	Af	23.8	31.4	27.6	7	2,622	79
Mindanao	Bangsamoro Autonomous Region in Muslim Mindanao	Af	22.2	31.2	26.7	6	2,126	43
	Region IX	Af, Am	21.9	31.3	26.6	7	2,436	50
	Region X	Af, Cfb	21.8	30.9	26.4	7	2,630	55
	Region XI	Af, Cfb	22.3	31.2	26.8	6	2,060	43
	Region XII	Af, Cwb, Cfb	22.7	31.4	27.0	5	1,879	40
	Region XIII	Af, Cfb	22.6	30.9	26.7	7	2,496	55

Extreme weather events

Climate variability is a natural phenomenon that can affect meteorological factors. One type of climate variability examined in this study is exposure to the El Niño Southern Oscillation (ENSO) and its relation to extreme weather events and tropical cyclones. We obtained ENSO data from the National Oceanic and Atmospheric Administration (NOAA) to identify ENSO exposure and occurrences in monthly and annual data. We then compared the number of disease cases and incidence rates based on ENSO exposure. Data on extreme weather events, such as the intensity of tropical cyclones, were also investigated, along with additional extreme indices, including hot days, cold nights, and threshold data. ENSO exposure and intensity generally influence the country's average temperature by approximately +5°C during an El Niño or -5°C during a La Niña event, along with changes in precipitation.

In 2007, the IPCC reported that there was an observed significant shift in precipitation patterns between 1990 and 2005, and Central Asia experienced an increase in precipitation, while parts of Southern Asia witnessed a decline. There was also a decrease in the cold days and nights, while an increase in hot days and nights (Bernstein and IPCC, 2008). Overall, the results show that the ENSO exposure consisted of 10 years of El Niño, 9 years of La Niña, 9 years when the country experienced both El Niño and La Niña in the same year, and 2 years of neutral phase from 1991 to 2020. During this phase, we observed a higher number of hot days and warm nights, as well as more extreme hot days and warm nights, compared to the other phases. Further, the analysis also explored the intensity of ENSO exposure and its regional effects (Table 2.2).

Table 2.2. ENSO and Extreme Indices Exposure from 1991 to 2020

ENSO Exposure	Number of Years Exposed	Tropical Cyclone Frequency	Ave. Cold days (<P10)	Aver. Cold nights (<P10)	Ave. Extreme Hot Days (>P95)	Ave. Extreme warm nights (>P95)	Ave. Hot Days (>P90)	Ave. warm nights (>P90)
Both	9	60	234	238	253	226	456	431
El Niño	10	66	425	522	173	183	367	365
La Niña	9	70	353	255	84	115	202	240
Neutral	2	27	83	81	36	25	72	59

Climate change and dengue

Introduction

Dengue is a viral infection transmitted through the bite of an infected female Aedes aegypti and Aedes albopictus mosquitoes. It is caused by four distinct dengue virus (DENV) serotypes (-1, -2, -3, or -4) and all these serotypes circulate in the Philippines. A person can be infected with dengue multiple times. On the first DENV infection, an individual will obtain life-long immunity to the same infecting serotype while transient immunity will be obtained from the other serotypes. The second infection usually manifests as severe disease. The majority of dengue infections remain asymptomatic and resolve spontaneously due to mild symptoms such as fever, rash, body aches, and nausea. While some patients may develop severe dengue or hemorrhagic complications, necessitating hospitalization and even death. There is currently no specific drug to treat dengue.

The implementation of dengue immunization in the Philippines was suspended in 2017. A new dengue vaccine is available in other countries but is not widely used. With these, dengue remains to be a public health concern and the risk of infection is compounded by changes in climate. Recent projections show that dengue cases will peak this century, after which they are expected to decline due to unfavorable climate conditions that could affect mosquito survival (Colón-González *et al.*, 2023). Linking dengue surveillance data to climate information is crucial in understanding our future risk of dengue.

The project implemented two studies for dengue: Climate factors affecting dengue in the Philippines which aims to determine the climate variables (temperature, rainfall, humidity) associated with dengue incidence in the Philippines from January 1, 1991, to December 31, 2020 (30 years); and Modulating climate-change effects of dengue virus serotypes in mosquitoes through community-based genomic surveillance – a barangay level modular approach which aims to develop a non-linear differential equation that could model the effects of climate change with persistence of DENV serotypes. Both studies were reviewed and approved by the University of the Philippines Manila -Research Ethics Board (UPM-REB).

Climate factors affecting dengue in the Philippines

A. Methods

Data Collection

This study obtained secondary regional dengue surveillance data from the Department of Health (DOH). The evolution of the dengue case definition and reporting mechanisms over the study period was considered. The historical data from 1991 to 2020 were collected using the Field Health Service Information System (FHSIS) data, which functions as a passive reporting system reliant on aggregate data submitted by primary care centers within the local government units (LGUs). To enhance disease surveillance, the DOH introduced the Philippine Integrated Disease Surveillance and Response (PIDSR) system in 2008. PIDSR is a case-based, active surveillance system designed to strengthen LGU capacity for early epidemic detection and response. Data from this system, which typically reports a much higher incidence, was collected for the period 2008 to 2020. Climate data was obtained from the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), and socio-demographic data from the Philippine Statistics Authority (PSA). To ensure data consistency across the 17 regions from 1991 to 2020, data processing was conducted to align geographic and temporal information for all collected data. Data were collated using Microsoft Excel and processed using the Tableau Prep Builder program.

Data Analysis

Dengue incidence was estimated by dividing the number of dengue cases by the annual population per 100,000. Age distribution of dengue cases were reported as proportions. Spatial mapping of dengue cases and over time was conducted using ArCGIS. We conducted analyses at both the country and regional levels to assess the relationship and impact of these meteorological factors on dengue incidence. Climate has an indirect effect on the epidemiology of dengue disease, but it directly affects environmental, sociological, and vector dynamics (Chan *et al.*, 1999). Localized climate conditions need investigation because, although the country generally has a tropical climate, different regions have varying climate conditions that are more suitable for mosquito survival. Furthermore, the expansion of areas suitable for mosquitoes was identified.

B. Key Findings

Incidence and cases of dengue in the Philippines

Based on the FHSIS Reports, the mean incidence of dengue from 1991 to 2020 was 20 per 100,000 population. There is an observed cyclical pattern with peak incidence of 33 per 100,000 population during the period of 1998 to 1999. The rate declined 8 per 100,000 population from 2010 to 2012, then a sharp increase of 38 per 100,000 population in 2017-2018. Using the PIDSR report from 2008, there was a tenfold increase in the mean incidence, with 188 per 100,000 population from 2008 to 2020. There was an upward trend from 2008 until 2014, with observed epidemic peaks in 2012 and 2019 of nearly 400 per 100,000 population, and then it dropped in 2020 during the Coronavirus Disease-2019 (COVID-19) pandemic (Figure 4.1).

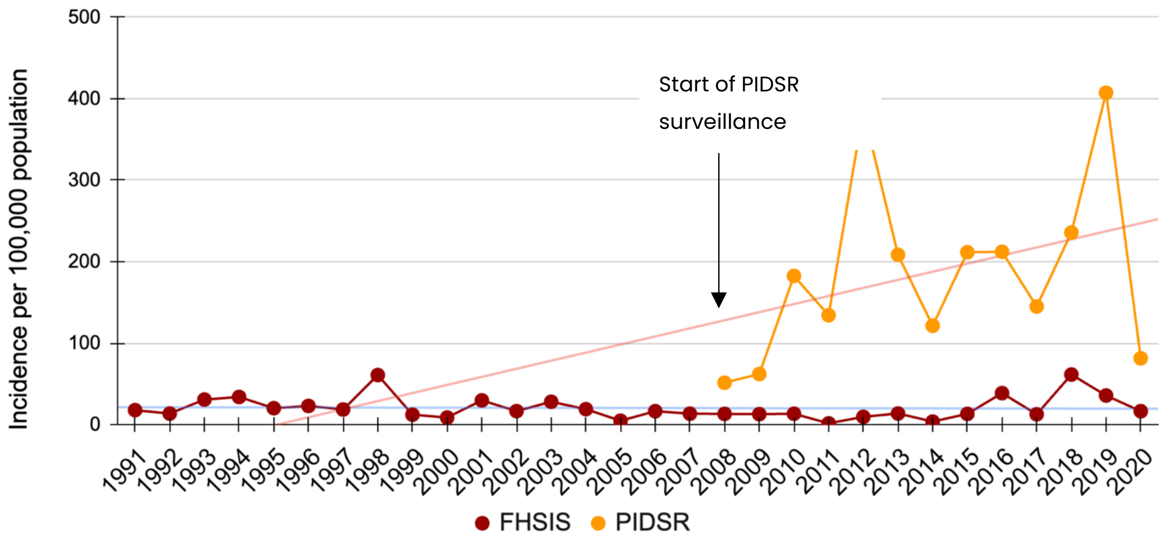

Figure 4.1. Dengue Incidence per 100,000 population from 1991 – 2020

We conducted time series analysis to analyze the pattern of dengue cases comprehensively. A marked increase in dengue cases was observed in 2019. An increasing trend in dengue cases over time was observed. There was an annual repeating pattern of cases, especially during the rainy season. Then, for the random/residual component, we observed unexplained variations which may be due to outbreaks or dengue prevention measures implemented in the community, or can be associated with environmental or extreme weather events (Figure 4.2).

