An exploratory analysis of the spatial variation of malaria cases and associated household socio-economic factors in flood-prone areas of Mbire district, Zimbabwe

Tawanda Manyangadze · Emmanuel Mavhura · Chipo Mudavanhu · Ezra Pedzisai

Abstract Although floods are well known for promoting the transmission of malaria, not much effort has been put to determine the spatial distribution of this disease at micro-geographical scale in flood prone areas. Therefore, this paper examines the spatial variation of malaria and associated socio-demographic factors in flood-prone areas of Mbire district, Zimbabwe. A cross-sectional household survey was conducted between 2018 and 2019 to collect data on malaria and socio-demographic factors. The study used the Bernoulli model to determine malaria hotspots, i.e. area with high number of cases compared to the surrounding areas. This was followed by a geographically weighted logistic regression model used to explore the spatial variation of malaria cases in relation to socio-demographic factors at household level. Descriptive statistics and chi-square showed that types of house material, water sources and age of the household head had a significant association with malaria cases ($p < 0.05$). The study has demonstrated that some local communities in flood prone areas experience increased numbers of malaria cases as indicated by one significant cluster ($p < 0.05$). There was high malaria risk (2.68) in the significant cluster compared to its outside. The GWLM model with water sources and the type of house material as exploratory variables showed the minimum corrected Akaike's Information Criterion compared to other models. Higher level of spatial variability was observed in type of house material (DIFF of criterion = − 5.742) compared to water sources (DIFF of criterion = − 1.064). The coefficients of these two exploratory variables were varying across the study area and significant (t-values ± 1.96) and high in other parts including the identified hotspots. The coefficients of the type of house material ranged from − 1.136 to 1.323. These were higher than those for water sources which were between − 0.781 and 0.605. These results may be used for development and implementation of place-specific malaria intervention strategies in flood prone areas.

Keywords Floods · Geospatial analysis · GWLRM · Malaria · Risk · Water-related diseases

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Introduction

Floods are amongst the most damaging hydro-meteorological disasters worldwide, posing danger to

human health and socio-economic life of millions of people (Matheswaran et al., 2019; Rana & Routray, 2018; Shivaprasad et al., 2017). The floods can result in unprecedented losses to national economies and bring pathogens which cause outbreak of diseases (Dandapat & Panda, 2017; Tehrany et al., 2015) such as typhoid fever, cholera and malaria. Malaria is one of the most common water related vector-borne diseases in flood prone areas of Mbire District, Zimbabwe and other similar settings around the world (Mudavanhu et al., 2015; Ochola, 2009; Olanrewaju et al., 2019; Watson et al., 2007). It is envisaged that climate change may exacerbate the impact of floods globally (Watson et al., 2007), which may increase the outbreaks of water related diseases (Kouadio et al., 2012). For example, floods will likely promote the transmission of malaria at micro-geographical scales in malaria endemic areas. Where weak disease surveillance systems exist, this may adversely affect the health of individuals during and after flood events (Watson et al., 2007). Hence, floods tend to affect people by creating new or exacerbating existing inequalities and challenges in public healthcare systems (Davis et al., 2010). In view of this, an understanding of the spatial distribution of malaria during and immediately after floods is important for health system preparedness and response.

Exposure to floodwaters pose direct dangers to human health including the risk of malaria infection (Paterson et al., 2018). Flooding can affect mosquito breeding sites and malaria transmission differently. For example, at the beginning, floods tend to clear the breeding sites for mosquitos but later create new breeding areas that may even stay longer. This may result in an increase of mosquito population and associated malaria cases (Minamiguchi, 2008; Watson et al., 2007). There is potential for creating areas with higher number of malaria cases, i.e., hotspots of malaria at micro-geographical scale as determined by the flood extent and the socio-economic factors at household level. This calls for malaria surveillance in areas affected by floods in order to understand the latter's influence at micro-geographical scale. However, it is not always easy to obtain appropriate surveillance data in such settings (Watson et al., 2007) due to limited resources and inaccessibility of these areas during and immediately after floods. Therefore, the aim of this study was to examine the spatial distribution of malaria and the associated socio-

demographic factors in malaria and flood prone areas of Mbire District in Zimbabwe. The specific objectives were (1) to identify and map the significant malaria clusters and (2) to examine the socio-economic factors associated with the identified malaria spatial patterns. By examining the spatial distribution of malaria and its associated socio-demographic factors, this study will contribute to informed preparedness and appropriate response at the local level during the different phases of flooding.

Literature review

Malaria is a mosquito-borne disease which is caused by protozoan parasite species, key among them are *Plasmodium falciparum, P. vivax, P. ovale*, *P. malariae*, and *P. knowlesi* (Rosas-aguirre et al., 2015). It is transmitted by infected female *Anopheles* mosquitoes in both humans and other animals through a bite (Bannister-Tyrrell et al., 2018; Yang et al., 2017). The disease is endemic in tropical and subtropical regions (Bannister-Tyrrell et al., 2018; Qayum et al., 2015; Ramdhani et al., 2018). The epidemiology of malaria is complex. It is influenced by climate and other factors pertaining to the malaria parasites, the insect vectors, the human hosts, and the physical environment (Chirebvu et al., 2014; Rouamba et al., 2019). As a result, efforts to eliminate malaria are fraught with many challenges. Currently, malaria is one of the major tropical health challenges facing the developing countries (Ibor & Okoronkwo, 2017). For example, the Sub-Saharan Africa (SSA) recorded 92% of global malaria cases reported in 2017 (WHO, 2020).

