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Geospatial Variability of Cholera Cases in Malawi Based on Climatic and Socioeconomic Influences

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Abstract

Cholera remains a public health threat in most developing countries in Asia and Africa including Malawi with seasonal recurrent outbreaks. Malawi's recent Cholera outbreak in 2022 and 2023, exhibited higher morbidity and mortality rates than the past two decades. Lack of spatiotemporal-based technology and variability assessment tools in Malawi's Cholera monitoring and management, limit our understanding of the disease's epidemiology. The present work developed a spatiotemporal variability model for Cholera disease at district level and its relationship to socioeconomic and climatic factors based on cumulative confirmed Cholera cases in Malawi from March 2022 to July 2023 using Z-score statistic and multiscale geographically weighted regression (MGWR) in a Geographical Information System (GIS). We found out that socioeconomic factors such as access to safe drinking water, population density and poverty level, and climatic factors including temperature and rainfall strongly influenced Cholera prevalence in a complex and multifaceted manner. The model shows that Lilongwe, Mangochi, Blantyre and Balaka districts were highly vulnerable to Cholera disease followed by lakeshore districts of Salima, Nkhotakota, Nkhata-Bay and Karonga than other districts. We recommend strategic measures such as Water, Sanitation, and Hygiene (WASH) interventions, community awareness on proper water storage, Cholera case management, vaccination campaigns and spatial-based surveillance systems in the most affected districts. This research has shown that MGWR, as a surveillance system, has the potential of providing insights on the disease's spatial patterns for public health authorities to identify high-risk districts and implement early response interventions to reduce the spread of the disease.

Keywords

Cholera, Geospatial Variability, Prevalence, GIS, MGWR, Vulnerability, Malawi

1. Introduction

Cholera is an acute watery diarrheal illness which remains a major global concern and it has become an endemic disease in most countries in Asia and Africa [1]. Cholera is caused by an intestinal infection with a toxin-producing bacterium known as *Vibrio cholerae* [2]. Fleming *et al*., [3] states that *Vibrio cholerae* is a motile, comma-shaped gram-negative bacteria with a single polar flagellum. It contains hundreds of serogroups that include pathogenic and non-pathogenic strains [4]. Historically, Cholera has emerged through several occurrence of epidemics, with the first to have occurred in the Ganges-Brahmaputra Delta, South Asia in the 1800s which spread throughout Asia. The second epidemic included most countries in Africa, Europe, and Australia in 1817 [5]. The disease is mostly characterized by diarrhea, vomiting and severe dehydration. According to Crooks and Hailegiorgis [6], Cholera is mainly transmitted through drinking water or eating food that is contaminated with *Vibrio cholerae* bacterium which finds its way into the environment via stools from people that are infected with the disease. Despite the fact that Cholera is preventable and treatable through various ways such as adequate hygiene and proper sanitation, provision of clean drinking water and intensifying oral Cholera vaccines, it still remains a health threat in so many developing countries where such preventive measures are minimal to nearly impossible [7] [8] [9]. In March 2022, Malawi registered several cases of Cholera, with the first case detected in Machinga district [10]. Following the spread of the disease to most southern districts of Malawi, and later throughout the country, the Malawi Ministry of Health (MOH) declared a Cholera outbreak, whose prevalence persisted throughout the year until mid-year of 2023 [11]. This recent outbreak is one of the rare cases in which the Malawi health system was overstretched with enormous cases each passing day. The Government of Malawi officially launched the national Cholera fight campaigns, among which included the provision of Oral Cholera Vaccines (OCVs), Water, Sanitation, and Hygiene (WASH) initiatives and setting up of treatment facilities through the MOH with the aim of controlling and stopping further spreading of the disease [12]. As of 24 July 2023, Malawi had reported 58,944 cases across all the 28 administrative districts, with 1766 deaths registered [12]. Over 14,000 of the active cases were children and 219 of them were reported dead [13]. This was the most severe case of Cholera disease epidemics reported in Malawi over the past two decades.

Malawi had previously reported several other Cholera cases in the past with most notable cases in the years 1998-1999, 2001-2002 and 2008-2009 epidemics which resulted in 25,000, 33,546, and 5751 cases with corresponding deaths of 968, 860 and 125 respectively [14].

Geographic Information Systems Technology (GIST) is a critical location-based tool that has been useful in assessing and monitoring the spread of most infectious diseases such as Cholera [15]. Using historical mortality data between 1891 and 1940 from 24 districts of Bengal, Bouma and Pascua [16], found that climatic conditions and geography play vital roles in the geospatial dynamics of Cholera endemic. In a recent study, Idoga *et al.*, [17] indicated that in the Benue State, Nigeria, from 2008 to 2017, infections and spread of Cholera cases were influenced by factors such as improper sewage disposal and lack of access to clean water. Further, Leckebusch and Abdussalam [18] demonstrated in their case study that Cholera morbidity and mortality were highly influenced by temperature, rainfall, population density, absolute poverty, adult literacy and access to piped water. For the case of Malawi, there are no open-source geospatial models that can be used in monitoring and modeling the spatiotemporal variability of Cholera cases. This lack of readily available spatiotemporal-based assessment tools impedes the understanding of Cholera outbreak epidemiological dynamics.

In this study, we utilized GIST [19] to develop a spatiotemporal variability model for Cholera disease for Malawi at district level and its relationship to socioeconomic and climatic factors based on cumulative confirmed Cholera cases from March 2022 to July 2023. Using the climatic and socioeconomic factors as known Cholera influencing determinants [18], we employed a Z-score statistic of these influencing factors and Multi-scale Geographic Weighted Regression (MGWR) to propose a GIST-based cholera vulnerability model for Malawi.