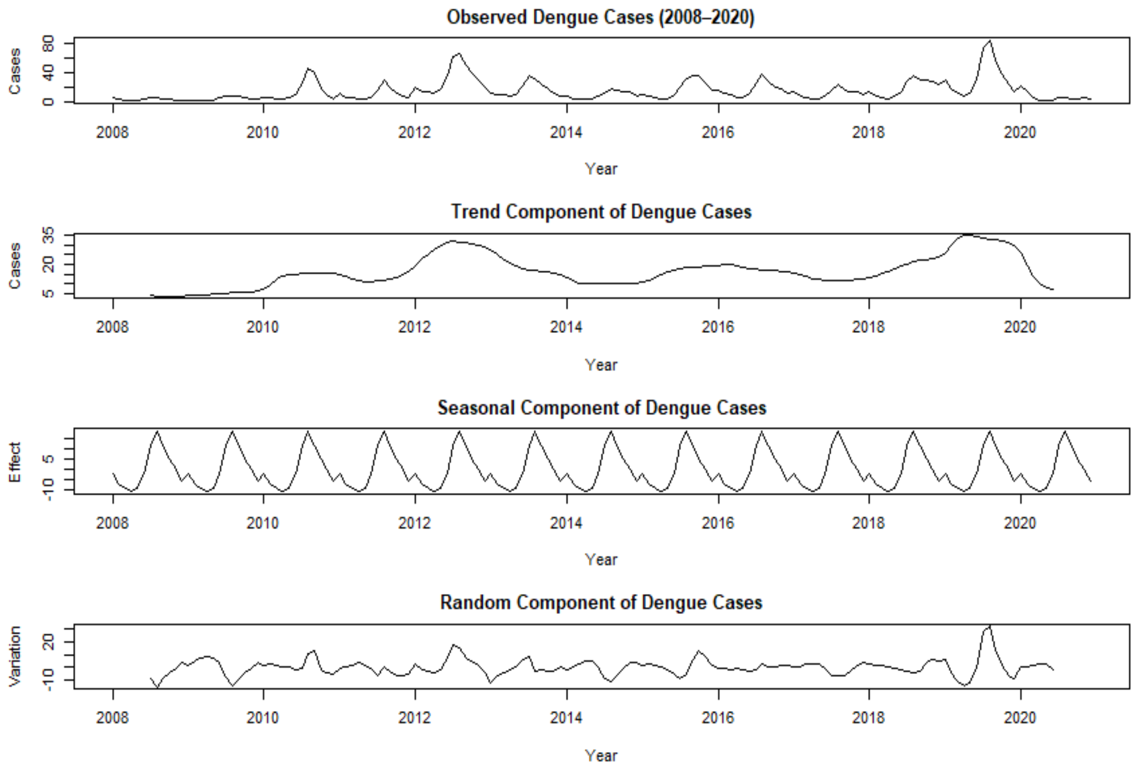

Figure 4.2. Time Series Decomposition from 2008 to 2020

We examined the demographic characteristics of dengue cases from FHSIS data. Fifty-two percent of dengue cases were males. Dengue morbidity was highest among 5-14-year-olds (41%) and 15-49-year-olds (35%). The proportion of dengue cases by age varied per region (Figure 4.3).

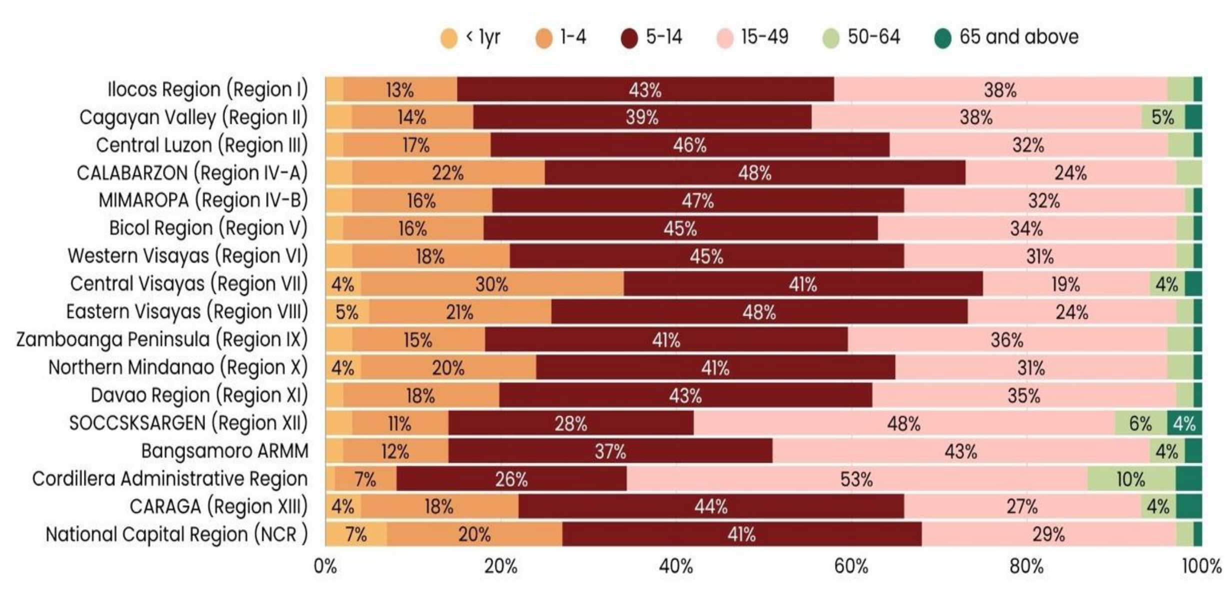

Figure 4.3. Percentage of Affected Dengue per age group per region from 1991 to 2020

Spatio-temporal distribution of dengue

We analyzed the spatio-temporal distribution of dengue incidence from 1991 to 2020 to visualize the disease burden across the country. Overall, the high-incidence areas were concentrated in the Mindanao and Visayas regions, with the highest median incidence at 80 per 100,000 population in the Soccsksargen (Region XII), and the lowest was observed in Autonomous Region for Muslim Mindanao (ARMM) with 8 per 100,000 population (Figure 4.4). We noted a consistent increase in dengue cases in the Mindanao region from 1991 to 1995. From 1996 to 2000, the incidence started to increase in northern Luzon and the Visayas islands. There was also a marked increase and spread of dengue in 1998 across all regions. From 2001 to 2005, dengue incidence continued to increase in northern Luzon and the southeastern part of the Mindanao Region. From 2006 to 2007, based on the FHSIS data, dengue incidence in Visayas started to increase once again. Starting 2008, we used data from PIDSR in the geographic distribution. We observed a spike in cases across all regions, most likely due to efficiency of disease notification. An outbreak was noted in 2019, with an increase of 120->200 dengue cases. A sudden decrease in cases was observed in 2020 that could be associated with the start of the COVID-19 pandemic. (Figure 4.5).