In Zimbabwe, malaria continues to be a major public health problem. About seven million people are at risk of contracting malaria (Chikodzi, 2013; Mundagowa & Chimberengwa, 2020). Although there is a declining burden of malaria, periodic outbreaks still exist which exhibit spatial heterogeneity across different regions through time and space (Gwitira et al., 2020). *Plasmodium falciparum* is the most common parasite that accounted for 99.7% of the malaria cases in Zimbabwe reported in 2018 (Gwitira et al., 2020). Essentially, malaria is an environmental disease since the vectors and the parasites require specific habitats with surface water, humidity and certain temperatures for their reproduction, development and survival. Hence, frequent floods in some

parts of Zimbabwe including Mbire district provide suitable conditions for the survival and breeding of the vector mosquitoes. In addition to environmental conditions, Ibor and Okoronkwo (2017) noted that socio-economic factors also play a significant role in the prevalence of malaria. An understanding of environmental and socio-economic factors associated to the spatio-temporal dynamics of malaria is of high importance to control the spreading of the disease (Rouamba et al., 2019). As argued by Tewara andet al. (2018) and Stresman et al. (2019), the understanding of the distribution of malaria cases will help inform malaria control programs at a smaller scale. In specific, understanding the transmission spectrum of malaria can enhance its monitoring and control (Coulibaly et al., 2013; Stresman et al., 2019). Studies have revealed that the malaria risk factors influence the variation in malaria vector distribution, transmission rates, and incidence over short distances, between neighbouring villages and even within a single settlement (Chirebvu et al., 2014). Hence the need for more researches in this domain.

Many studies have also identified household and individual level factors associated with malaria transmission (Chirebvu et al., 2014). For example, Sharma et al. (2015) considered how the demographic, socio-economic and behavioural risk factors contributed to malaria cases in India. Lowassa et al. (2012) also assessed the influence of household social economic status on malaria cases in northern Tanzania. Likewise, Degarege et al (2019) noted that lack of education, low income, low wealth, living in poorly constructed houses, and having an occupation in farming may increase risk of Plasmodium infection among people in SSA. Thus, the epidemiology and control of malaria is complicated by poverty (Sharma et al., 2015). Poor people are at increased risk of becoming frequently infected with malaria (Ibor & Okoronkwo, 2017). Poorly constructed houses allow easy entrance of Plasmodium-carrying vectors and increase chances of infection among family members (Lindsay et al., 2003). However, there is lack of empirical evidence about how such factors influence the spread of malaria in Mbire District. Hence, the current study determined the contribution of socio-economic factors to the spatial variation of malaria occurrence at household level in flood prone areas. An understanding of this variation is important in the

detection of high-risk groups and for targeted interventions (Chirebvu et al., 2014).

Methods

Study area

This study was conducted in traditionally flood-prone areas of Mbire District (Wards 3—Kanongo, 9—Mushumbi, 10—Chitsungo, 12—Chikafa and 16—Monozi) in the northern low veld of Zimbabwe (Fig. 1). These wards are adjacent to the Hunyani River a tributary of the Zambezi River. The five ward communities are all exposed to riverine floods that are precipitated by convectional rains, tropical cyclones or backflows from the consequent rivers. The floods usually occur at the peak of the rainy season: January and February of each year (Mavhura, 2019). The flood period period coincides with the development of an intense low-pressure area over northern Zimbabwe and Zambia. As a result, the inter-tropical convergence zone (ITCZ) shifts over the northern lowveld, a situation that brings a lot of warm moisture from both the Indian Ocean and the Zaire Airflow to create continuous rains (Spear et al., 2018). At this time of the year, tropical cyclones develop in the Indian Ocean and, at times penetrate through the vast plains of northern Mozambique to reach Mbire district. As a result, flooding occurs in Mbire district. A network of river systems that cut across the communities creating interfluves and low-lying floodplains compounds the flood problem. Tributaries of major rivers may fail to empty their waters into consequent rivers, a situation that leads to back flowing of waters into adjustment low-lying areas. In some areas, the floods last for few hours while in other, they last for several days. When this happens, crops and livestock are washed away while dwellings and other critical infrastructure are damaged (Mavhura, 2019). The floods are also related to the increase in malaria outbreaks as they provide the habitats and breeding sites for vector mosquitoes. This area is also malaria endemic. In 2018, a total of 9 488 cases and 4 deaths were recorded in Mbire district (President's Malaria Initiative Zimbabwe (PMI) 2018).

