RESEARCH ARTICLE

Analysis of Dengue Cases Using Geographic Information Systems: Evidence from Baguio City, Philippines

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Abstract

Dengue is a global health issue and is also regarded as one of the major public health concerns in the Philippines. Presented in this paper is the application of a geographic information system (GIS) in mapping dengue cases in Baguio City. A descriptive research design was utilized and mapped dengue cases were reconciled with environmental correlates such as land cover, housing information (independent, mixed, or interconnected), hydrology (water bodies and canals), urbanization level (urban or rural), elevation, soil, and land surface temperature. Moreover, demographic factors and practices were utilized for further analysis. Results show that interconnected housing, urbanization, land surface temperature, hydrology, and population density are predictors of dengue cases in Baguio City with the predictive power of 0.3810 (strong), 0.3426 (strong), 0.2509 (medium), 0.1675 (medium), and 0.1323 (medium), respectively. In the context of dengue, several data gaps in health information systems exist. Although the Manual of Procedures for the Philippine Integrated Disease Surveillance and Response (PIDSR) published by the Department of Health (DOH) of 2014 provides a detailed guide in the management and surveillance of communicable disease, the use of GIS was noted to be unspecified. Using GIS provides the possibility of harmonizing several data sets to better inform policymakers.

Keywords: *Dengue, Geographic Information Systems, Weight of Evidence, Information Value, Getis Ord G**

Introduction

Globally, the World Health Organization (WHO, 2020) reported that the number of dengue cases increased in the last 20 years. 505,430 cases were recorded in the year 2000 which significantly increased to 4.2 million in 2019 (WHO, 2020). Dengue as a public health concern, is experienced in tropical regions like Asia. Singh and Soman (2021) reported that dengue is a major public health problem in India, Adnan et al. (2021) noted various outbreaks in Malaysia, and Rahman et al. (2021) expressed the presence of the four dengue serotypes in Thailand. Deaths that resulted from dengue have likewise increased from 960 to 4032 between the years 2000 and 2015 (WHO, 2020). Based on data from the Baguio City Health Services Office, 292 cases were recorded from January 1 to July 27, 2019, whereas in 2018, only 252 cases were recorded in the same period (Agoot, 2019). Despite Baguio City's increasing dengue cases during the declared national dengue epidemic in 2019, the Cordillera Administrative Region (CAR) has remained one of the regions with the second-lowest cases among the seventeen (17) regions where most of the reported cases were from regions in Western Visayas and Southern Mindanao (DOH, 2019; ReliefWeb, 2019).

Presented in this paper is the application of geographic information systems (GIS) in mapping dengue cases in Baguio City, Philippines. The Manual of Procedures for the Philippine Integrated Disease Surveillance and Response (PIDSR) published by the Department of Health (DOH) (2014) provides a detailed guide on mapping diseases in the country. The

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PIDSR manual is intended for nurses, community health volunteers, and other health professionals who take part in the management and surveillance of communicable diseases. However, the use of GIS was noted to be unspecified in its content. In addition, the PIDSR was observed to be mainly focused on cases that are significant in the early detection of epidemics. In this regard, the authors of this paper present the application of GIS in mapping dengue to identify some common environmental predictors that may be significantly associated with it. Numerous mathematical models were used to model dengue but varies according to frameworks and model variation due to scope, analytical approach, and structural form, including model validation and parameter estimation using empirical data (Aguiar et al., 2022). In Baguio, Addawe et al. (2016) used mathematical modeling in forecasting dengue cases. The spatial aspect of epidemiology still plays an important role in analysis and intervention design.

Known factors influencing dengue cases are demographic, environmental, and climatic. Demographic factors include the socio-economic profile of the community, housing information, and community practices. On the other hand, environmental factors include the physical attributes and the natural resources of the area of concern. Lastly, climatic factors include rainfall, temperature, and relative humidity.