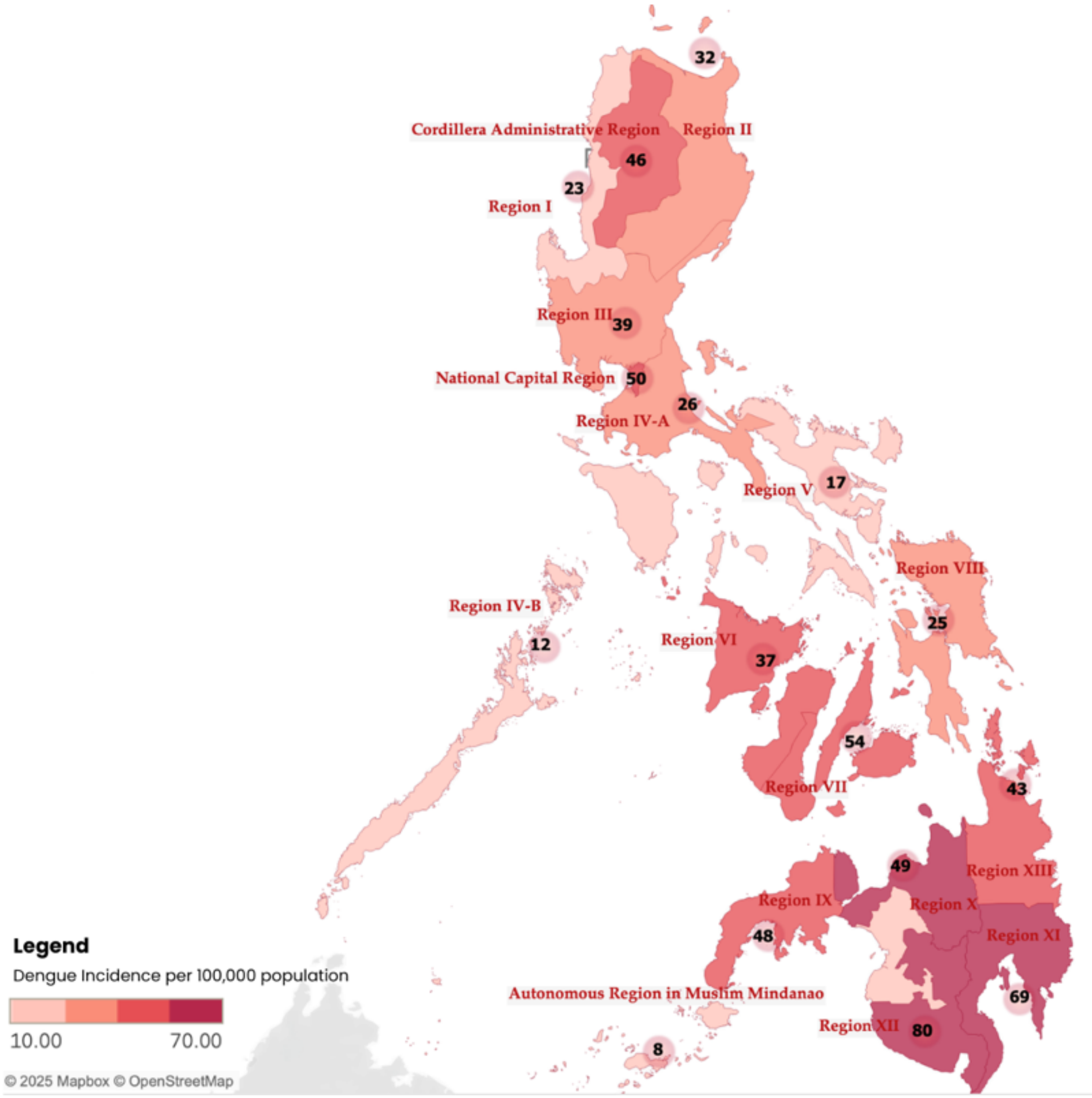

Figure 4.4 Overall Geographic Distribution of Dengue Incidence per 100,000 population from 1991 to 2020

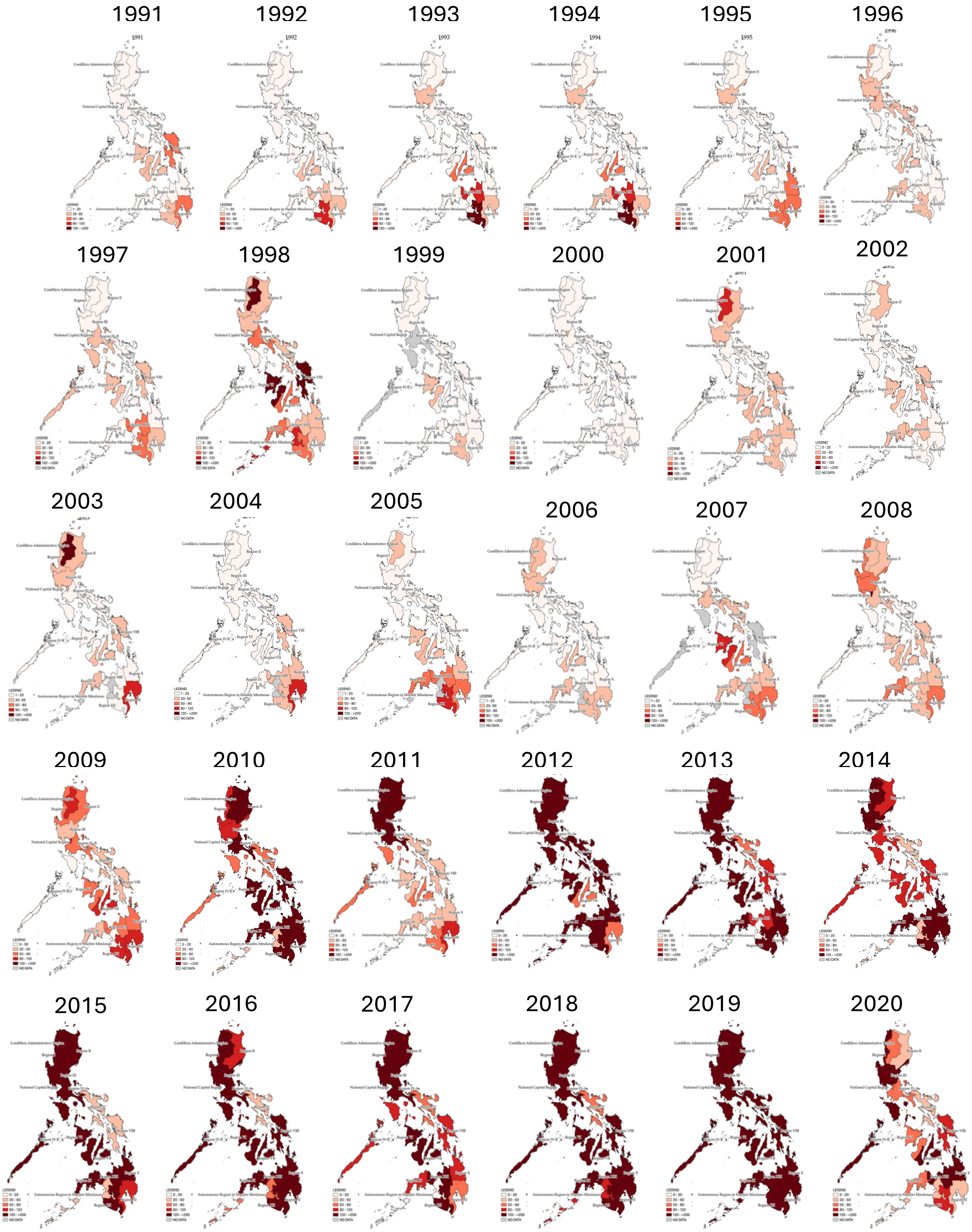

Figure 4.5. Geographic Distribution of Dengue Incidence per 100,000 population per year from 1991 to 2020

Climate and dengue correlations

We first analyzed the distribution of dengue and climate variables to assess if it is normally distributed. Results showed that the distribution of dengue incidence was skewed, which suggests a non-parametric approach in analyzing the correlation with climate variables. We conducted Spearman correlation, and the result showed that dengue incidence per 100,000 population has a significant correlation with climate variables: Temperature variables have a weak to moderate positive correlation with maximum temperature (Tx) (r = 0.328, p-value <0.0001) and a moderate negative correlation with relative humidity (Rh) (r = -0.27, p-value <0.0001)(Figure 4.6). This nonlinear effect can be influenced by lag impacts of climate conditions on mosquito survival (Chan *et al.*, 1999).

We conducted further analysis using the monthly regional climate and dengue incidence data from 2008 to 2020. It is important to note that the climate variables analyzed span a more recent period compared to the 30-year data. Consequently, the climate variables within this period differ from those in the 30-year dataset. Similar to the 30-year data, results show that the data is not normally distributed, and Spearman correlation analysis results show there is a negative correlation between dengue incidence and minimum temperature (Tn) (r = -0.146, p-value = <0.0001) and mean temperature (Tm) (r = -0.036, p-value = 0.065). Additionally, there is a positive correlation with average rainfall (r) (r = 0.112, p-value = <0.0001), while relative humidity (Rh) (r = 0.054, p-value = 0.005) and maximum temperature (Tx) (r = 0.033, p-value = 0.093) exhibited a positive but very weak correlation (Figure 4.7). Based on these findings, we will further investigate and identify the temperature and rainfall range associated with high dengue incidence for the past years, then compare the differences among the regions.

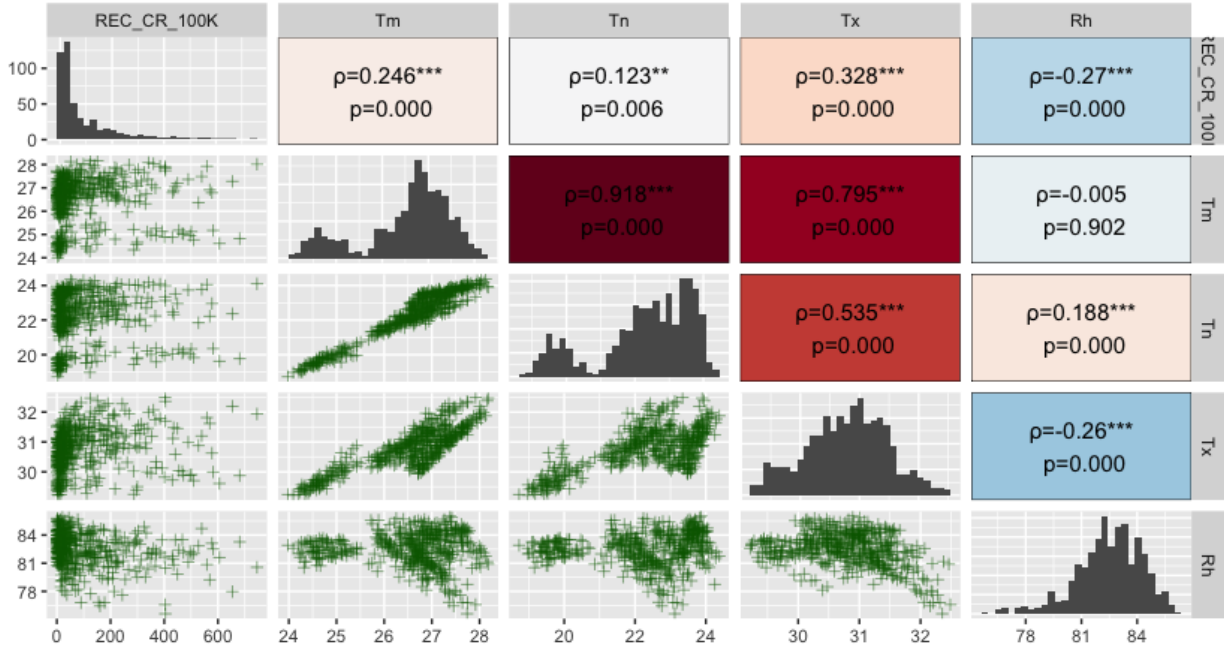

Figure 4.6. Scatter plot (green), distribution (bar column), and Spearman correlation of dengue incidence with temperature and relative humidity from 1991 to 2020