2. Materials and Methods

2.1. Study Area

With a population of 18 million, Malawi is a southeast African country covering an area of over 118,484 Km^2 according to the 2018 National Census [20]. Malawi borders Zambia on the east, the United Republic of Tanzania on the northern side and Mozambique on the west and south, and is located at latitude 13.25˚S and longitude 34.30˚E of the Greenwich Mean Time. Malawi has a subtropical savanna climate with average annual rainfall range of 725 mm to 2500 mm and a mean annual temperature range of 17˚C to 28˚C [21]. **Figure 1** illustrates the geographic location of Malawi and historic cumulative time-series Cholera disease confirmed cases and deaths during the endemics between 2001 and 2018.

2.2. Data Collection and Preprocessing

We utilized cumulative Cholera cases data from March 3, 2022 to July 24, 2023

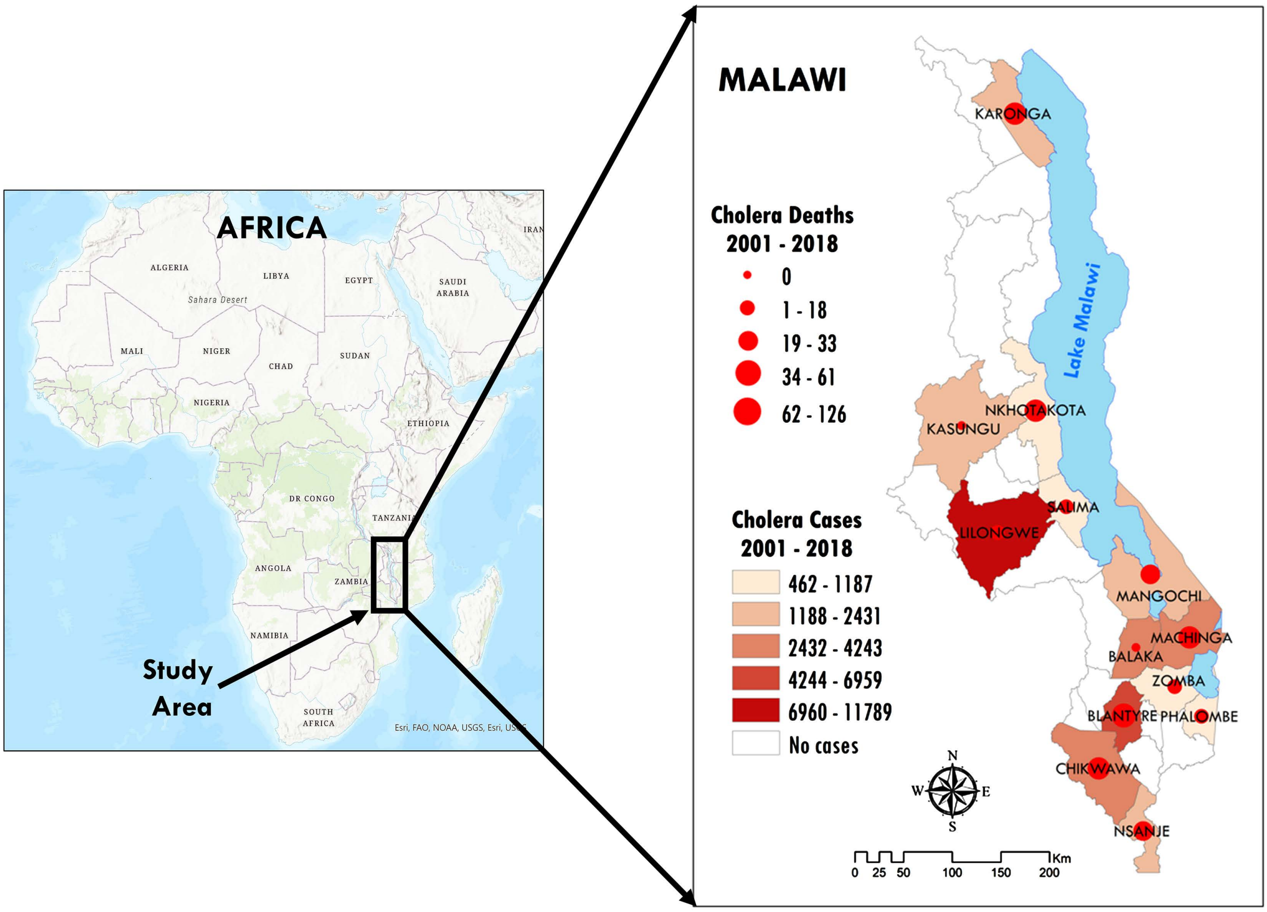


Figure 1. Study area location.

collected from the Public Health Institute of Malawi's website PHIM (http://phim.health.gov.mw/) [22]. The Public Health Institute of Malawi (PHIM) has been collecting and publishing district level Cholera cases surveillance data since the on-set of the 2022-2023 outbreak. Climatic and socioeconomic Cholera disease influencing factors [18] collected from Department of Climate Change and Meteorological Services (DCCMS) (https://www.metmalawi.gov.mw/) [23] and Malawi's National Statistical Office (NSO) [20] respectively, were prepared and visualized in ArcGIS 2.8. **Table 1** shows a summary of Cholera influencing factors used in this study. A composite statistical Z-Score and MGWR algorithm were used to develop a spatial variability model of Cholera cases in Malawi. A detailed modeling framework is illustrated in a **Figure 2**.

2.3. Cholera Epidemiological Data

The World Health Organization describes Malawi's frequent Cholera outbreaks as endemic with notable annual cases occurring during the rainy season from the month of November to May, particularly in the southern region districts of Malawi [24]. **Figure 3** illustrate the spatiotemporal Cholera cases in Malawi from 2001 to 2018 using time-series cumulative data.