Demographic factors influencing dengue incidences include socio-economic profiles such as livelihood activities, presence of urban poor or poverty, level of literacy and income, and age (Fareed et al., 2016; Duncombe et al., 2013; Garcia Jr & De Las Llagas, 2011; Jeefoo et al., 2011). Community practices include waste segregation, sanitation and container stockpiling for mosquito breeding sites, and construction activities (Fareed et al., 2016; Garcia Jr & De Las Llagas, 2011). Bhandari et al. (2008) identified practices such as frequency of cleaning water storage containers, using flowerpots or home gardens, and mosquito protection and awareness. Housing information includes the house type (independent, mixed, or interconnected), house population, number of dengue patients, presence of house garden, flowerpots, water storage containers, number of washrooms, number of rooms, and number of buildings. Garcia & De Las Llagas (2011) and Bhandari et al. (2008) identified the housing density index as a factor affecting dengue incidences. The higher the population, the more dengue incidences are expected (Fareed et al., 2016; Garcia Jr & De Las Llagas, 2011; Jeefoo et al., 2011). Urbanization is likewise related to dengue cases. Built-up structures and the location of the community's facilities affect the abundance of mosquitoes (Garcia & De Las Llagas, 2011), while Fareed et al. (2016) specified its effects of building canopies. Both Jeefo et al. (2011) and Fareed et al. (2016) agreed that travel dynamics or the increased movement of people affects dengue incidences.

Garcia & De Las Llagas (2011) identified environmental factors influencing dengue incidences, including physical attributes such as land use and land cover. Jeefo et al. (2011) further identified higher dengue risk in residential areas and revealed the dynamics of dengue for mixed land use, including residential-commercial-industrial linkages. Garcia & De Las Llagas (2011) emphasized the presence of cemeteries which significantly contributes to the presence of dengue cases. Dumpsite facilities and areas with high soil organic carbon (SOC) content provide breeding sites for mosquitoes (Jemal and Al-Thukair, 2016). Forest and vegetation land cover were also related to the proliferation of dengue cases (Jemal and Al-Thukair, 2016; Fareed et al.,2016).

Furthermore, Fareed et al. (2016) identified hydrology, elevation, topography, soils type, and land-use change as contributing factors in the presence of dengue cases. On the other hand, Jemal and Al-Thukair (2016) identified infrastructures such as poor sanitary and sewerage systems, the presence of water reservoirs, and irrigation ditches. Inadequate water supply affects sanitation, which causes multiple breeding sites for mosquitoes (Jeefo et al., 2011). Presence of water bodies were identified by Garcia & De Las Llagas (2011) as a dominant characteristic of areas with high dengue cases wherein Fareed et al. (2016) found canal cleanliness to exacerbate the prevalence of dengue cases. Francisco et al. (2021) concluded the combined effect of climate and landscape in dengue dynamics. Strong influencers of dengue are rainfall and temperature (Kakarla et al, 2020).

According to Dayrit et al., (2018), the DOH in 2005 issued policies that would systematize all data sources and information systems related to health. However, it is evident that 15 years later, harmonizing all empirical data so that it may better guide health and social policymakers remains to be a challenge.

The use of GIS, as demonstrated in this research, illustrates how different data sets can be integrated into rendering a holistic view of a timely health phenomenon, i.e., dengue. Results of the study can aid in developing programs and projects to address dengue.

Thus, the objectives of this paper are as follows: (1) to identify the clusters of dengue cases in Baguio City from 2013-2017; and (2) to determine the predictive strength of environmental variables and how they correlate to the occurrence of dengue in Baguio City from 2013-2017.

The study was limited to the available data in the level of the local government unit as well as the open map resolution available. The health data available was clustered into barangays which gives a higher abstraction of analysis. The weight of evidence and information values was aimed to identify predictor variables; however, the methodology is also dependent on the specificity of the data.

Methods and Methodology

The study utilized a descriptive research design. Environmental factors affecting dengue need to be analyzed prior to conducting analytical studies. Close coordination and adherence to communication protocols with the local government of Baguio as the main project beneficiary The study covers the one hundred twenty-nine (129) barangays of Baguio City.