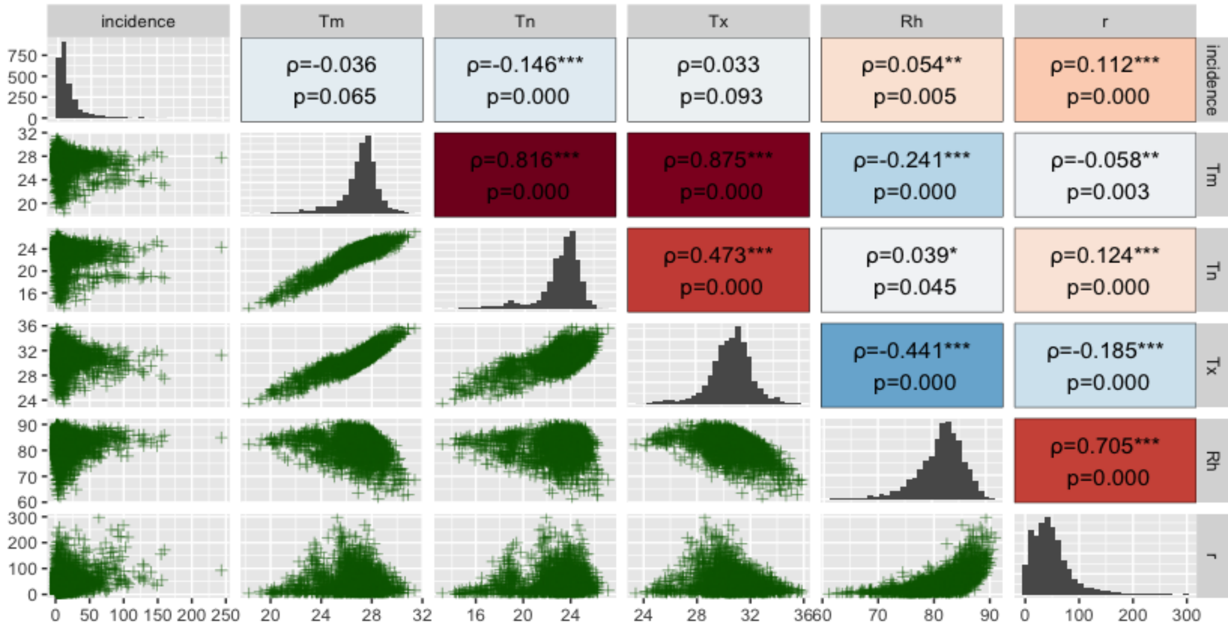

Figure 4.7. Scatter plot (green), distribution (bar column), and Spearman correlation of dengue incidence with temperature, relative humidity and rainfall from 2008 to 2020

Association of extreme weather events, such as typhoons, with dengue incidence

Climate variability is a natural phenomenon that can affect meteorological factors. One type of climate variability examined in this study is exposure to the El Niño Southern Oscillation (ENSO) and its relation to extreme weather events and tropical cyclones. We obtained ENSO data from the National Oceanic and Atmospheric Administration (NOAA) to identify ENSO exposure and occurrences in monthly and annual data. We then compared the number of dengue cases and incidence rates based on ENSO exposure. Data on extreme weather events, such as tropical cyclones, were also collected, along with additional extreme indices, including hot days, cold nights, and threshold data, to better understand changes in meteorological factors. ENSO exposure and intensity generally influence the country's average temperature by approximately +5°C during an El Niño or -5°C during a La Niña event, along with changes in precipitation.

From 1991 to 2020, the ENSO exposure consisted of 10 years of El Niño, 9 years of La Niña, 9 years when the country experienced both El Niño and La Niña in the same year, and 2 years of Neutral phase. Among these, the years with ENSO shifts had the highest recorded dengue cases at 211,222. During this phase, we observed a higher number of hot days and warm nights, as well as more extreme hot days and warm nights, compared to the other phases. This initial finding suggests that years with ENSO shifts and increased hot days and nights were associated with a higher number of dengue cases (Table 4.1). The characteristic of ENSO exposure, such as its intensity and duration of climate conditions, was also investigated to understand the lag effect on dengue incidence. The monthly data from 2008 to 2020 showed that after 8 months of weak to moderate El Niño exposure in 2009 - 2010, there was an increase in dengue incidence. However, in an 18-month moderate to very strong El Niño exposure in 2014-2016, the incidence is lower than in the previous years; in contrast, the 11-month exposure to a weak El Niño to Neutral phase in 2018 to 2019 resulted in a very high incidence (Figure 4.8). Climate variability, such as extreme warm conditions and drought, influences viral replication, vector development, and mosquito habitats, which can later affect dengue transmission that can lead to outbreaks (Tian *et al.*, 2025). This is the reason why understanding climate factors affecting dengue incidence is very important, and the regional associations and analysis will be very useful and were generated by this study to locally investigate the differences in the regions.

Table 4.1 ENSO and Extreme Indices Exposure from 1991 to 2020

ENSO Exposure	Number of Years Exposed	Tropical Cyclone Frequency	FHSIS Dengue Cases	Ave. Cold days (<P10)	Aver. Cold nights (<P10)	Ave. Extreme Hot Days (>P95)	Ave. Extreme warm nights (>P95)	Ave. Hot Days (>P90)	Ave. warm nights (>P90)
Both	9	60	211,222	234	238	253	226	456	431
El Niño	10	66	152,438	425	522	173	183	367	365
La Niña	9	70	109,581	353	255	84	115	202	240
Neutral	2	27	34,596	83	81	36	25	72	59

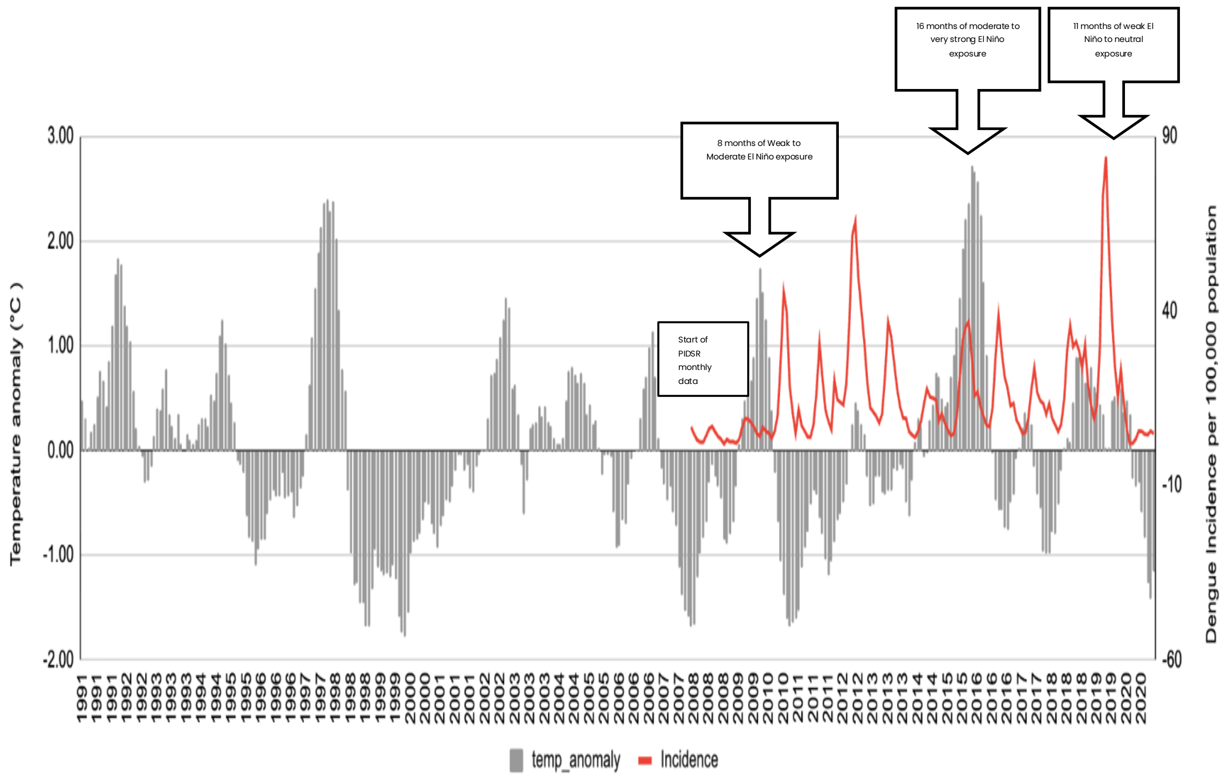

Figure 4.8. Temperature Anomaly, ENSO Exposure, and Monthly Dengue Incidence from 2008 to 2020

Limitations and recommendations

Limitations

1. Data inconsistency in the region

The study projected maps and analyzed the dengue incidences in the 17 administrative regions of the country. However, we encountered data inconsistencies; the regional DOH reports changed from the 1990s to the 2000s, and for uniformity with the recent years' regional assignments, the data were processed. The regional reporting for Region 4A (CALABARZON) dengue cases and 4B (MIMAROPA) was combined from 1991 to 1998 based on the data from the Philippine Health Statistics (PHS) report and the FHSIS annual reports. A similar situation was encountered in Mindanao, Regions IX, X, XI, XII, XIII, and ARMM (or BARMM). Some provinces belonged to different regions between 1991 and 2020, and some regions were not yet created in 1991.