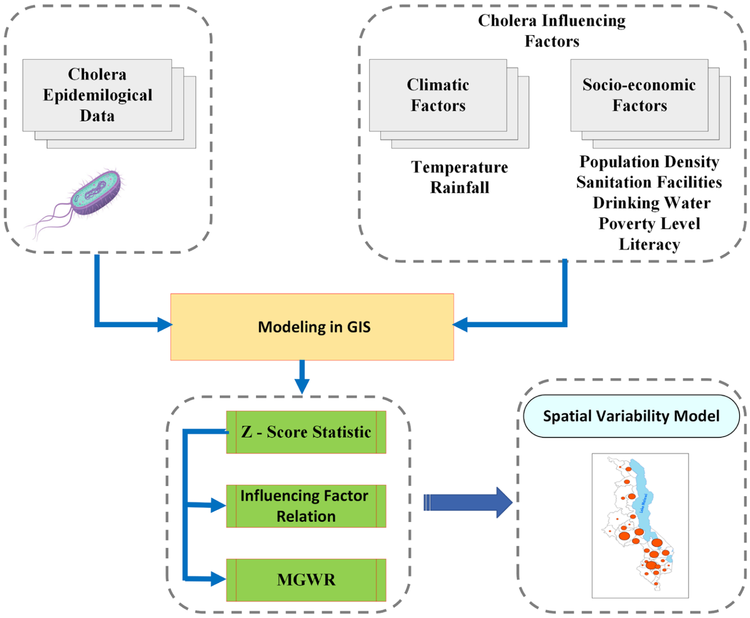


Figure 2. Research modelling methodology.

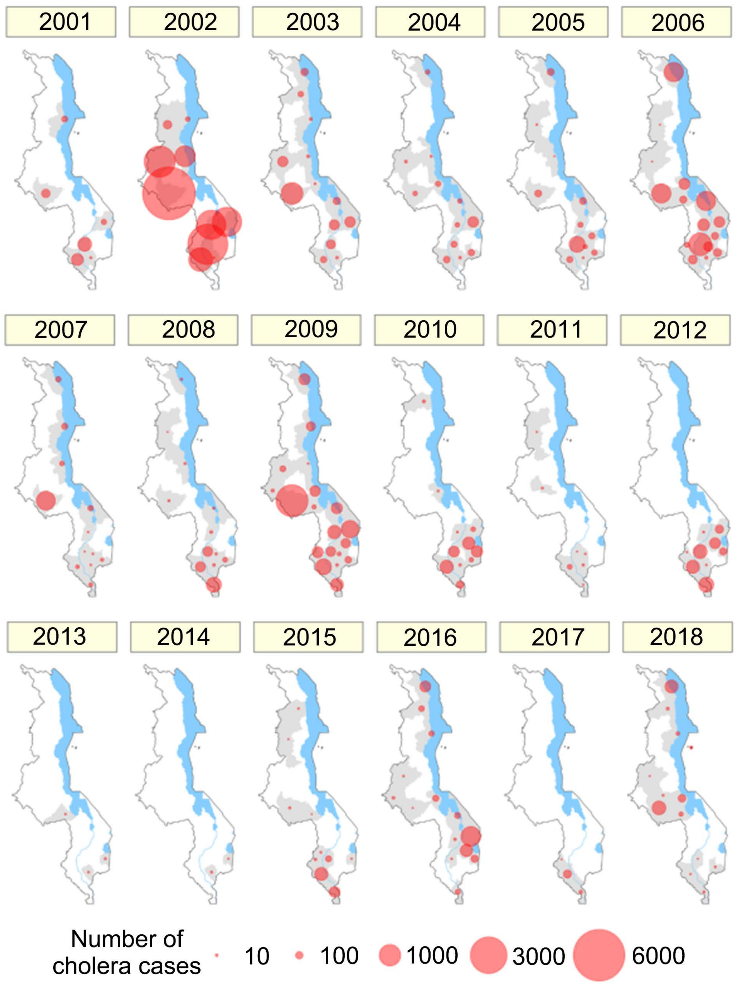


Figure 3. Malawi Cholera cases from 2001 to 2018.

Table 1. Cholera disease influencing factors and variables used in this study.

Factor	Variable	Temporal Scale	Description	Data Source
		Climatic data		
Rainfall	Minimum, maximum and average rainfall	2022-2023	Rainfall values recorded in each district	DCCMS (https://www.metmalawi.gov.mw/)
Temperature	Minimum, maximum and average temperature	2022-2023	Temperature values recorded in each district	DCCMS (https://www.metmalawi.gov.mw/)
		Socioeconomic and demographic data		
Poverty level	Poverty rate	2018 Census	Poverty rate recorded per district	NSO [20]
literacy	Number of literate people	2018 Census	Illiterate population	NSO [20]
Access to toilet	Number of households with access to toilet	2018 Census	Total number of household recorded have a toilet	NSO [20]
Access to safe drinking water	Number of households with access to safe drinking water	2018 Census	Total number of household recorded have a safe drinking water	NSO [20]
Population	Population density	2018 Census	Proportion to the number of people living in a specific district	NSO [20]

Based on PHIM reports from March 3, 2022 to July 24, 2023, Malawi had reported a total number of cumulative Cholera cases of approximately 58,944 with most cases occurring in Lilongwe (8985), Mangochi (8028) and Blantyre (6760) [25]. Out of these cases, the fatality cases were reported to be 1766 country wide. **Figure 4(a)** shows the spatial pattern of cholera confirmed cumulative cases and **Figure 4(b)** shows the case fatality rate from March 2022 to July 2023.

2.4. Cholera Influencing Factors

2.4.1. Climatic Data

Jutla *et al.*, [26] and Idoga *et al.*, [27] indicate that *Vibrio cholerae* is an autochthonous bacterium within an aquatic environment whose global outbreak in endemic regions shows that there is a strong climatic influence to its occurrence and spread. Epidemiological observation of cholera outbreaks has shown to be influenced by climatic seasonal variations which are mostly dependent on temperature and rainfall [28] [29]. Malawi has two main seasons: the hot wet season (rainy season) between November and April and the cool dry season which spans between the months of May to October [30]. In recent years, the rainy season in Malawi is known to be associated with floods, a natural event that favors the breeding and spread of *Vibrio cholerae* bacteria, resulting in Cholera seasonal infections [31] [32]. **Figure 5** shows the 2022-2023 epidemiological weekly trends indicating high correlation of Cholera case fatality rates during the rainy season. In this study, temperature and rainfall [33] [34] were considered as