The study area is also entirely rural, drought-prone, with high indices of poverty (ZimStat, 2015; Zim-VAC, 2019). Smallholder farming is the mainstay of
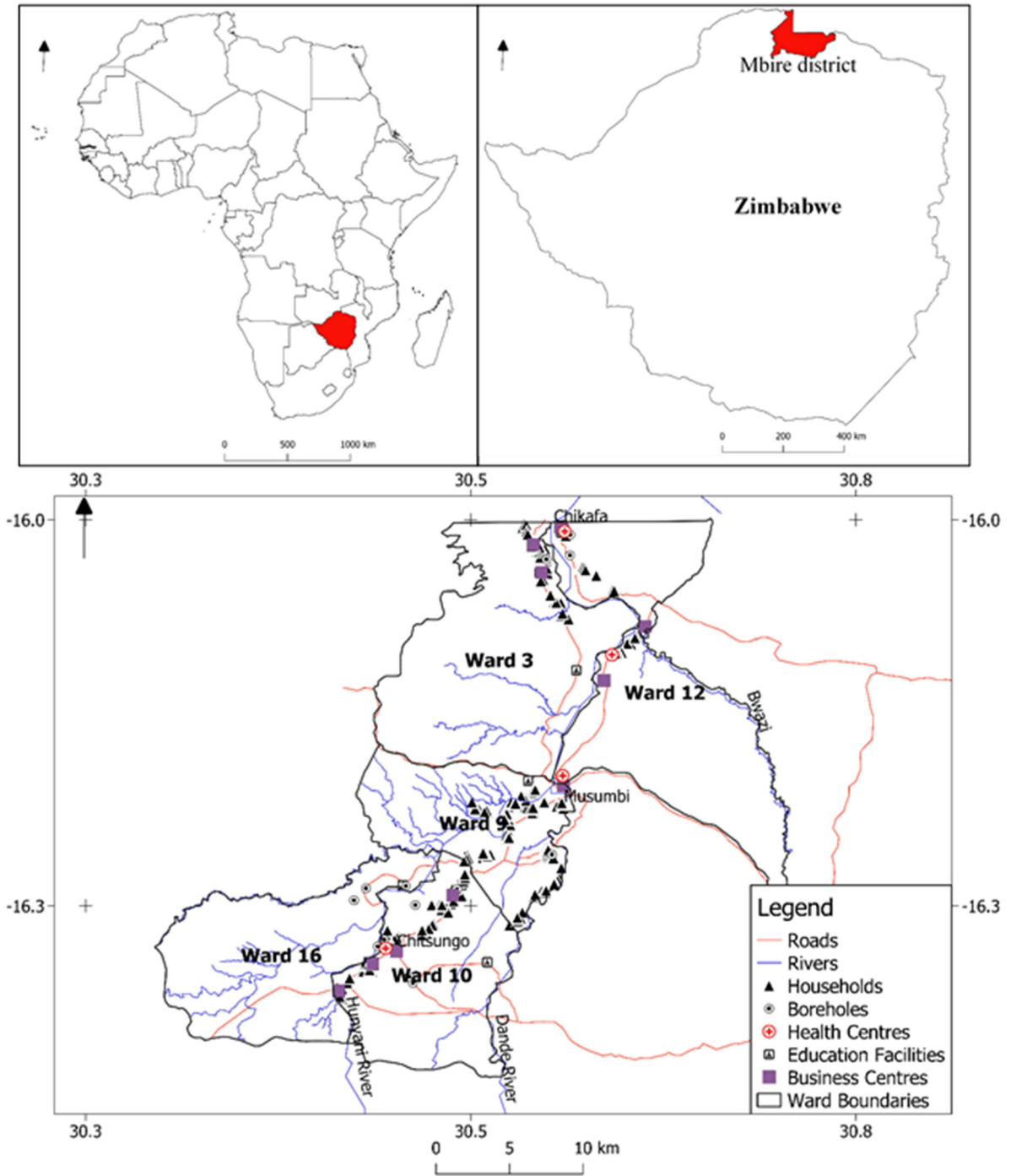
Fig. 1 Study area—Wards 3; 9; 10; 12 and 16 of Mbire District in Zimbabwe (*Source* Mavhura et al., 2020)

the economy, that serve a population of about 70 000 (ZimStat, 2012). Major food crops grown include maize, sorghum and millet. These crops are mostly grown along the floodplain, where there is increased exposure to floods and malaria. Literacy rate is approximately 83.6%, 79.6% have no water and sanitation facilities and 82.6% of the population are in pole and dagga huts (Mavhura, 2020; UNDP, 2016). These conditions may also contribute to the transmission of malaria in these wards. A number malaria prevention and control strategies are being implemented in Mbire district. These include indoor residual spraying, distribution and use of long-lasting insecticidal nets (LLINs), and larviciding as well as intermittent preventive therapy or parasitological confirmation of the malaria through Ministry of Health and Child Care and different stakeholders including PMI. These strategies are implemented in the context of the roll back malaria initiative which is still guiding malaria control and elimination. However, malaria is still problematic in the study area.

Study design, sample size and sampling procedure

A cross-sectional survey involving 333 household heads from five purposively selected flood-prone wards in Mbire District was conducted between December 2018 and April 2019. Following Olanrewaju et al. (2019), this study adopted a historic approach to flood disasters based on the household survey relating disasters to human health with a focus on malaria and related socio-economic factors. This design enabled obtaining historical data of malaria cases that occurred during and immediately after floods in the past two decades. The sample size was 10% (304) of estimated number of households in the flood plain (3042) plus 10% (33) attrition rate to make it 337. However, only 333 questionnaires were valid and this was above the required minimum sample size. The study participants were proportionally distributed across the wards and randomly selected.

Data collection

Data of malaria cases reported within the household and socio-economic factors related to the household including age, gender, education of the household head and types of dwellings, material flooded, were collected using household structured questionnaires.

The use of open data kit (ODK) with GPS on tablets enabled us to georeference all the households (333) in our sample. The socio-demographic risk factors considered in this study include age, gender, water sources, level of education, type of house material, size of the household and whether the household was flooded or not. These factors have also been considered in other non-spatial studies (Yadav et al., 2014; Yang et al., 2020). Where the head of the household was not available, we interviewed an adult family member knowledgeable about floods that affected the household in the past.