2. Different dengue surveillance data sources

The dengue surveillance data from FHSIS and the Philippine Integrated Disease Surveillance and Response (PIDSR) have different sources, and the case definition for reporting has changed over time. Therefore, for this study, these surveillance data were analyzed separately and utilized based on the type of climate data aggregation. FHSIS was limited to annual reports of Dengue Fever and Dengue Hemorrhagic Fever, which are used in long-term correlation and trends. While the PIDSR data was aggregated into weekly and monthly data, it was limited to 2008–2020 only, so these are used in seasonal analysis and other extreme weather event analysis. Because of the different variables, data uniformity appeared to be a challenge, and it was addressed by preparing several datasets with different time scales to align the climate data with health and socio-demographic variables.

3. Potential underreporting of cases

Dengue surveillance in the Philippines is passive surveillance, and individuals have different health-seeking behavior. Some communities in the Philippines are also remote and access to health care can be limited. Unavailability of sensitive point-of-care dengue diagnostic tests to immediately detect dengue cases in the community may be observed. These lead to underestimating the true number of dengue cases reported in the study.

Burden of malaria in Palawan and its correlation with climate variables

Introduction

Malaria is a parasitic infection caused by the protozoan parasite *Plasmodium* species, primarily transmitted through the bites of the infected female Anopheles mosquitoes. It has been a public health concern in the Philippines since the 1520s. Over the years, the country has made significant progress in reducing malaria transmission and eliminating malaria-related deaths. Recent data showed an increasing trend of cases in Palawan, from 3,230 cases in 2022 to 6,188 cases in 2023 (Montemayor, 2024). Palawan remains a key focus area for intensified malaria control and elimination efforts (DOH, 2023). Climate factors such as temperature, rainfall, and relative humidity can increase the risk of malaria transmission and resurgence (Wickremasinghe, et al., 2012).

This study examined the burden of malaria in Palawan from 2012 to 2023, with a particular focus on the relationship between malaria cases and selected climate variables – temperature, rainfall, and humidity. We analyzed epidemiologic trends and patterns in confirmed cases and climate variables, spatial distribution of outbreaks and seasonal patterns of malaria, as well as to assess the correlations between malaria cases and climate variables.

Methods

This study is a retrospective cross-sectional study. Secondary data on confirmed malaria cases between January 2012 and December 2023 were collected from the Provincial Health Office. An individual was defined as a confirmed malaria case if malaria parasites were detected either through microscopy or rapid diagnostic tests (RDTs).

Data on selected climate variables from 2013 until 2020—including yearly and monthly mean temperatures (minimum, mean, maximum), mean rainfall, and mean relative humidity, were obtained from the DOST-PAGASA. Data were available for the entire island of Palawan as well as at the municipal level.

Data were analyzed using descriptive statistics and time series analysis. Spatio-temporal mapping was done in Quantum Geographic Information System (QGIS), while heatmaps were generated in Python. Pearson's correlation and regression analysis were performed to examine associations between climate variables and malaria incidence. This study was reviewed and approved by the UP Manila Research Ethics Board (UPMREB).

Key findings

Incidence and cases of malaria

Between 2012 and 2023, there were 65,154 confirmed malaria cases recorded in Palawan. While the absolute number of cases showed an overall increasing trend, malaria incidence demonstrated a consistent decline over the same period. The incidence rate was defined as the number of individual cases per 100,000 population.

Malaria incidence significantly declined from 2012 to 2023 (Figure 5.1). The highest incidence rate was recorded in 2018 (827.22 per 100,000), while the lowest occurred in 2022 (258.03 per 100,000). Overall, there was a 2.20% reduction of incidence rate across the study period, despite a 49.36% increase in the total number of cases.

Two sharp peaks in incidence rate were observed: in 2015 (651.02 per 100,000) and in 2018 (827.22 per 100,000). This was followed by a notable decline from 2020 to 2022, coinciding with the COVID-19 pandemic, during which human and financial resources were redirected toward pandemic response efforts (DOH, 2023). An average of 453 individuals out of 100,000 had malaria infections annually during this period.

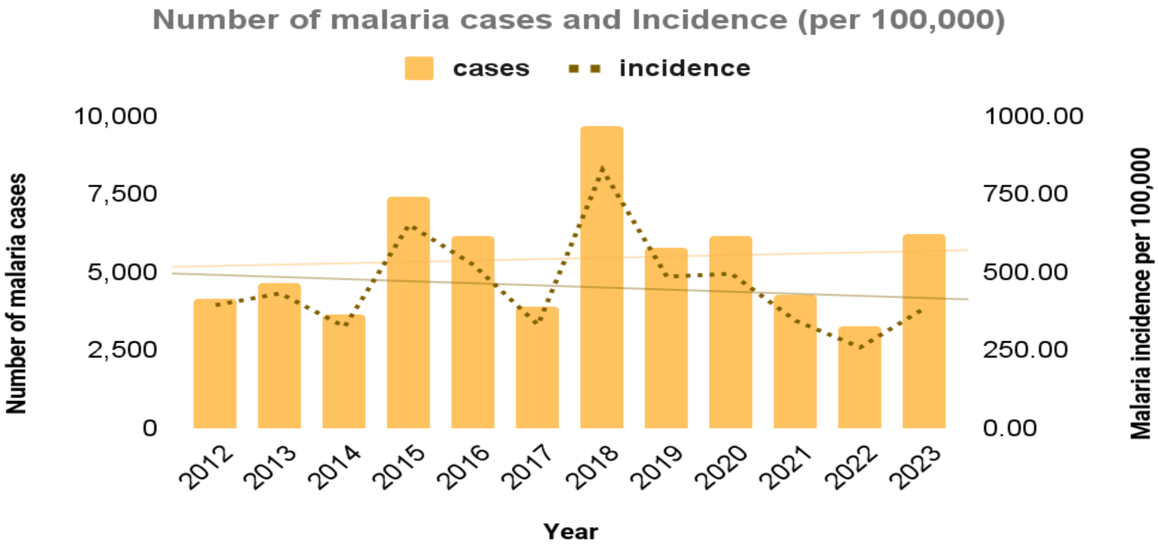

Figure 5.1. Annual malaria cases and incidence rate, 2012-2023.

Children aged 1-10 accounted for the highest number of malaria cases (48.95%), followed by adolescents aged 11-20 (23.26%) (Figure 5.2). From age 11 and above, malaria cases seem to gradually decrease. Malaria was seen less in older adults, from age 51 years and above (4.38%). Malaria infections were higher among males (56.90%) compared to females (43.08%), while 0.01% have no data. Majority of the cases belong to the indigenous group Palaw'an, accounting for 58.26% of the total cases (Figure 5.3). However, a huge percentage (34.59%) have no data, as this information was not encoded for some years by the Provincial Health Office.

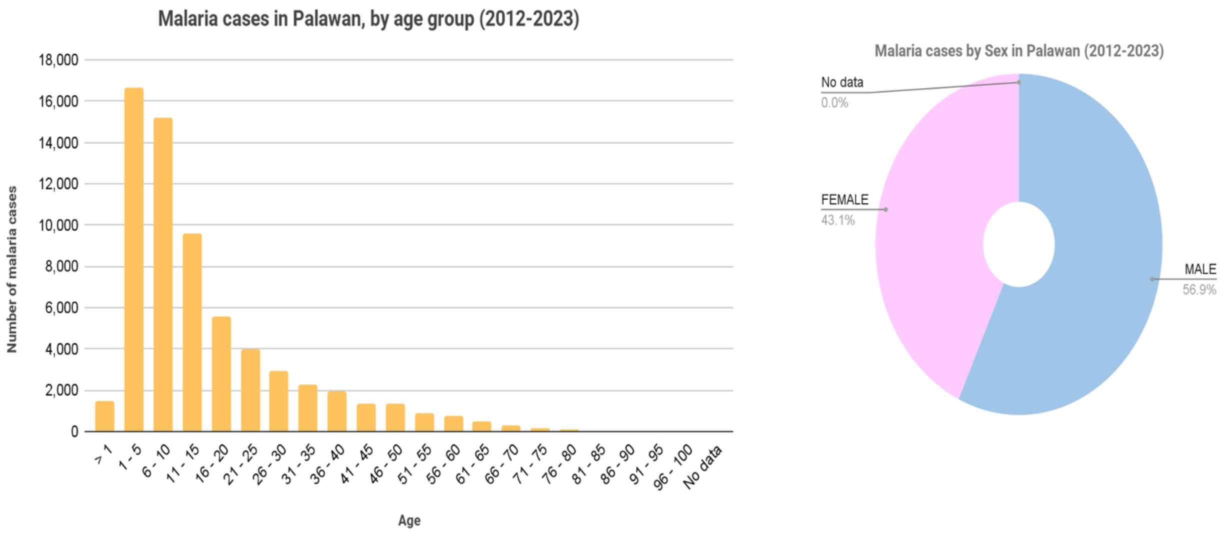

Figure 5.2. Distribution of malaria cases by age and sex, 2012-2023.