Among the data requested from the City of Baguio are the updated barangay maps, updated road maps, locator map for barangay halls, barangay health centers, schools, water body maps, existing and proposed land use maps, vegetative cover map, rainfall map, slope map, temperature map, topographic map, and the demographic data per barangay which include age, gender, literacy rate, urbanization, poverty incidence, annual income, and other relevant data. Other pertinent documents were also inclusive in the request like comprehensive land use plan (CLUP), local climate change action plan (LCCAP), and the disaster risk reduction and management plan (DRRMP) for the purpose of a deeper analysis of the dengue phenomenon in the barangay level and at a macro scale. The researchers also sent the letters of request to various government line agencies and local water district for relevant data needed in the project.

GIS is a computer system that is primarily used in displaying, integrating, and analyzing data in relation to specific locations on the surface of the Earth (WHO, 2018). The use of GIS facilitates the creation of maps which can be connected to existing databases for creation of spatial models. In the health sector, the use of GIS technology has been documented in areas such as workforce planning (ESRI, 2010), comparing social determinants in relation to perinatal health (Bloch et al., 2017), and assessing community health (Faruque et al., 2003).

The use of GIS as a tool in analyzing dengue cases is very evident as a contemporary approach. Garcia and Llagas (2011) utilized choropleth maps and analytical methods like map overlay, simple statistics, and information value methods to better understand the dengue cases in Quezon City. However, choropleth maps cannot provide specific analysis of dengue cases. Indeed, point maps of dengue cases were used by Fareed et al. (2016), Jeefo et al. (2011), Duncombe et al. (2012), Jemal and Al-Thukair (2016), and Bhandari et al. (2008).

Data and spatial analysis utilize GIS functions such as map viewing and clustering to analyze geographical distribution for dengue. Data and spatial analysis framework were based using the framework of map viewing of Garcia and Llagas (2011) and the use of Getis-Ord G* for hotspot detection. These data analysis frameworks are similar studies where choropleth maps were used vis a vis annual time frame of dengue cases. Map overlay and visualization were also adopted as methods of analysis in the study. Hotspot analysis demonstrated by Fareed et al. (2016) to determine dengue fever outbreaks was also utilized in the study. Furthermore, to determine the predictor variables, weight of evidence (WOE) and information value (IV) were utilized.

Mapped dengue cases were reconciled with environmental correlates such as interconnected and independent housing, urbanization, land surface temperature, hydrology, water bodies and canals, soil, elevation, and land cover. Moreover, demographic factors and practices were utilized for further analysis.

All the 129 barangays of Baguio were included in the study. Cases based on the records of the Baguio City Health Services Office Epidemiology and Surveillance Unit (BCHSO CESU) with information such as age, gender, and date on-set were gathered. Specifically, all clinically diagnosed dengue cases reported in the PIDSR from January 1, 2013 to December 31, 2017 in the city of Baguio were included. Secondary data were gathered from the records of BCHO CESU for monthly dengue cases from 2013-2017.

Data entries with missing attributes or with onset dates outside of 2013 to 2017 were discarded from the table. Barangay names were corrected to their standard names to fit geospatial data for data joins. There are a total of 7189 dengue case entries from 2013 to 2017.

GIS vector data for Baguio City on administrative boundary level 4 or the barangay level were retrieved from the Database of Global Administrative Areas (GADM). On close inspection, the boundaries were found to be off when overlaid on satellite imagery. The boundaries were manually corrected by visually moving the vector layer approximately in place on known boundaries. The adjusted boundaries were moved south-west by 687m from their original location.

Housing data was retrieved from OpenStreetMap building features as of September 2019. Building features that were within 3 meters (m) from each other were classified as 'Interconnected' while building features over 3 meters (m) were classified as 'Independent'. Areas for each building feature were calculated then summed up within each barangay to estimate the amount of each housing classification.