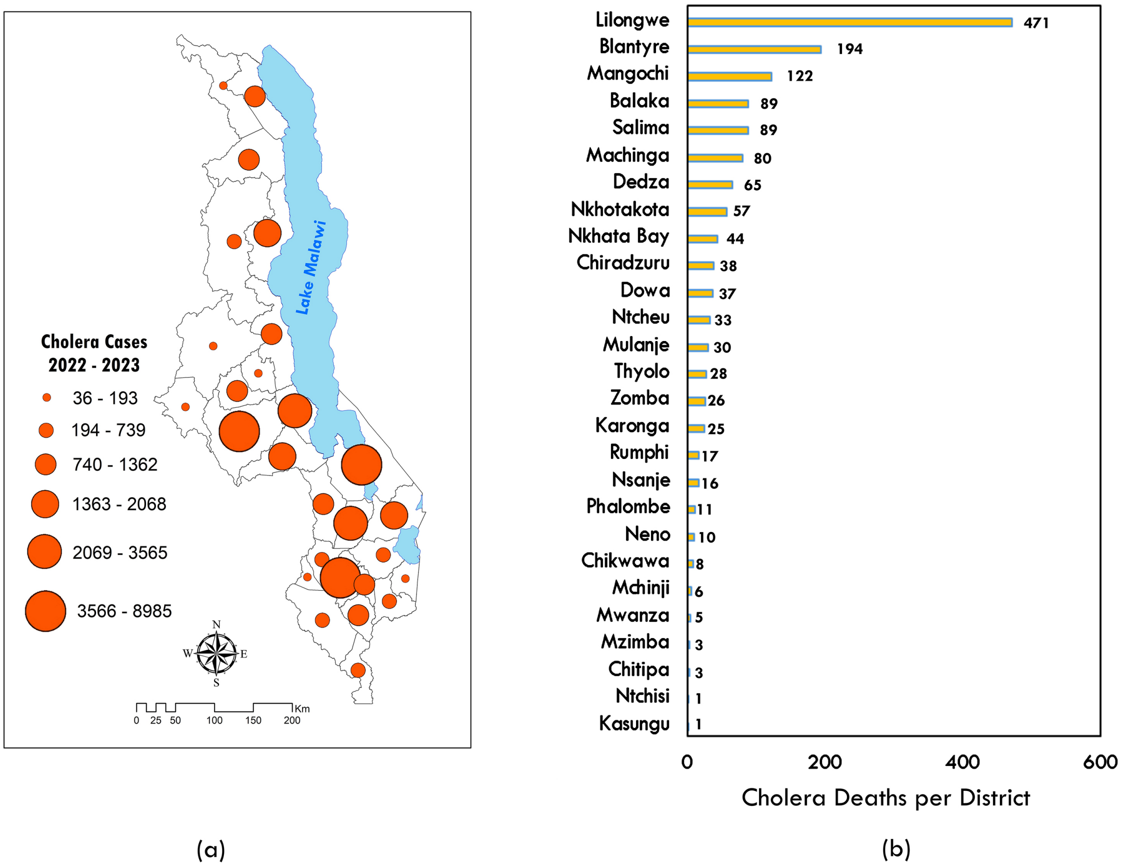


Figure 4. Spatial distribution of cholera cases per district (a) and Cholera deaths (b) reported per corresponding district from March 2022 to July 2023.

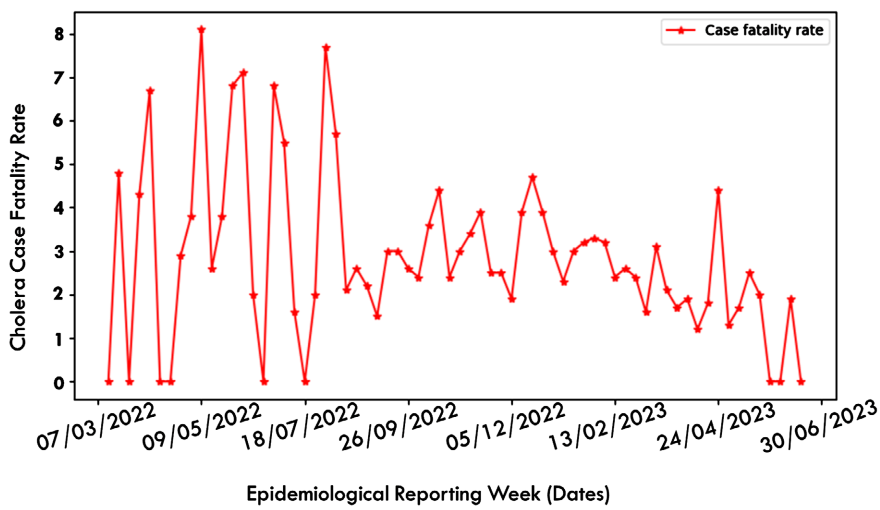


Figure 5. Cholera cases fatality for 2022-2023 Cholera outbreak.

climatic influencing factors in the spatial variability modeling of Cholera cases in Malawi. Temperature and rainfall intensities are known to control the distribution, growth, and subsequently incidence rates of Cholera cases [35] [36] [37] [38].

Annual average temperature and cumulative rainfall data from DCCMS for the study period, from March 2022 to July 2023 [23], were preprocessed and used in the variability modeling. ArcGIS Pro 2.8 was used to visualize the spatial distribution of temperature and rainfall data as shown in **Figure 6**.

2.4.2. Socioeconomic and Demographic Data

Both at country and household levels, socioeconomic conditions are associated with the outbreak, management and further spread of the acute Cholera disease [39] [40]. In this study, we obtained Malawi's country-level socioeconomic data from the National Statistics Office based on the 2018 census report [20]. The socioeconomic factors used in the Cholera variability modeling include: 1) population density, 2) poverty rate, 3) literacy, 4) number of households with access to toilet, and 5) number of households with access to safe drinking water [41] [42] [43]. The spatial distribution of these socioeconomic data is depicted in **Figure 7**.