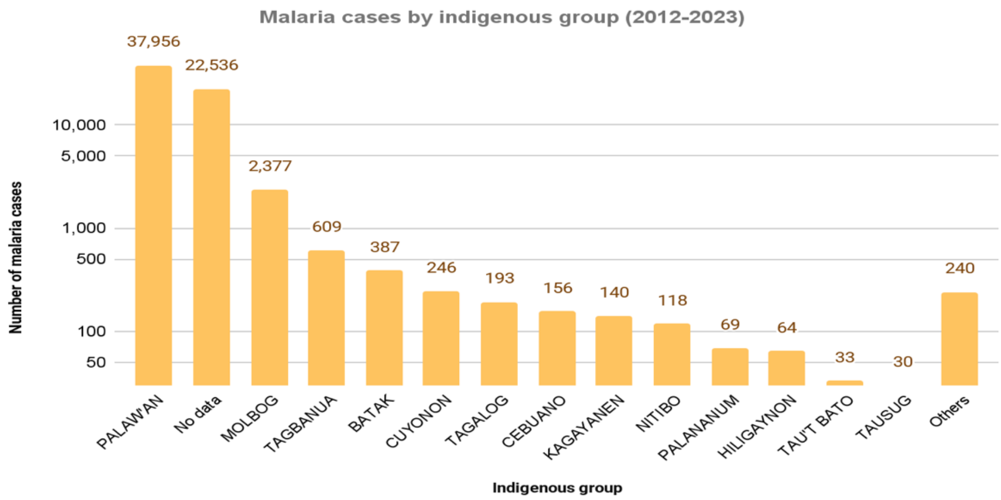

Figure 5.3. Distribution of malaria cases by indigenous groups, 2012-2023..

Malaria transmission in Palawan occurred year-round from 2012 to 2023, but clear seasonal patterns were observed. The highest malaria incidence was consistently recorded between May and July, with elevated case numbers sustained throughout the rainy season from May to September. Peak monthly incidence was recorded in May 2015, June 2016 and June 2018, coinciding with the transition from the hot dry season to the onset of the rainy season. In contrast, the lowest number of malaria infections were recorded during the cooler months of November up to February, with the lowest monthly count observed in December 2019 (Figure 5.4).

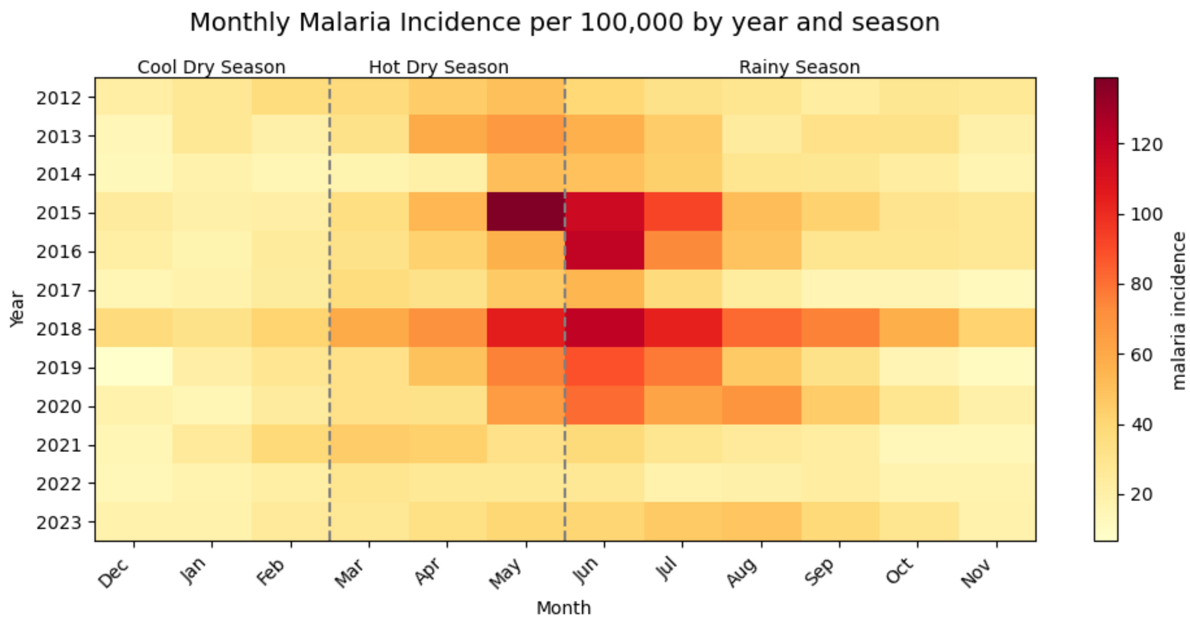

Figure 5.4. Annual and monthly malaria incidence per 100,000 by season, 2012-2023.

Mean temperature showed a relatively stable trend across months, with slightly higher values during the hot dry season (March - May) (Figure 5.5). The monthly mean temperature increased by 0.1 ◦C from 27.51◦C in 2012 to 27.82 ◦C in 2020.

Seasonal variation was evident: the highest mean minimum temperature was observed in May (26.14 ◦C) and the lowest in February (24.64 ◦C). The highest mean temperature was also observed in May (28.97 ◦C) and lowest was in February (27.27 ◦C). The highest mean maximum temperature was seen in May (31.80 ◦C) while the lowest was in January (29.75 ◦C).

Monthly mean rainfall fluctuated from 2012-2023, ranging from 0.88 mm to 483.98 mm. The highest mean rainfall was observed in July (3,53.74 mm) and lowest in March (37.42 mm).

There was a decreasing trend in monthly mean relative humidity in the province from 84.02% in 2012 to 79.05% in 2020. The highest mean relative humidity was seen in July (84.49%) and the lowest in April (76.94%).

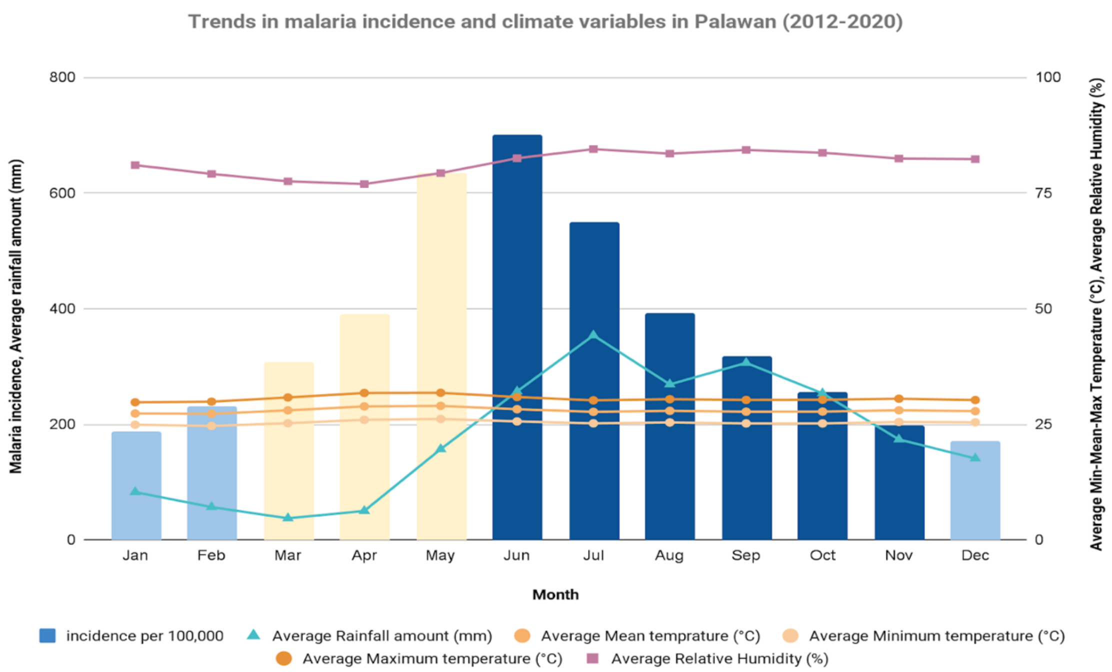

Figure 5.5 Trends in malaria incidence and climate variables in Palawan, 2012-2023.