Elevation data was retrieved from ASTER GDEM with a spatial resolution of 30 meters (m). The hydrology of the city was delineated using the DEM. Mean elevation was calculated for

Table 1. *Variables, data sources, and data processing*

Variables	Data Source	Process
Interconnected Housing (m2)	OpenStreetMap	Geometry statistics, area covered per barangay
Housing-Independent (m2)	OpenStreetMap	Geometry statistics, area covered per barangay
Urbanization (Urban/Rural)	Philippine Statistics Authority (PSA)	Categorized per barangay
Population Density	Philippine Statistics Authority (PSA)	Geometry statistics, barangay area/barangay population
Age	Philippine Statistics Authority (PSA)	Aggregated by age group
Sex	Philippine Statistics Authority (PSA)	Aggregated by sex
Hydrology (m)	Delineated from ASTER GDEM	Geometry statistics, length of catchments per barangay
Land Surface Temperature (°C)	Climate Engine, Landsat	Geometry statistics, Mean LST per barangay
Soil	Bureau of Soils and Water Management (BSWM)	Geometry statistics, area per soil type
Elevation (m)	ASTER GDEM	Geometry statistics, mean elevation per barangay
Land Cover	National Mapping and Resource Information Authority (NAMRIA)	Geometry statistics, mean land cover area

each barangay, while the length of processed streams and canals were summed within each barangay.

Land Surface Temperature (LST) data were retrieved using Climate Engine (Huntington et al. 2017), a cloud-based web application for analyzing climate and remote sensing data. Yearly average LST was processed then the mean was taken for each barangay.

Consolidated dengue cases from the years 2013 to 2017 were processed with Getis-Ord G*, a local spatial autocorrelation statistical analysis. Dzul-Manzanilla et al. (2021) used Getis-Ord G* to identify dengue spatial hotspots in cities in Mexico. The analysis was implemented with queen contiguity as its spatial weights. The results of the analysis include high dengue clusters where barangays with high number of dengue cases are neighbored with other barangays with high number of dengue cases; likewise low dengue clusters where barangays with low number of dengue cases are neighbored with other barangays with low number of dengue cases.

The weight of evidence (WoE) was used to compute the strength of independent variables (socio-demographic profile and physical attributes) across groupings within a particular attribute. The probability computation across groupings reveals the variable influence. Positive values for WoE mean less effect while negative values mean greater effect.

In this study, frequency of good values is defined as low clustered cases and frequency of bad values is defined as high clustered cases.

The value of WoE will be 0 if the odds of the relative frequency of low clustered dengue cases divided by the relative frequency of high clustered dengue cases is equal to 1. If the relative frequency of high clustered dengue cases in a group is greater than the relative frequency of low clustered dengue cases, the odds ratio will be less than 1 and the WoE will be a negative number; if the relative frequency of low clustered dengue cases is greater than the frequency of high clustered dengue cases in a group, the WoE value will be a positive number.

Since WoE uses two (2) definite frequencies, the low and high dengue case clusters were incorporated using the concept based on the results of the Getis Ord G* classification of each barangay.

Statistical data binning through frequency table method was utilized to determine the number of bins of the continuous variables. With respect to the 129 barangays in the city and for

$$WoE = [\ln \frac{Relative\ Frequency\ of\ Low\ Clustered\ Dengue\ Cases}{Relative\ Frequency\ of\ High\ Clustered\ Dengue\ Cases}] \times 100$$

consistency, eleven (11) bins were created for continuous variables with high range differences such as housing, hydrology, population density, and elevation while four (4) bins were used for the land surface temperature data because of low range difference. With the data binning method, local smoothing on the data and reduction on chances of overfitting was considered. The continuous variables were turned into categorical values in which the original data values fall in an interval, thus, making the data fit for WoE.

Information value (IV) method was used in the reduction of independent variables. The IV computation follows in succession the WoE. The overall strength of the independent variable will be determined using IV. Values for the IV are interpreted as less than 0.02 as not useful for modeling; 0.02 to 0.1 as weak predictor; 0.1 to 0.3 as medium predictor; and 0.3 to 0.5 as strong predictor and above 0.5 as suspicious or too good to be true. Information value increases as the categories of the variables increase. With respect to the 129 barangays in the city and for consistency, eleven (11) bins were created for continuous variables with high range differences. Variables with predictive power of higher than 0.5 are suspicious or good to be true because the concentration of the cases in the categories of the variables are hardly distributed. The IV of a predictor is related to the sum of the absolute values of WoE over all groups. Thus, it expresses the amount of diagnostic information of a predictor variable for separating the good from the bad.