Data analysis

Descriptive statistics and chi-square test were performed to assess the association between malaria cases and socio-demographic risk factors at household level using SPSS version 24. The Bernoulli model in SaTScan (Kulldorff, 2015; Warden, 2008) was used to ascertain the distribution patterns of reported malaria cases based on the Global Positioning Systems (GPS) coordinates from the ODK. Bernoulli model is mainly used in detecting hotspots or significant clusters, in this case areas with increased numbers of malaria cases compared to the surrounding areas. The Bernoulli model was applied to identify significant spatial clusters of households ($p < 0.05$) where malaria cases were reported during and after floods. Spatial cluster was defined as an area of households that are close together where malaria cases or incidences were greater than in the adjacent areas (Bousema et al., 2016). Those households with reported cases were coded "1" while households without cases of malaria were coded "0". The last group acted as controls. SaTScan uses a moving window, and in this case, it was circular and for each window the following were determined and recorded: location and size, the number of observed and expected observations, percentage cases in area and relative risk inside the window, likelihood ratio and relative risk (RR) (Kulldorff, 2015; Warden, 2008).

Equation 1 shows the mathematical notation for relative risk (Kulldorff, 2018). It compares the risk inside and outside the identified cluster.

$$RR = \frac{c/E[c]}{(C-c)/(E[C]-E[c])} = \frac{c/E[c]}{(C-c)/(C-E[c])}$$

(1)

where c is the number of observed cases within the cluster and C is the total number of cases in the data set, $E[c]$ is expected cases within the cluster and $E[C]$ is expected total number of cases and in this case $E[C] = C$.

Equation 2 indicates the likelihood function for the Bernoulli model (Kulldorff, 2018; Kulldorff & Nagarwalla, 1995):

$$\left(\frac{c}{n}\right)^c \left(\frac{n-c}{n}\right)^{n-c} \left(\frac{C-c}{N-n}\right)^{C-c} \left(\frac{(N-n)-(C-c)}{N-n}\right)^{(N-n)-(C-c)} I()$$

(2)

where C is the total number of cases, c is the observed number of cases within the window, n is the total number of cases (households where malaria cases were recorded) and controls (households with no recorded malaria cases) within the window, while N is the combined total number of cases and controls in the data set.

The characteristics of these circular windows tended to differ as they depended on the spreading of the presented cases in relation to the households with no recorded malaria cases which acted as controls across the study area, hence showing the spatial pattern. The high-risk clusters were defined as having up to 50% (cases) of the total number of households in a moving window and the 999 Monte-Carlo replications were used for evaluation of their statistical significance (Manyangadze et al., 2016; Meurs et al., 2013; Nagi et al., 2014). Only significant clusters ($p < 0.05$) were reported in our study.

Additionally, a Geographically Weighted Logistic Regression (GWLR) in GWR4.09 was used to determine the spatial distribution of the reported cases and these socio-demographic factors in the study area. GWLR is a form of GWR capable of handling binary dependent or response variable that vary across space, i.e., X and Y coordinates (Albuquerque et al., 2016; Xiao et al., 2019; Yasuo & Nishiura, 2019) and allows the spatial variation of the local regression coefficients (Yasuo & Nishiura, 2019). The GWLRM method has been extensively used to estimate local spatial heterogeneity in the factors that explain the binary data in many fields including diseases modeling (Liévanos, 2018; Mayfield et al., 2018). As noted by Zhang et al. (2014), the analysis in this study was extended to GWLRM because the logistic regression was not capable of presenting the spatial heterogeneity of the

exploratory variables' coefficients. The GWLRM showed the spatial variability of the disease in relation to the exploratory variables. GWLR is expressed as follows (Nakaya, 2016a, 2016b):

$$y_i \sim Bernouli[p_i]$$

(3)

The dependent variable y_i must be 0 or 1. pi is the modelled probability that the dependent variable becomes one.

$$logit(p_i) = \sum_k \beta_k(u_i, v_i) x_{k,i}$$

(4)

where pi is the modelled probability the dependent variable becomes one i.e. the dependent variable, $x_{k,i}$ is the kth independent variable (u_i, v_i) is the x–y coordinate of the ith location; and coefficients $\beta_k(u_i, v_i)$ are varying conditionals on the location.

Adaptive bi-square kernel was used together with golden search method for optimal bandwidth search. AICc was used to select the optimal bandwidth. Adaptive bi-square method is as shown below:

$$w_{ij} = \begin{cases} \left(1 - d_{ij}^2/\theta_{i(k)}\right)^2 & d_{ij} < \theta_{i(k)} \\ 0 & d_{ij} > \theta_{i(k)} \end{cases}$$

(5)

where i is the regression point index; j is the locational index; wij is the weight value of observation at location j for estimating the coefficient at location i; dij is the Euclidean distance between i and j; θ is a fixed bandwidth size defined by a distance metric measure. $\theta_{i(k)}$ is an adaptive bandwidth size defined as the kth nearest neighbour distance.

We produced a set of GWLRM models and then compared it with the global logistic model (which does not consider the spatial variation of the regression coefficients) based on the AICc (Guo et al., 2016; Manyangadze et al., 2017; Nakaya, 2016a, 2016b). The model with smaller value of AICc has better performance. Table 1 below shows the performance of different models that were tested in this study. Model 9 (Table 1) performed better than other models as it had the lowest AICc. Hence, this model was chosen for spatial modelling of malaria cases and related factors (water sources and type of house material). These are the only variables, which were included in the GWLRM in addition to the intercept. The optimum or best bandwidth size was 125 with the smallest AICc (366.681).