2.5. Cholera Variability Modeling

Two modeling approaches were utilized in this study to understand the spatial variability of the cholera cases in the 2022-2023 Malawi Cholera disease outbreak, which by far was the huge epidemic since the 1990s. The first approach

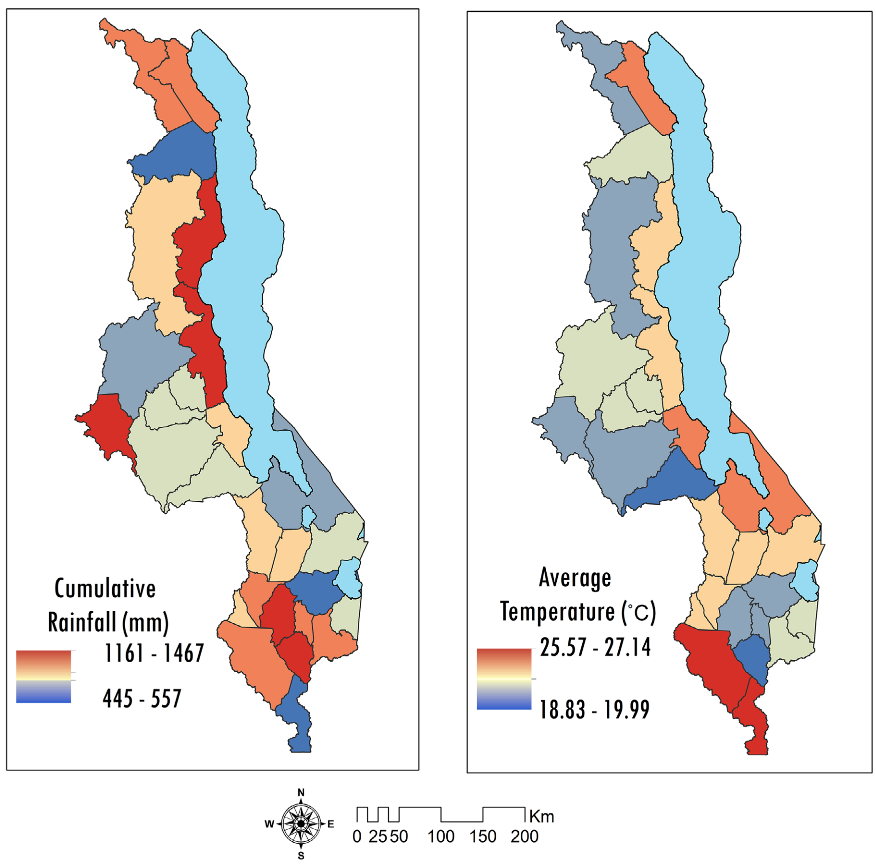


Figure 6. Climatic influencing factors of Cholera disease.

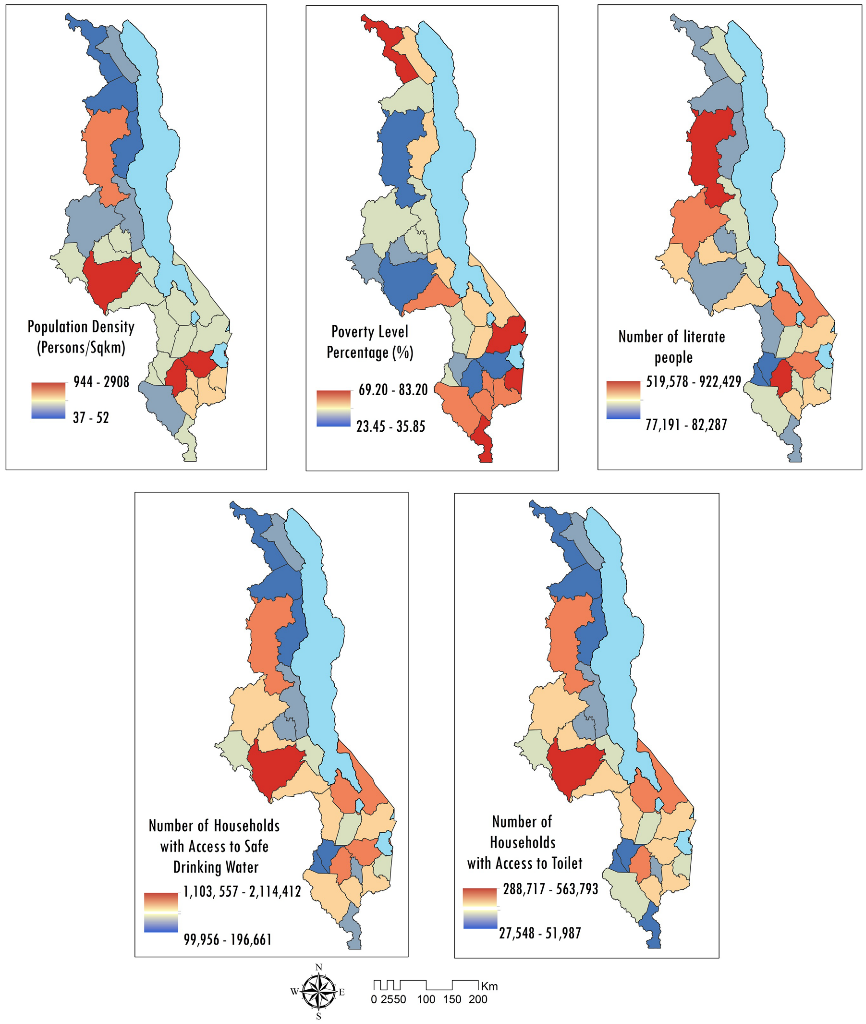


Figure 7. Socioeconomic influencing factors of Cholera disease.

known as the Composite Z-score statistics [44] was used to understand the spatial relationship between various socioeconomic and climatic indicators on the spatiotemporal spread on the Cholera cases. The second modeling approach used in this study is the MGWR [45]. MGWR, a localized regression model [46], was used to develop the Cholera cases variability model by considering the spatial and temporal geographic weighted influence of each of the Cholera cases influencing factors.