Results and Discussion

Data gaps in the barangays and lack of updated GIS data at the local government level were challenges encountered during data collection and fieldwork. Coordination for data gathering and interviews to the LGU and barangays was a challenge to the researchers due to availability and commitments. Adjustments and negotiations of schedules for the researchers, government agencies and barangay captains were conducted before the data gatherings and interviews were conducted.

During the actual visit to the barangays for field validation and site inspection, the researchers took photos at areas with predictors for dengue cases with the full consent from the barangays. Obstacles in penetrating the areas to inspect like misbehaved dogs and uncooperative residents who did not like the researchers to take photos were also encountered.

With Getis-ord G*, barangays were clustered into hot and cold spots then scored by their significance. Significant barangays are then further analyzed against possible dengue factors using Weight of Evidence and Information Values to determine the predictive power for each factor.

High case dengue clusters were found mostly in the western areas towards the southern areas of Baguio City with some isolated cases in the south-eastern areas. Low case dengue clusters were found to be in the central areas of Baguio City save for a few isolated cases in the northeastern areas. Most clusters were found in barangays large in area size with high population, while low case dengue clusters were found in high population dense barangays.

Figure 1. *Dengue Cases in Baguio City 2013-2017*

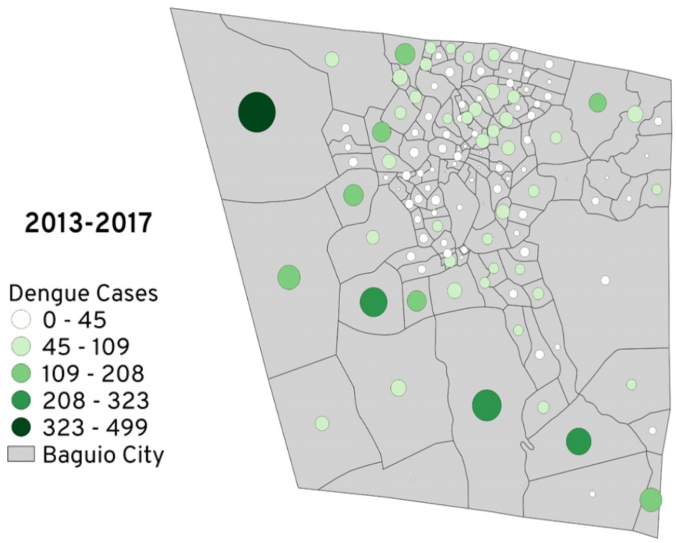
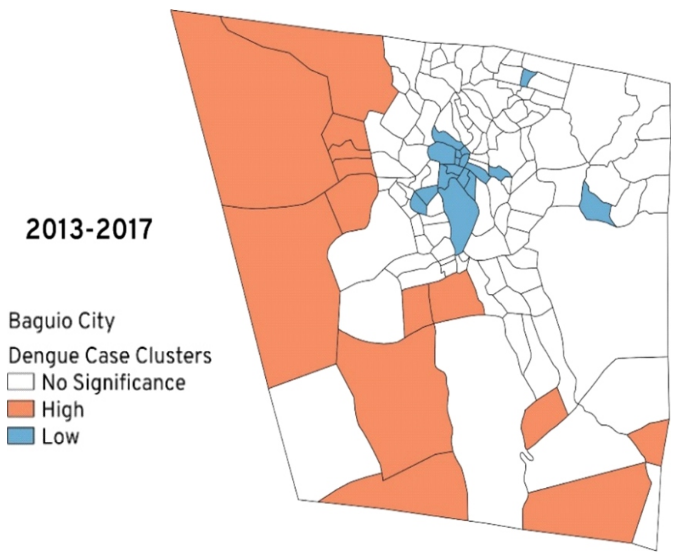
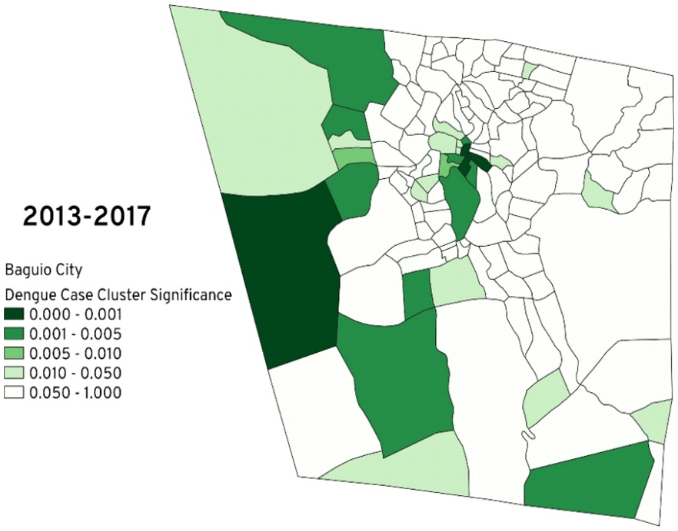