Table 1 Comparison of the GWLR and the global logistic model

Model	Coefficients	Global AICc	GWLR AICc and Bi-square kernel bandwidth
1	Intercept; water sources	386.381	370.203 (57)
2	Intercept; household head occupation	403.767	378.613 (103)
3	Intercept; house material	397.977	368.007 (82)
4	Intercept; household head gender	403.676	373.005
5	Intercept; house flooded	402.336	367.749
6	Intercept; household head education level	402.920	373.843
7	Intercept; household Size	403.776347	369.337 (74)
8	Intercept, household head age	399.321650	369.238 (57)
9*	Intercept; water sources; house material	386.095	366.681 (125)
10	Intercept, house material, house flooded	399.329	369.607 (99)
11	Intercept; house material, house flooded; household head gender	401.173	376.065 (138)
12	Intercept; house material, house flooded; household head gender; household head age	377.131	377.132 (154)
13	Intercept; house material, house flooded; household head gender; household head age; household size	399.680	379.296 (158)
14	Intercept; house material, house flooded; household head gender; household head age; household size, household head education level	401.736	385.319 (251)
15	Intercept; house material, house flooded; household head gender; household head age; household size, household head education level; household head occupation	403.826268	389.711 (312)
16	Intercept; house material, house flooded; household head gender; household head age; household size, household head education level; household head occupation; water sources	392.587981	386.559633 (325)

*Best performing model based on AICc

We also performed the geographical variability tests of local coefficients in GWR4.09 to identify variables with spatial variability. In this test, negative values of DIFF of criterion (in our cases AICc) indicates spatial variability and positive values indicate no spatial variability in terms of model selection criteria. The DIFF of criterion was added to the convenient 5-number summary that defined the extent of the variability in the parameter estimates across the study area. These estimates include minimum, 25 percentile, median, 75 percentile and maximum values as presented by Manyangadze et al. (2016).

GWLR does not provide the estimates of regression coefficients at unknown points or points with no observation. To show the spatial variation of the regression coefficients kriging method was used to perform interpolation of the estimated coefficients and the significant levels (t-values) in ArcGIS 10.4 across the study area as done by Zhang et al. (2014) and Manyangadze et al. (2016). The t-value maps were shown as isolines and overlaid on the corresponding regression coefficients as advised by Matthews and Yang (2012). The Global Moran's I was used to calculate spatial autocorrelation coefficients for the residuals of the GWLR model. The smaller the value of the Global Moran's I, the smaller the residual spatial dependence and the better the performance of the model fitting, including more spatial relations (Zhang et al., 2014). This means that if Moran's I of the residuals is not significant the model is well specified. All maps were created in ArcGIS10.4. The Moran's I indicated no spatial autocorrelation to the GWLR residuals (Index 0.005, ZScore: 0.315, p-value: 0.753) indicating that the model was correctly specified.

Results

Socio-demographic risk factors in relation to malaria cases

Three variables showed significant association with malaria cases i.e., types of house material; water sources and age of the household head (Table 2). Other factors considered in this study (Table 2) did not show significant association with malaria cases. For example, during the flooding periods whether the household was flooded or not was not be major factor for the transmission of malaria. However, as people fetched water from different sources, they also had different levels of exposure to malaria vector mosquito bites. Those with no safe source of water were more exposed (39.2%) followed by those accessing water from

unprotected wells in other villages (38.5). Those accessing water from their local boreholes were less exposed to malaria (12.8%).

Type of house material also showed a significant association with malaria cases. Pole, anddagga with thatched roofs were associated with higher number of cases (45.2%) compared to the other two types of house material i.e., bricks, cement and thatching and Bricks, cement and asbestos or iron sheets which had 25.1 and 25.0% respectively. The age of the household head also showed a significant association with malaria cases. Household heads aged above 25 years and below 66 years showed a higher exposure to malaria compared to those below 25 and above 66 years.

Table 2 Household socio-demographic factors in relation to malaria cases

Socio-demographic variables	Categories	Frequency	Malaria case(s) Yes (%)	Chi-square	p-value
Type of house material	Pole, dagga and thatching (1)	62	28 (45.2)	9.905	0.007*
	Bricks, cement and thatching (2)	195	49 (25.1)		
	Bricks, cement and asbestos or iron sheets (3)	76	19 (25.0)		
Houses flooded	Yes (1)	141	46 (32.6)	1.717	0.190
	No (2)	192	50 (26.0)		
Gender (household head)	Male (1)	189	52 (27.5)	0.369	0.544
	Female (2)	144	44 (30.6)		
Water sources	Local borehole (1)	86	11 (12.8)	19.036	< 0.001*
	Other village borehole (2)	78	20 (25.6)		
	Other village well closed (3)	26	9 (34.6)		
	Other village well unprotected (4)	13	5 (38.5)		
	No other source of water—open (5)	130	51 (39.2)		
Age (household head)	15–25 (1)	62	9 (14.5)	13.836	0.017*
	26–35 (2)	70	20 (28.6)		
	36–45 (3)	74	21 (28.4)		
	46–55 (4)	52	21 (40.4)		
	56–65 (5)	40	17 (42.5)		
	66 and above (6)	35	8 (22.9)		
Size of the household	5 and below (1)	180	51 (28.3)	1.0	0.607
	6–10 (2)	141	40 (28.4)		
	11–15 (3)	12	5 (41.7)		
Level of education (household head)	Primary level and below (1)	247	75 (30.4)	1.099	0.294
	Secondary level and above (2)	86	21 (24.4)		

*Statistically significant, < 0.05

Malaria cases hotspots

Figure 2 indicates the spatial distribution of the households with cases of malaria and the consequential clusters or hotspots. One significant cluster ($p < 0.05$) was observed in ward 10 (Chitsungo) and 16 (Monozi) (Fig. 2) with high risk to malaria (2.68) when compared to its outside. The characteristics of this cluster are shown in Table 3.