2.5.1. Statistical Modeling

Composite Z-Score statistics

Statistical Z-scores for each of the socioeconomic and climatic factors were firstly calculated irrespective of each other and secondly, as a composite Z-score for all the seven influencing factors. The Z-score is calculated by subtracting the population mean from individual raw data and dividing the difference by the population standard deviation. The score becomes a linear transformation of the original data [47]. The Z-score is expressed as:

$$Z_{ij} = \frac{X_{ij} - \mu_i}{\sigma} \quad (1)$$

where Z_{ij} = Standardized value (Z-score) of the parameter *i* in district *j*.

X_{ij} = Actual value of parameter *i* in district *j*.

μ_i = Mean value of parameter *i* in all the districts.

σ_i = Standard deviation of parameter *i* all districts.

The Z-scores of all influencing factors for each district were added, from which the average known as a composite Z-score for each district was computed. The formula for the composite Z-score is as follows:

$$CS = \sum Z_{ij} / N \quad (2)$$

CS = Composite Score.

Z_{ij} = Z-scores for all the parameters *i* in district *j*.

N = Number of variables.

Positive Z-scores represent high influence of socioeconomic and climatic factors to the Cholera cases in the districts and the negative values shows the low influence of the factors to the Cholera cases in the districts. The results were visualized using bivariate approach.

2.5.2. Local Regression Modeling

Multi-scale Geographic Weighted Regression

MGWR, a recent spatially localized regression model, is an extension and improved model based on the pre-existing Geographic Weighted Regression (GWR) model for geospatial statistical modeling [48]. Wolf *et al.*, [49] argues that MGWR achieves higher accuracy in analyzing location-based relationships of spatially referenced data compared to GWR, whose implementation assumes that all relations in the analysis have a constant scale. This assumption of constant spatial scale in GWR is inappropriate since most spatial variables have properties with multiple complex processes and diverse spatial scales [15]. Therefore, in this study, we used MGWR since it takes into consideration the variations of spatial scales of input variable relations in order to rectify the fixed scale issues that are caused by GWR in modeling Cholera cases variability [45]. A such, MGWR model does not depend on the rigid concept that all spatial variable exhibit a single scale [50]. In other words, MGWR is a spatial regression model with geographically varying parameters. Hence, spatial variation during modeling may occur between the independent variable and dependent variables with respect varying spatial scales throughout the study space, improving model reliability [51]. The MGWR model is represented as follows:

$$y_i(\mu) = \beta_{0i}(\mu) + \sum_{j=1}^{m} \beta_{bwj}(\mu) x_{ij} \quad (3)$$

where;

y is the dependent spatial variable at a given point *u*, *x* is the independent variable at given point *u*, *bwj* stands for the bandwidth that has been used in the model calibration of the conditional relationship of *j*th in β_{bwj}, and β is the model estimator, expressed as:

$$\hat{\beta}(\mu) = \left(x^{\mathrm{T}} w(\mu) x\right)^{-1} x^{\mathrm{T}} w(\mu) y \tag{4}$$

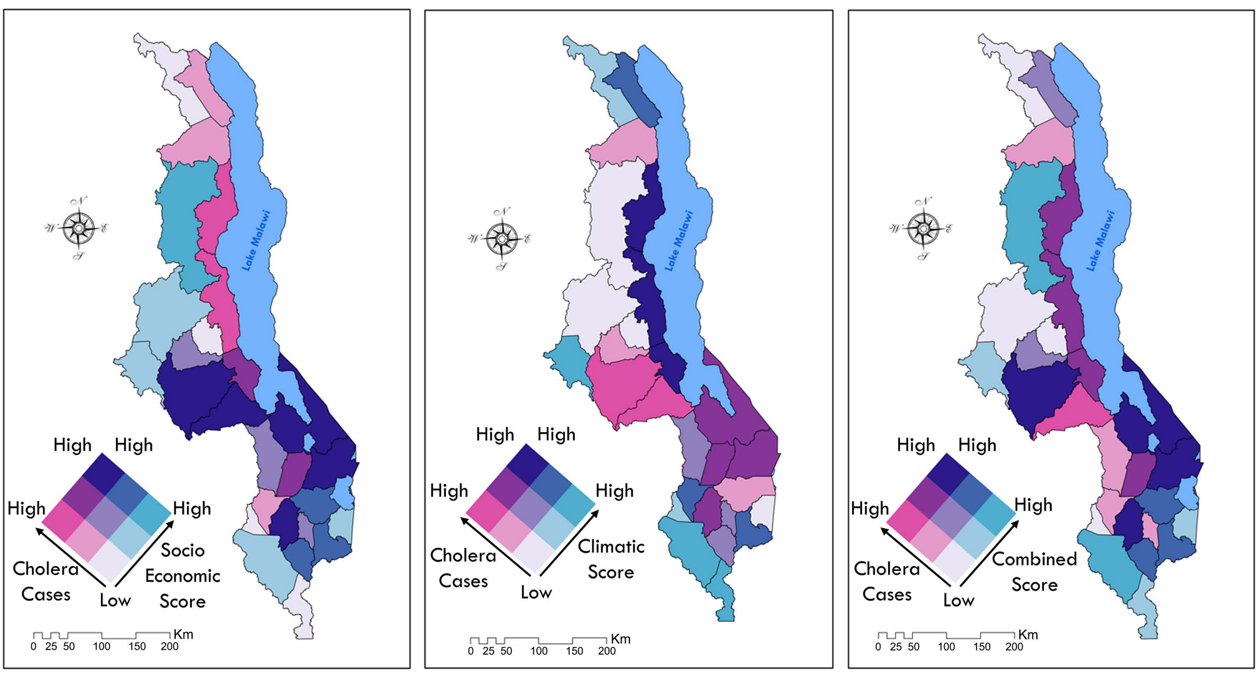
$x^{\mathrm{T}} w(\mu) x$ is a spatially weighted covariance matrix, $w(\mu)$ stands for square matrix of weights at any given point u, in the study area and y denotes the value of the dependent variable at any point u.