Figure 2. *Getis Ord G* Clusters of Dengue Cases in Baguio City 2013-2017*



Significant barangays from high dengue clusters were Asin Road with a p-value of 0.001. Among the low dengue clusters there were four (4) significant barangays, all with a p-value of 0.001; Abanao-Zandueta-Kayang-Chugum-Otek, Bagong Lipunan, Kabayanihan, and Malcolm Square-Perfecto.

Figure 3. *Getis Ord G* Cluster Significance of Dengue Cases in Baguio City 2013-2017*



Hotspots are important for vector control interventions (Dzul-Manzanilla, 2021).

Information values with less than 0.02 are not useful for modeling; values ranging from 0.02 to 0.1 are weak predictors; values from 0.1 to 0.3 are medium predictors; and values from 0.3 to 0.5 are strong predictors and values above 0.5 are suspicious or too good to be true. From the results, housing-interconnected has 0.3810 information value and urbanization has 0.3426 information value. These indicate that interconnected houses and urbanization are strong predictors of dengue cases in the city. Urban areas are high transmission areas for dengue (Dzul-Manzanilla, 2021). Land surface temperature (LST) has 0.2509, hydrology has 0.1675, and population density has 0.1323 information values indicating that these variables have medium predictive power. Moreover, age and sex variables have 0.0038 and 0.0002 information values interpreted as weak predictors and lastly, housing-independent, soil, elevation, and land cover are variables with information values higher than 0.5 implying that these variables are suspicious or too good to be true predictors which means that the concentration of cases in the categories of the variables are hardly distributed. Kakarla et al. (2020) recommended control measures to limit dengue spread in warmer climates.

Table 2. *Getis Ord G* High Dengue Clusters Barangays in Baguio City 2013-2017*

Rank	Barangay	Population	Cases	P-Value
1	Asin Road	64748	208	0.001
2	Pinsao Proper	29717	89	0.002
3	Quezon Hill, Upper	13250	37	0.002
4	Santo Tomas Proper	31882	107	0.002
5	Fort Del Pilar	18830	20	0.004
6	San Luis Village	40695	166	0.004
7	Bakakeng North	48287	156	0.005
8	Victoria Village	16868	41	0.009
9	Middle Quezon Hill Subdivision	19152	25	0.012
10	Liwanag-Loakan	18745	66	0.019
11	Santo Tomas School Area	6269	5	0.029
12	San Vicente	25856	97	0.04
13	Atok Trail	8570	29	0.045
14	Irisan	160298	499	0.045