Local variation of socio-economic variables in determining the heterogeneity of malaria

In the spatial analysis, only two factors showed spatial variability in relation to malaria cases. These are water sources and the types of house material. Table 4 shows the summary statistics of the coefficients of the locally varying variables considered in this study.

DIFF of criterion shows the geographical variability levels of the local coefficients of the exploratory variables. Intercept, water sources and type of house material indicated spatial variability in terms of the GWLRM used in this study (negative values of DIFF of criterion i.e., AICc). Higher level of spatial variability was observed in type of house material (DIFF of criterion = − 5.742) compared to water sources (DIFF of criterion = − 1.064).

The local coefficients of water sources and type of house material showed spatial variation across the flood prone areas in Mbire District (Table 4). The coefficients (or odds rations) of the type of house material ranged from − 1.136 to 1.323. These were higher than those for water sources which were between − 0.781 and 0.605. The spatial variation and significant levels of the interpolated estimated coefficients of the varying local coefficients (through kriging) are shown in Fig. 3.

These coefficients (Fig. 3) indicate how much malaria cases change with changes in the respective exploratory variables. Figure 3 also shows that the
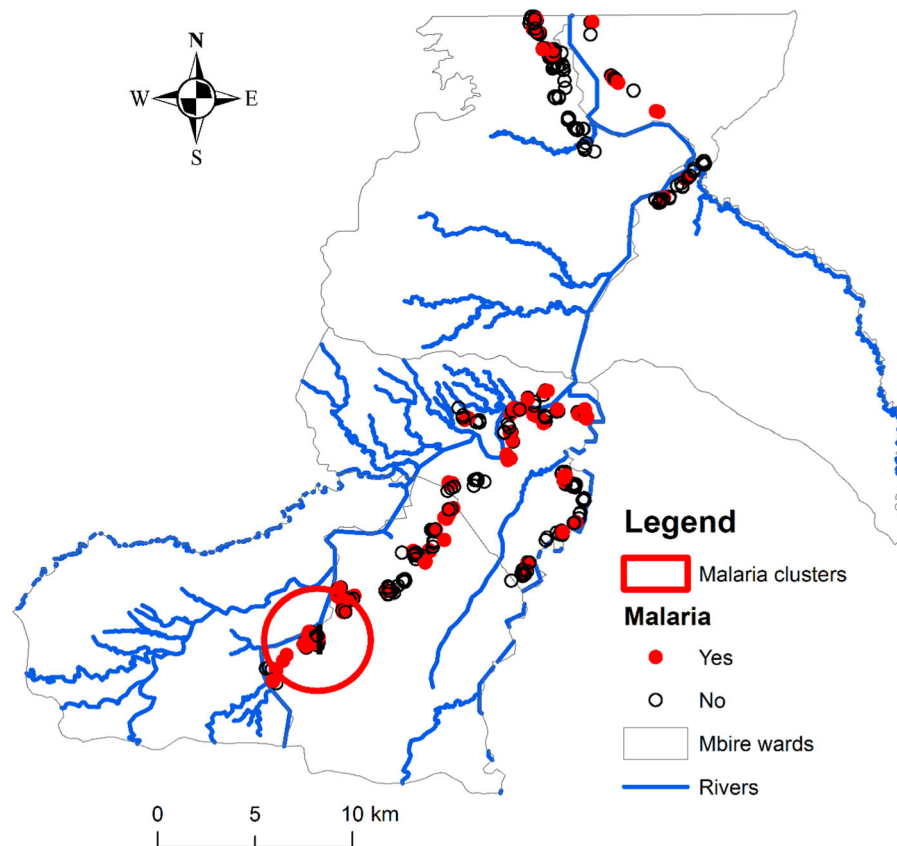

Fig. 2 Spatial distribution of malaria cases and the detected cluster/hotspots

Table 3 Characteristics of malaria cluster detected in the flood prone area in Mbire District

Property	Cluster 1
Coordinates/radius	(16.289837 S, 30.435586 E)/2.62 km
Locality	Ward 10 and 16
Population	40
Number of cases	26
Expected cases	11.53
Observed/expected	2.25
Relative risk (RR)	2.72
Percent cases in area	65.0
Log likelihood ratio (LLR)	13.0
P-value	< 0.001*

*Significant *p*-value < 0.05

Table 4 Summary statistics of varying (local) coefficients in geographically weighted logistic regression for malaria reported cases, Mbire

Parameter	Minimum	25 percentile	Median	75 percentile	Maximum	DIFF of criterion
Intercept	− 4.308	− 3.497	− 0.083	0.170	3.043	− 3.742[a]
Water sources	− 0.781	0.087	0.141	0.454	0.605	− 1.064[a]
Type of house material	− 1.136	− 1.073	− 0.579	0.002	1.323	− 5.742[a]

[a]Negative values of DIFF of criterion indicate spatial variability

significance (t-values + / − 1.96) of these coefficients also varied across the study area. Higher coefficients or odds ratios a variable designates that it has more effect in that particular area. Intercept coefficients were high to the northern part (ward 3 and 12) of the study area and were lower and also significant (t-values − 1.96) to the south western part (part of ward 9, 10 and 16) including the malaria cluster shown in Fig. 2. Type of house material coefficients were the opposite of the intercept as they were high to the southern part and lower in the northern side and were significant in the middle part of the study area and northern part of the identified cluster or hotspot. Coefficients for water sources were also high and significant in the southern part of the study area including parts of the identified hotspot.