Plasmodium falciparum is the most dominant species across almost all municipalities except in Busuanga and Coron where *Plasmodium vivax* and *Plasmodium malariae* are more common, respectively, though case numbers remain very low. *Plasmodium vivax* is observed in some municipalities with relatively high proportions seen in northern Palawan. The municipality of Rizal clearly showed the highest burden of malaria, with *Plasmodium falciparum* being the most dominant species followed by *Plasmodium malariae* (Figure 5.6). There is a diversity of species in the municipality of Coron and *Plasmodium malariae* was the most dominant species, however cases remain very low. Mixed infections were less common and showed a scattered distribution, appearing in only a few municipalities.

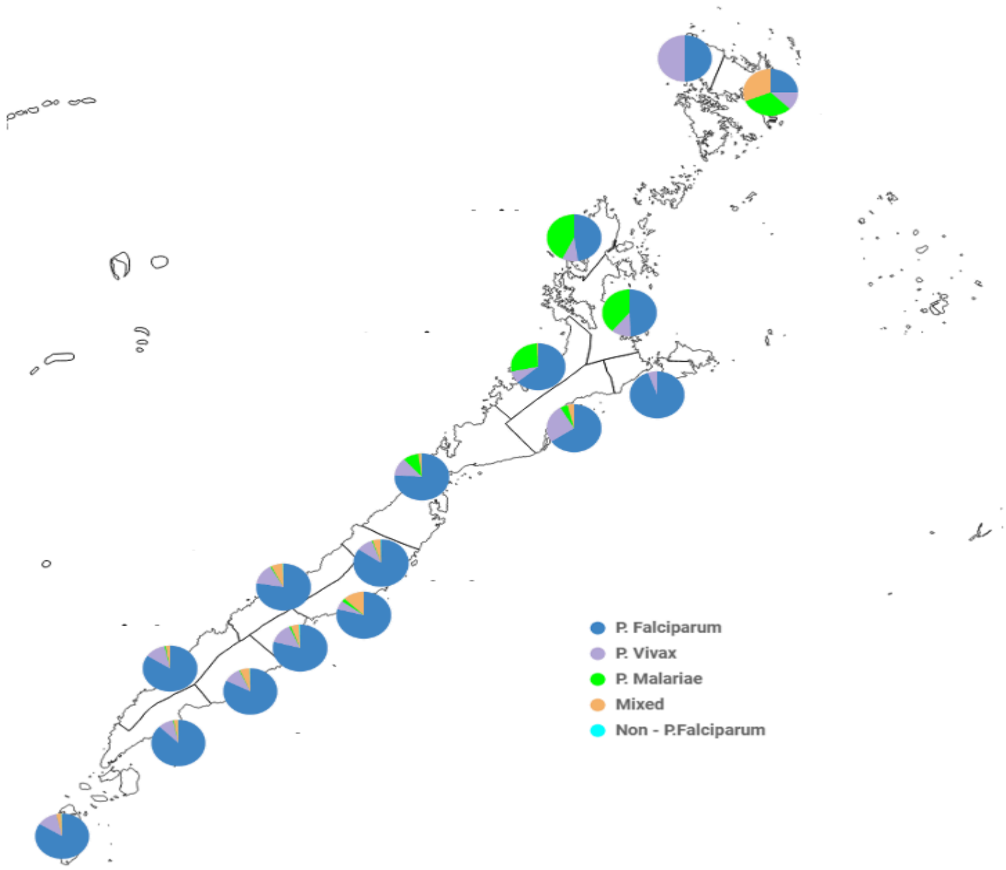

Figure 5.6. Geographic distribution of malaria cases according to species per municipality, 2013-2023. (No data available for 2012)

Spatio-temporal distribution

Between 2012 and 2023, three municipalities consistently recorded the highest malaria incidence: Rizal (annual average of 5,006 cases per 100,000), Brooke's Point (1,041 per 100,000), and Bataraza (868 per 100,000). Balabac and Quezon followed, ranking fourth and fifth, respectively. All five municipalities are situated in the southern part of the province (Figure 5.7).

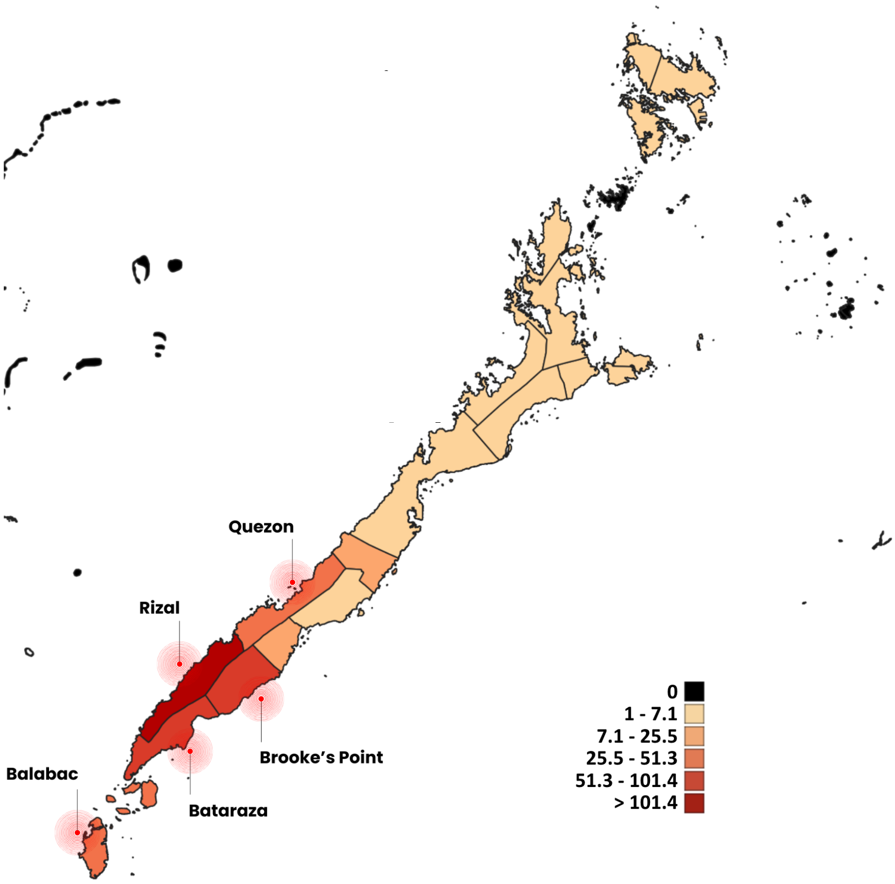

Figure 5.7. Top 5 municipalities with highest average malaria incidence, 2012-2023.

In contrast, 7 municipalities have not recorded any malaria infection during the same period—Agutaya, Araceli, Cagayancillo, Cuyo, Kalayaan, Linapacan, and Magsaysay (Figure 5.8). Rizal alone accounted for 32,176 malaria cases, representing over half of the total reported cases (50.45%). This highlights the disproportionate burden of malaria in the southern municipalities compared to the rest of the province.