Table 3. *Getis Ord G* Low Dengue Clusters Barangays in Baguio City 2013-2017*

Rank	Barangay	Population	Cases	P-Value
1	Bagong Lipunan	57	0	0.001
2	Kabayanihan	797	5	0.001
3	Malcolm Square-Perfecto	413	0	0.001
4	Abanao-Zandueta-Kayong-Chugum-Otek	2911	13	0.002
5	Harrison-Claudio Carantes	1645	12	0.002
6	Legarda-Burnham-Kisad	5472	19	0.003
7	Magsaysay, Upper	588	9	0.005
8	Rizal Monument Area	384	1	0.008
9	Palma-Urbano	6467	24	0.012
10	Kayang-Hilltop	6908	37	0.013
11	Camp Allen	12414	38	0.016
12	Country Club Village	11147	30	0.016
13	Holy Ghost Proper	11566	34	0.022
14	City Camp Central	11357	37	0.032
15	Padre Zamora	12759	33	0.033
16	Bayan Park Village	4794	26	0.035
17	Market Subdivision, Upper	5851	7	0.046

Table 4. *Information Values of the independent variables and its predictive power*

Variable	Information Value (IV)	Predictive Power
Housing-Interconnected (m^2)	0.3810	Strong predictor
Urbanization	0.3426	Strong predictor
Land Surface Temperature (°C)	0.2509	Medium predictor
Hydrology (m)	0.1675	Medium predictor
Population Density	0.1323	Medium predictor
Age	0.0038	Weak predictor
Sex	0.0002	Weak predictor
Housing-Independent (m^2)	1.1160	Suspicious or too good to be true
Soil	1.1516	Suspicious or too good to be true
Elevation (m)	1.5313	Suspicious or too good to be true
Land Cover	2.3270	Suspicious or too good to be true

Four (4) of the variables were suspicious or too good to be true predictors, and the land cover variable was the most suspicious. Taking for instance the variable that is categorical by nature with 4 pre-defined bins, cases in the categories of the variables are hardly distributed and are concentrated in 1 or 2 certain categories. Moreover, the data itself was retrieved from the Database of Global Administrative Areas (GADM), which means that chances of the IV to be more accurate is attainable using a more localized data.

The application of GIS-based methodologies and identification of environmental predictors in the occurrence of dengue can be related to the nursing theories of Florence Nightingale and Rozanno Locsin. Nightingale's environmental theory posits that a healthy environment is important for the restoration/ maintenance of health (Pfettscher, 2014). Her description of sanitary conditions in England and Crimea, with the incorporation of statistical data, made scholars consider her as a notable empirical researcher (Pfettscher, 2014). For Nightingale, diseases can be prevented and health maintained via controlling environmental factors (Zborowsky, 2014). The environmental features of the contemporary period, although bearing some resemblance to the historical epoch observed by Nightingale, have become so complex due to factors brought about by globalization. Locsin's technological competency as caring in nursing, however, forwards the assumption that to be caring is to be technologically competent as a means of understanding or knowing other persons (Locsin, 2010). Persons, according to Locsin (2010), must not be viewed as unchanging or static but rather, as beings that are capable of growing and changing. This concept of change can be very much depicted on the characteristics of the environment in which people live. In the context of this study, knowing the significant predictors of dengue using GIS technology can call policymakers and stakeholders into action to effectively modify the environment for the promotion of health and prevention of diseases.

For Nieva (2020), the paucity of resources related to information and communication technology (ICT) coupled with the challenge of harmonizing existing health information systems prompted the DOH to issue policies, procedures, and guidelines related to ICT work in 2005. One of these initiatives was the development of the PIDSR that originally aimed to detect and investigate emerging threats to public health like epidemics (Nieva, 2020). However, challenges continue to come to the fore at present such as the limited ability of the DOH to involve IT specialists from other sectors (Nieva, 2020). Determining what factors are significant in the prevention of dengue while integrating numerous data sets can be accomplished with the use of GIS.

Conclusions and Recommendations

GIS-based methodologies such as Getis Ord G* can spatially identify dengue clusters. In the case of Baguio City from 2013-2017, 31 barangays out of 129 or about 24% are dengue clusters.