In this study, we implement MGWR modeling using a freely and open-source python-based framework [45] available on the website https://sgsup.asu.edu/sparc/mgwr. On one hand, the number of Cholera cases reported in each district was used as dependent variable, and on the other hand, the socioeconomic and climatic data, as influencing factors, were used as independent variables.

3. Results and Discussion

3.1. Cholera Cases Relationship with Socioeconomic and Climatic Factors

The spatial relationships between socioeconomic Z-scores and Cholera cases are visualized in Figure 8(a). The results indicate that districts such as Lilongwe, Dedza, Mangochi, Machinga and Blantyre with high socioeconomic Z-score recorded high cases of Cholera disease cases. This is attributed to increased population density in these districts. High population density within a district, as depicted in population density map in Figure 7, allows high physical interaction through overcrowding [52] which influences and results in higher Cholera case



(a) (b) (c)

Figure 8. Spatial relationship between Cholera Cases and (a) Socioeconomic Z-score, (b) Climatic Z-score and (c) Combined (Composite) Z-score of both socioeconomic and climatic influencing factors.

infections. Our study indicates that districts such as Zomba, Mulanje and Thyolo have medium Cholera disease cases with high socioeconomic Z-score values. The high Cholera cases along the lakeshore districts of Malawi including Salima, Nkhotakota and Nkhata-Bay are well explained in **Figure 8(b)** whose Cholera cases are influenced by high climatic conditions, primarily temperature [53]. The relationship between increased temperature and the prevalence of Cholera is complex, however, high temperatures in these district as depicted on the average temperature map in **Figure 6**, result in warming the surface water that support bacterial growth [54]. The *Vibrio cholerae* tends to multiply more rapidly in warm water which lead to increased bacterial replication in aquatic environments, such as rivers, wetlands, and lakeshore waters, where the bacterium thrives, contributing to increased risk of Cholera cases [55] [56] [57].

In **Figure 8(c)**, the combined relationship between composite Z-score for socioeconomic and climatic factors, and the prevalence of Cholera disease at district level is visualized. In this combined modeling, we consider the significance of socioeconomic factors including poverty level, literacy, access to toilet, access to safe drinking water and population density, and climatic factors; average temperature and cumulative rainfall as they play crucial role in the spread of Cholera. The relationship between a composite Z-score of these factors and infectious diseases, including cholera, underscores the importance of addressing both environmental and social determinants to effectively mitigate the impact of such diseases. As shown in **Figure 8(c)**, the districts Lilongwe, Mangochi, Machinga and Blantyre indicate high Cholera disease cases and also high composite Z-score values between 0.1572 and 1.0748. Our analysis shows that the Malawi 2022-2023 Cholera endemic transmission was influenced by a combination of climatic conditions and socioeconomic factors whose interaction between these elements played a crucial role in the spread and prevalence of the disease. On one hand, based on climatic conditions, *Vibrio cholera* thrives in warm temperatures resulting into increased bacterial growth and survival in water sources, facilitating the persistence of the pathogen. And heavy rainfall and flooding contaminates water supplies with fecal matter, carrying the *Vibrio cholera* bacterium. Floods, for instance caused by Cyclone Freddy in Southern Malawi districts, contributed to the overwhelming of sanitation systems, leading to the spread of the disease within the southern region districts [58]. On the other hand, socioeconomic factors, poor access to clean water and inadequate sanitation facilities (for example access to toilets) contribute significantly to Cholera transmission. Communities with limited or no access to safe drinking water are even at a higher risk. Beside these, high population density, especially in urban slums and crowded areas, facilitated the rapid spread of Cholera. Further, communities with higher levels of education and awareness about hygiene and sanitation are better equipped to prevent and control Cholera outbreaks. Thus, addressing Cholera in Malawi requires a comprehensive approach that considers both climatic and socioeconomic indicators.

3.2. Analysis Based on Multi-Scale Geographic Weighted Regression

The MGWR model was used to determine the Cholera disease variability in Malawi at a district level implemented based on the influencing socioeconomic and climatic factors outlined in **Table 1**. MGWR is implemented by assigning more relative weights to closer observations and less to those that are far and distant from each other through Tobler first law of geography [59]. In its implementation, we determine factors that have more weight in the variability modeling using a Fixed Spatial Kernel with a Gaussian distribution [45]. In this study, cumulative registered Cholera disease statistics in each of the Malawi's 28 districts and the seven influencing factors, both socioeconomic and climatic factors, were used to model the variability of the Cholera disease prevalence in Malawi using the MGWR model. **Table 3** indicates the summary statistics of the Cholera disease modeling using these seven influencing factors. Based on the model results, all factors with positive number of coefficients were highly influenced the spread of Cholera disease within the districts. These included access to safe drinking water, temperature, rainfall, population density and poverty level. The factors literacy and access to toilet had less influence on the spread of the disease. This result suggests that education and awareness about hygiene and sanitation campaigns have yielded the desired results in the communities as regards to prevention means and control of Cholera disease. Among the determined influencing factors, access to safe drinking has a stronger contributing coefficient value of 0.935 (**Table 2**). This means that the most communities do not have access safe drinking water and lack safe water storage or water treatment methods.

Therefore, we propose increased number of safe drinking water campaigns which include several water treatment methods in the most affected districts. These interventions may include use of piped water from larger-scale water treatment plants, boiling water before drinking to kill bacteria, viruses, and parasites, use of water filters such as those with activated carbon or ceramic filters, chlorination as a disinfectant, ultraviolet light treatment and community awareness on proper water storage and hygiene practices.

Table 2. Summary statistics for MGWR Model Cholera influencing factor estimates.