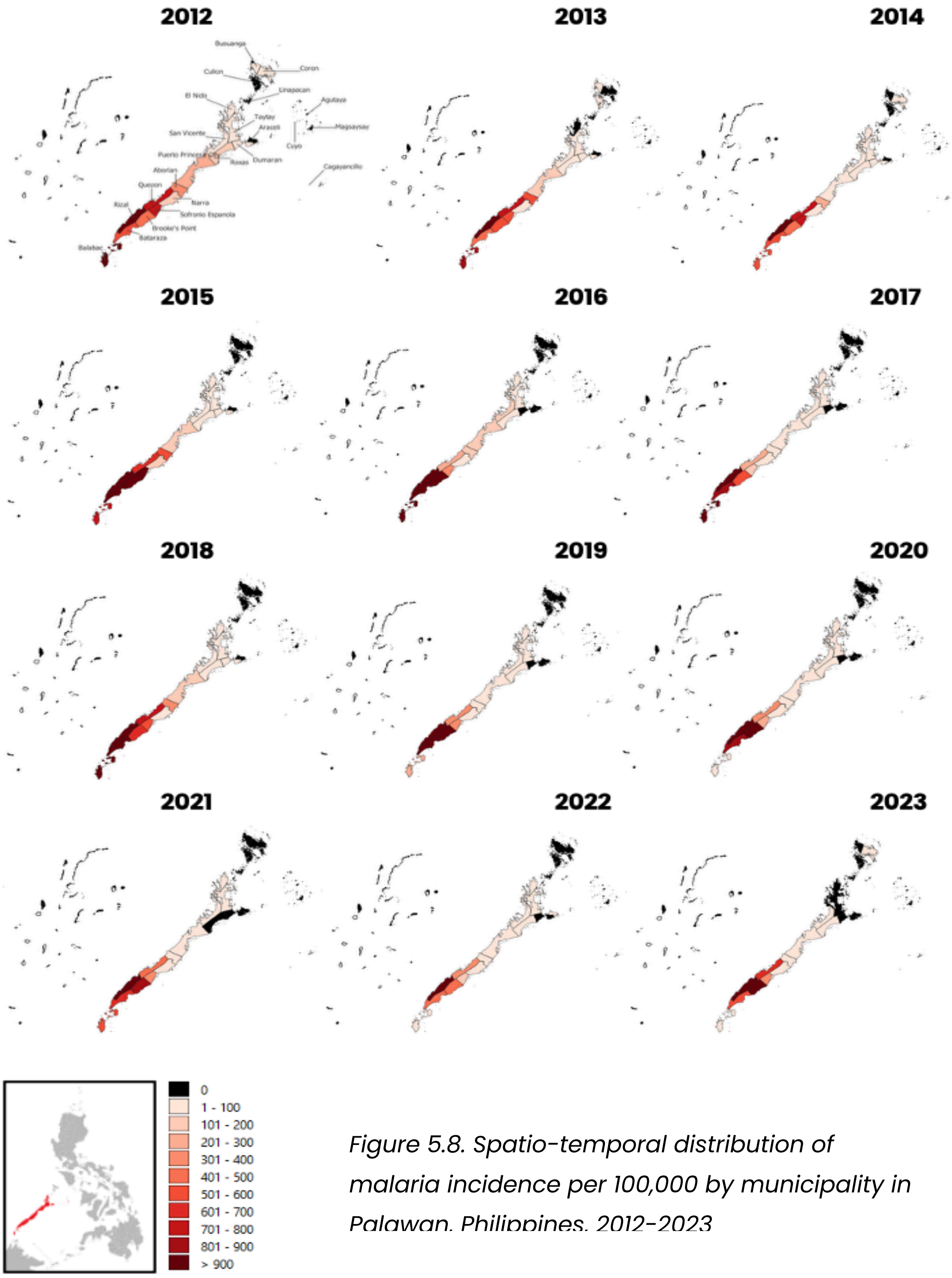

Figure 5.8. Spatio-temporal distribution of malaria incidence per 100,000 by municipality in Palawan, Philippines, 2012-2023

Climate and malaria correlations

Rainfall showed a weak positive correlation at Lag 0; moderate negative correlation at Lags 2–4. This suggests a lagged effect in which decreases in rainfall are followed by increases in malaria incidence 2 to 4 months later.

Relative humidity has a strong negative correlation at Lags 1–4, indicating an inverse relationship where malaria incidence tends to rise as humidity drops. However, this relationship was not statistically significant.

Temperature variables, on the other hand, showed more consistent positive correlations. A rise in average temperatures is directly correlated with increased malaria incidence within the first three months. Minimum temperature has a moderate positive correlation at Lag 0 to 3 then a negative correlation at Lag 4. Mean temperature has a strong positive correlation at Lag 0 to Lag 3. Maximum temperature has a strong positive correlation at Lag 0 to Lag 2, followed by a decline in Lag 3 (Figure 5.9).

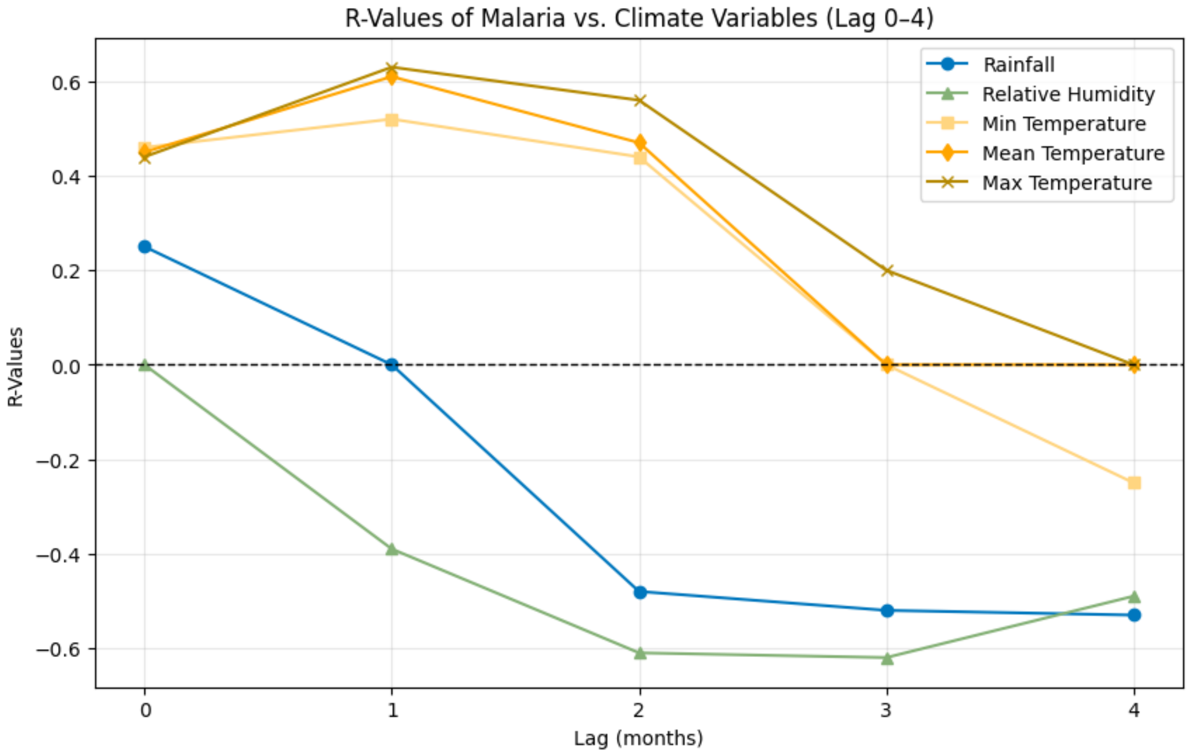

Figure 5.9. R-values of malaria incidence vs. climate variables.

Regression analysis identified mean rainfall and mean temperature as significant predictors of malaria incidence, while relative humidity was not statistically significant (Table 5.1, Figure 5.10). The model explained approximately 30.6% ($R^2 = 0.306$) of the variation in malaria incidence. The coefficient estimates show that, on average, malaria incidence increases by 0.105 cases for every 1 mm rise in mean rainfall, and by 19 cases for every 1°C increase in mean temperature.

Table 1. Linear regression model predicting malaria incidence based on mean rainfall, mean temperature and mean relative humidity.

Model Coefficients - INCIDENCE

			95% Confidence Interval				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**	**Stand. Estimate**
Intercept	-352.861	191.0055	-731.6322	25.910	-1.85	0.068	
RAINFALL	0.105	0.0295	0.0463	0.163	3.55	<.001	0.477
MEAN TEMP	19.021	4.4841	10.1290	27.913	4.24	<.001	0.419
RH	-1.922	1.1719	-4.2455	0.402	-1.64	0.104	-0.247

Model Fit Measures

Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**
1	0.553	0.306	0.286	22.0

Note. Models estimated using sample size of N=108

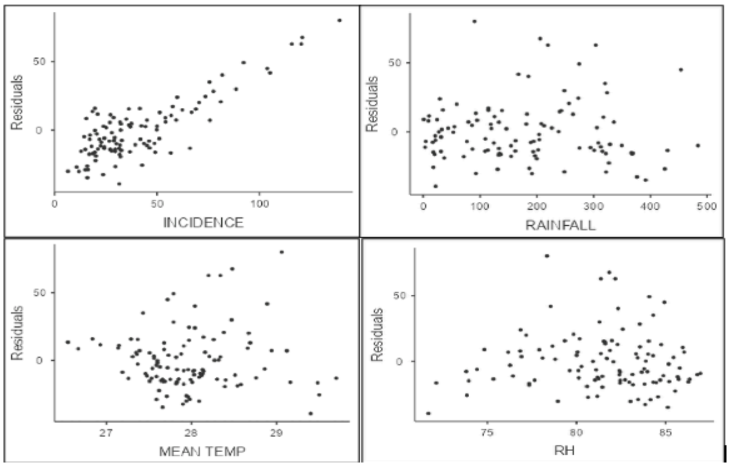

Figure 5.10. Linear regression model predicting malaria incidence based on mean rainfall, mean temperature and mean relative humidity.

Recommendations and limitations

Several limitations were identified in the review of malaria data. Incomplete or missing information was noted for some confirmed cases. Records with blank or incomplete entries were marked as "No data". Climate data and municipal-level monthly malaria data used for correlation analysis were available only from 2013 to 2020, limiting the scope of the time-series analysis. These constraints highlight the importance of strengthening surveillance systems to ensure that case reporting and data encoding are accurate, complete and consistently organized.

This study demonstrated that malaria incidence in Palawan follows a distinct seasonal pattern, with average rainfall and mean temperature emerging as significant predictors of incidence, while relative humidity was not statistically significant. The results suggest that climate variability plays an important role in shaping malaria transmission dynamics in the province. Based on these results, the following recommendations are proposed:

1. Climate-informed interventions: The timing of vector control programs such as delivery of malaria testing kits, net distribution, and indoor residual spraying in the province may be scheduled before malaria prone months.
2. Early warning systems: Climate-based surveillance and forecasting systems should be developed to anticipate high-risk periods and prevent outbreaks, especially in malaria-endemic municipalities and in areas that have already achieved malaria-free status.
3. Strengthening local capacity: Continuous coordination between national and local governments is critical to improve surveillance, monitoring, and

implementation of malaria control programs, thereby supporting the Philippines' goal of zero malaria transmission by 2030.

4. Further research: More granular analyses are needed to examine the relationship between climate variables and malaria incidence at the municipal level, with particular attention to high-burden and endemic areas in southern Palawan.