With the use of Weight of Evidence and Information Values, it can be inferred that predictive power of each factor affecting dengue cases. Interconnected houses and urbanization are strong predictors of dengue. These two variables are interrelated and are indicators of the presence of structures in the barangays. Indeed, Baloloy et al. (2019) highlighted the rapid urbanization that happened in Baguio City during the years 2014 to 2019 through a spatio-temporal analysis using GIS and remote sensing.

Mangay-Maglacas (2019) asserted that the health sciences like nursing must not myopically focus only on illness situations. As such, nurses and other health professionals alike must understand the complexity and interplay of environmental factors in which variables that directly and indirectly affect health are situated. While doing so may prove to be challenging, the use of GIS provides the possibility of harmonizing existing data sets into more sensible evidence that can better inform policymakers into taking actions that promote health and prevent diseases.

Last August 07, 2020, the Philippines was recorded to have the worst COVID-19 situation as compared to other Southeast Asian countries with cases over 120,000 (The Japan Times, 2020). The number of COVID-19 patients will continue to increase unless effective measures that are scientifically sound are put in place. The “covidization” of most news reports even carry with it the unintended consequence of overshadowing other relevant health issues like dengue and other infectious diseases that continue to burden low-income settings (Lasco & San Pedro, 2020).

In this paper, the authors forward the importance of tapping what GIS has to offer in mapping infectious diseases like dengue, the present COVID-19 pandemic, and other diseases that may arise in the future. With the use of GIS, variables that are related to the spread of the SARS-CoV-2 virus are better visualized for planning and mitigation like how it was executed by the city government of Baguio (Maramag, 2020). For Seal (2018), spatial data and mapping provide a platform for the integration of contrasting data sets. While the lockdown of communities proved to be important, the inclusion of the other social determinants of health through the use of GIS (e.g. income, employment, housing density, etc.) will be more likely included in the deliberation of health and social policymakers.

For Umali & Exconde (2003), however, challenges exist on actualizing the potentialities of GIS in the Philippines. These include the lack of expertise and manpower, the inadequacy of needed equipment, and the uncoordinated initiative of agencies that use remote sensing and GIS activities (Umali & Exconde, 2003). One ironic feature of globalization in our time is the fact that we do not only exchange goods and services for the betterment of life but we have also enabled the movement of viruses and other pathogenic organisms across geographic borders. Rendering how various diseases occur on maps vis-à-vis other social determinants may just be one of the many great leaps we need to take seriously in preparation for future outbreaks and pandemics. Thus, structural, and non-structural measures need to be implemented to address dengue. Tay et al. (2022) strongly suggests the focus on dengue infection rate for control strategies. Through environmental modeling, Baloloy et al. (2020) showed that LST can be reduced using different scenarios.

Highly dense neighborhoods were found to be significantly associated with the occurrence of dengue. The DOH (2011) recognizes that this phenomenon can be an offshoot of urbanization whereby other possible scenarios like neighborhood congestion and slum formation contribute to the vulnerability of populations to infectious and communicable diseases. Part of the Urban Health System Development (UHSD) Program of the DOH (2011) specifies the objective of increasing awareness of and guiding LGUs to efficiently respond to the challenges of contemporary urban health. The results of this study strengthen the need to anchor the use of GIS in various LGUs in the monitoring and surveillance of infectious and communicable diseases so that prompt and efficient responses are implemented.

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Acknowledgments

This project has been funded by the Philippine Council for Health Research and Development (PCHRD) through the endorsement of the Cordillera Regional Health Research and Development Consortia (CRHRDC). In addition, the project was implemented by the University of the Cordilleras and co-implemented by the Baguio City Health Services Office (BCHSO) and the Department of Health (DOH) Cordillera Administrative Region.

Ethics Clearance

Ethical clearance was obtained from the Cordillera Health Research and Development Consortium Research Ethics Committee (CRHRDC REC). The study underwent a rigorous process of review which included technical and ethics review. The main ethical principles adhered to in the study include upholding the data privacy of the patients, and scientific soundness.