Discussion

Spatial analysis of malaria cases has been widely done in different settings. However very limited studies have focused on micro-geographical scale especially in malaria endemic and flood prone areas. This study

has shown that malaria cases also vary at micro-geographical scale in flood prone areas. Hence, preparedness and control of this disease should be guided by this pattern and other related factors. Doing so is critical since resources are at times not available or insufficient to respond effectively to malaria outbreaks in time. GWLR helped in showing the spatial variation of the coefficients of the key variables, in this case types of house materials and water sources which are helpful to understanding the contribution of these exploratory variables to the spatial variation of malaria cases. It is also worth noting that malaria is common in Mbire District even during months without floods. Hence, floods may only exacerbate the underlying risk factors of this disease. This supports the observation by Kouadio et al. (2012) that natural disasters do not import diseases most of the time. Therefore, diseases that are not endemic in the areas affected by floods may not spread easily or naturally.

The socio-demographic factors considered in this study were also considered in other studies (Ibor & Okoronkwo, 2017; Yadav et al., 2014; Yang et al., 2020). Water sources and type of house material
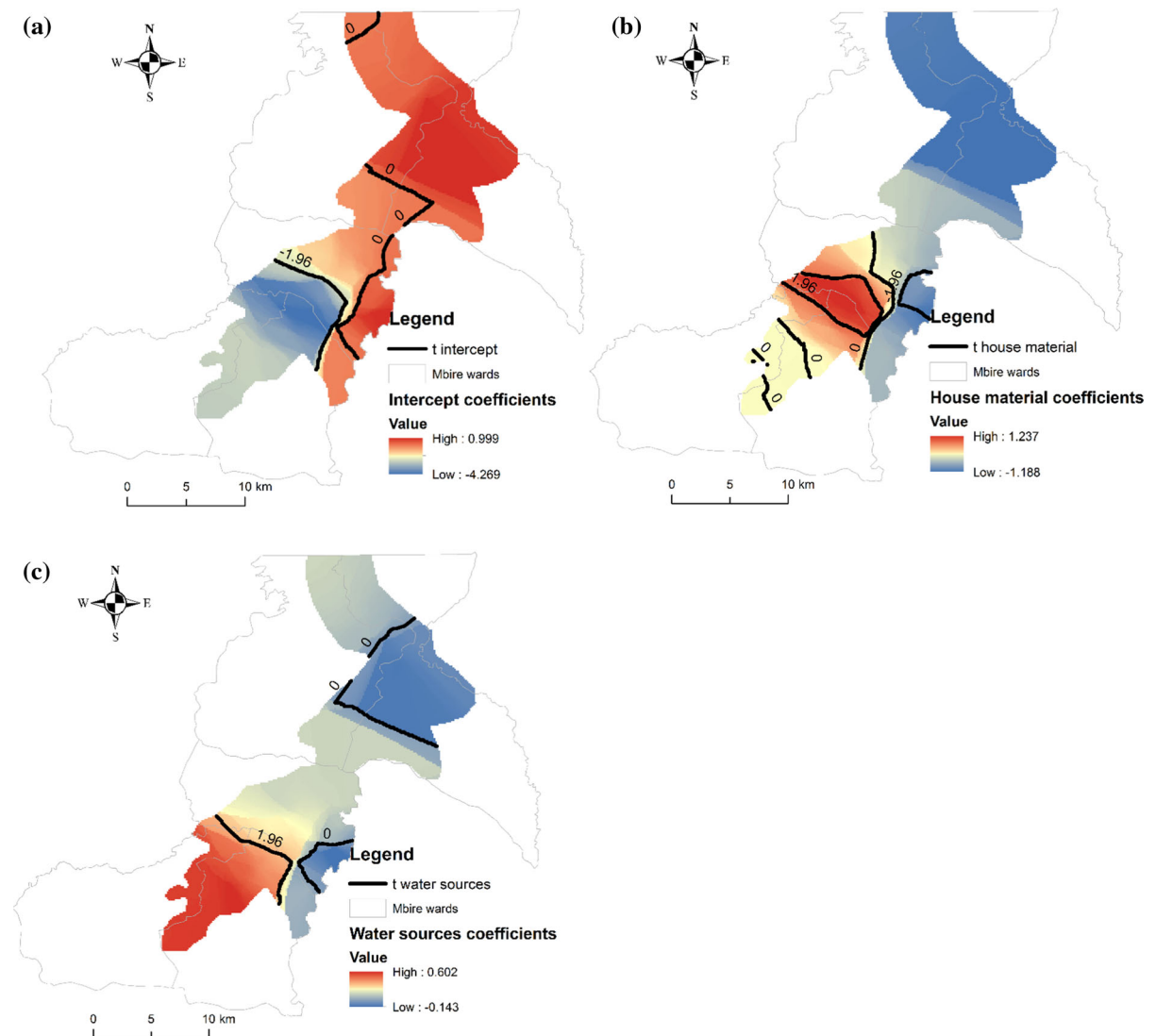
Fig. 3 Spatial variation and significant levels of the estimated coefficients variables in the best performing geographically weighted logistic regression model (GWLRM) applied in malaria endemic and flood prone areas in Mbire District: **a** intercept **b** house material and **c** water sources