Variable	Coefficient	Standard Error	Z-Score	P-Value
Population density	0.082	0.237	0.346	0.729
Access to safe drinking water	0.935	1.544	0.605	0.545
Literacy	−0.054	0.171	−0.315	0.753
Access to toilet	−0.084	1.529	−0.055	0.956
Poverty level	0.053	0.191	0.277	0.782
Temperature	0.226	0.196	1.153	0.249
Rainfall	0.111	0.237	0.346	0.729

In this study, climatic factors, temperature and rainfall also influenced the cholera cases variability in Malawi. This is evident by increased number of Cholera cases along the lakeshore districts of Mangochi, Salima, Machinga, Nkhotakota and Nkhata-Bay. Increased temperature provides favorable conditions for bacteria growth. And during the heavy rainy seasons, the Cholera cases increase due to flooding that contaminate water supplies with fecal matter. A similar pattern of Cholera cases prevalence corresponded with the Cholera dynamics observed by [60] in Bangladesh that during increased temperature and rainfall, the disease's prevalence increased. As such, climatic influences in the Malawi cholera viability is certain.

Table 3 indicates this study's measure of goodness-of-fit in the Cholera disease variability modeling. The value 0.81 of adjusted R^2 mean that the MGWR model used in this study was able to explain 81% of the total variations of Cholera incidence rates among the districts. This ability to deduce such a higher number of variability is associated with spatial variability scale that MGWR permits during modeling [61] and a lower AICc of 54.59%, also supports best-fit assertion of the modeling results. The 2022-2023 spatiotemporal cholera cases variability model for Malawi based on socioeconomic and climatic influencing factors is shown in **Figure 9**.

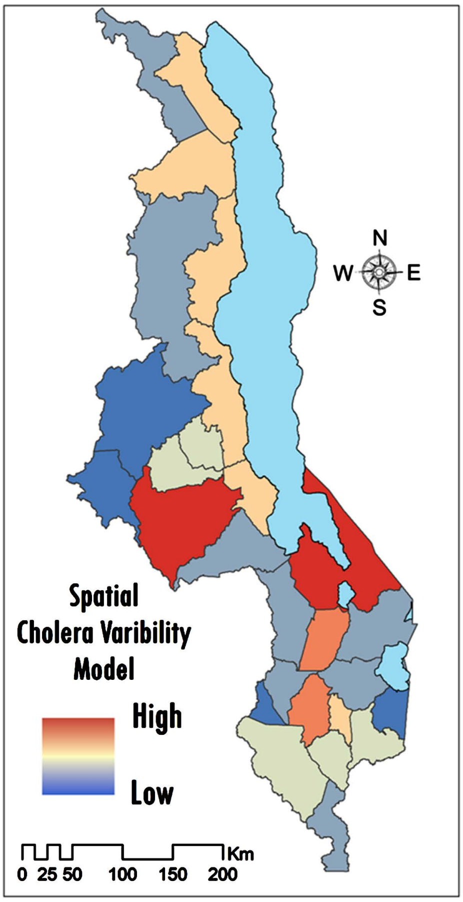


Figure 9. Cholera disease variability model using MGWR.

Table 3. Measure of goodness-of-fit for MGWR in modeling Cholera incidence rate.

AICc	54.59
AIC	74.19
R^2	0.81
Adjusted R^2	0.68

According to the MGWR modeling results, Lilongwe, Mangochi, Blantyre and Balaka districts are more vulnerable to Cholera disease based on their socioeconomic and climatic conditions compared to other districts. These districts are followed by Malawi's lakeshore districts of Salima, Nkhotakota, Nkhata-Bay, Karonga, and also Rumphi and Chiradzuru districts. As observed from this study, these districts have high Cholera prevalence due to a complex combination of their corresponding socioeconomic and climatic factors which include inadequate access to safe drinking water, high temperature, high rainfall patterns, high population density and increased poverty levels, contributing individually to the vulnerability.

4. Conclusion

In this present study, we develop a spatiotemporal variability model for Cholera disease for Malawi at district level and its relationship to socioeconomic and climatic factors based on cumulative confirmed Cholera cases from March 2022 to July 2023 using Z-score statistic and MGWR in a GIS environment. Cholera disease remains a global threat whose spread is associated with socioeconomic and climatic variations that play a huge role in its transmission. Our MGWR model results show that Cholera case determinants including access to safe drinking water, temperature, rainfall, population density and poverty level have greatly influenced Cholera cases prevalence in Malawi. The model shows that between March 2022 and July 2023, Lilongwe, Mangochi, Blantyre and Balaka districts were more vulnerable to Cholera disease than other districts followed by Malawi's lakeshore districts of Salima, Nkhotakota, Nkhata-Bay, Karonga, and other districts such as Rumphi and Chiradzuru. We found out that Cholera prevalence in Malawi is not a linear function but rather a complex multifaceted function with a combination of determinants of these corresponding socioeconomic and climatic factors, each contributing individually to the vulnerability and spread of the disease in space and time. These results indicate that these districts are Malawi's Cholera disease hotspots where public health professionals need to prepare an emergency action plan to respond to the affected groups and vulnerable areas. As such, an understanding of the complex dynamics of Cholera spread of this nature, is fundamental to the development of comprehensive and effective strategies for prevention, early detection, response, and treatment. It not only contributes to saving lives but also helps in building resilient and sustainable public health systems. The study suggests Cholera case modeling at sub-district level as a profound direction for future research avenues to improve the local epidemiology of the disease. We recommend strategic measures and interventions such as WASH interventions including boiling water before drinking, use of water filters, chlorination, community awareness on proper water storage, and Cholera case management and vaccination campaigns in the most affected districts. Additionally, we advocate for robust surveillance systems as essential tools for monitoring and controlling the spread of Cholera. Our GIST-based approach is an example of a robust and flexible surveillance tool with high-level capacity of adaptability. Using this tool, the Ministry of Health and other public health authorities can detect cholera outbreaks early, implement effective response measures, and prevent the further spread of the disease.

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Author Contribution

E. C: Conceptualization, Data Curation, Data Analysis, Post-Processing Analysis, Cartographic Visualization, Drafting, Editing, F. C: Conceptualization, Data Curation, Data Analysis, Review, Editing, B. K: Data Curation, Review, R. C: Conceptualization, Review, Editing, E. B. L: Review, Editing.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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