emerged as key variables in determining spatial variation of malaria cases at the household level in flood prone areas in Mbire disdict. Yadav et al. (2014) observed that house material was a significant predictor of malaria at household level. Yang et al. (2020) also noted that exposure to unprotected water was exposing the households to malaria. Unlike these studies, which were non-spatial, this study has gone further by using GWLR to show how the influence of these factors on malaria varies at micro-scale. GWLR indicated that the spatial associations between the

disease risk (in our case—malaria) and the exploratory factors vary across the landscape. This was also confirmed by Wu et al. (2016). The local estimates of parameters of socio-economic factors showed how they influenced the spatial variation or occurrence of malaria cases in the flood prone area in Mbire District. The maps clearly show the strengths and significance of these variables as indicated by the t-values especially for water sources and types of house material which were even significant in and around the identified cluster or hotspot.

Some of the factors did not show a significant association with malaria cases in this study. For example, whether the household was flooded or not, malaria cases remained the same. This could be so because mosquitoes can fly for an average distance of 3 km. Hence, all the households within the flood prone areas were equally exposed. Based on the chi-square, the middle-aged groups where more exposed to malaria compared to elderly and young age groups. This is mainly due to different levels of exposure to mosquito bites in flood prone areas. The middle-aged group are the most active people working in fields because the studied communities rely mainly on rainfed crop production along the flood plains.

Malaria hotspots observed in this study may be helpful in developing appropriate disease prevention and control measures that target specific local geographical areas (Bousema et al., 2013; Meurs et al., 2013; Platt et al., 2018). These hotspots need to be timely identified for targeted interventions (Manyangadze et al., 2017; WHO, 2007). Stocking contingency drugs in health facilities can go a long way in containing malaria during and after floods (Abeku, 2007). For this to be effective, public health officials should be on high alert to the outbreak of malaria during and after floods as mentioned by Greenoough et al. (2001). Hence, rapid disease risk assessment is required after every flood event of high magnitude. The risk assessment will help to determine appropriate key interventions (Kouadio et al., 2012) and inform decision making process that protects the health and wellbeing of people (Kouadio et al., 2012; Okaka & Odhiambo, 2018).

This study contributes to the increasing demand of information on disasters and diseases. In many occasions, disaster occurrences trigger the outbreak of diseases. For example, the Haiti earthquake of 2010 triggered tsunami floods which later led to the outbreak of cholera and malaria among other diseases (Schuller & Levey, 2014; Versluis, 2014). In Zimbabwe, the Tokwe-Mukorsi flood disaster of 2014 was associated with the outbreak of malaria within the flood dam basin (Mavhura, 2020). Thus, organizations providing humanitarian assistance following floods should also be on the lookout to the increased and potential spatial distribution malaria cases and related factors among the flooded communities.

The results of this study could also help in effective allocation of resources including drugs and personnel

during and after floods, to quickly rejuvenate community health programs that were functioning before the disaster. However, due to delays in accessing of some of the areas, resources need to be prepositioned in the places likely to be affected by floods. There is also need to consider other methods of delivering essential drugs, services and related emergency products/instruments. Such methods may include using drones despite their limited capacity. Some models have been developed that showed the effectiveness of using of drones in disaster response and relief operations (Chowdhury et al., 2017).

Although this study has shown the potential application of GWLR in flood-prone environments, further studies and improvements to the data and level of modelling are still required. There is need to generate data from active surveys and consider the prevention and control measures at household level such as indoor residual spraying (IRS) and use of insecticide treated nets (ITNs) as well as the role of passive immunity and infected asymptomatic individuals who act as reservoirs. Lack of such information may have affected the current results as there is limited understanding on the contribution of the prevention and control measures to the spatial variation of malaria cases at household level. Furthermore, we had no access to data on the vector mosquitoes, which could also explain the spatial variation of malaria cases. There is also need to consider semi-parametric geographically weighted logistic regression (s-GWLR) model that combines the local and global parameters. Hence, variables such as age, which did not show spatial variability, could be moved to global level. Despite these limitations, this study has shown the spatial pattern of malaria cases in flood prone areas and the spatial variation of the exploratory socio-demographic variables. This study has also shown the applicability of GWLR as an exploratory data analysis tool for malaria risk assessment at micro-geographical level that can be applied in similar settings.

Conclusion

This study examined the spatial distribution of malaria cases and the associated socio-demographic factors household level in flood prone areas of Mbire District in Zimbabwe. The use of the Bernoulli and GWLRMs allowed us to determine the spatial distribution of

malaria cases and key socio-demographic determinants. The type of house material and sources of water emerged the key factors in determining spatial variation of malaria cases at household level in flood prone and malaria endemic areas. Hence, some local communities experience increased number of cases of malaria during and after floods as determined by these factors. The maps produced in this study are supporting the initiatives for malaria risk assessment in the flood prone areas. Therefore, the results of this study could form the basis for place-specific malaria interventions in Mbire District and other similar settings. The methodology can also be applied in malaria endemic and flood-prone places across the globe.

Declarations

Conflict of interest We declare that there is no conflict of interest related to the submitted manuscript.

Human and animal rights There has been no involvement of animals in this study. The human participants involved were requested their consent to participate before the undertaking of this study.

Informed consent The human participation in this research was in form of responding to a household questionnaire. Gatekeeper permission was granted by the development coordinators for Mashonaland Central Province and Mbire District, ward councilors and village heads. Consent was obtained from all the participants prior to the survey. Confidentiality and anonymity were guaranteed to all the participants.

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