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Mapping and Modelling Malaria Risk Areas Using Climate, Socio-Demographic and Clinic Variables in Chimoio, Mozambique

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Abstract

Malaria disease continues to be one a major public health concern in Africa. Around 3.2 billion persons are still at risk to contract malaria in the World and, in 2015. Approximately 80% of deaths caused by malaria are concentrated in only 15 countries, mostly in Africa. These high-burden countries have achieved lower than average reduction in malaria incidence and mortality and Mozambique is among them. Malaria eradication is therefore, one of Mozambique's main priorities. Few studies on malaria were carried in Chimoio and there is no malaria map risk of the area. This map is important in order to identify areas at risk for Public Precision Health approach. By using GIS-based spatial modelling techniques, the research goal of this article is to map and model malaria risk areas, using climate, socio-demographic and clinic variables in Chimoio, Mozambique.

Methods: A 30m×30m Land sat image, ArcGis 10.2 and, BioclimData were used. A conceptual model for spatial problems was used to create the final risk Map. The risks factors used were: mean temperature, precipitation, altitude, slope, distance to water bodies, distance to roads, NDVI, land use and land cover, malaria prevalence and, population density. Layers were created in a raster dataset. For the class values comparison between layers, numeric values to classes within numeric each map layers were assigned, giving them the same importance. Ranks were performed to the input dataset with different weights according to their suitability. The combination of the reclassified outputs of the data was performed.

Results: Chimoio presents 96% with moderate risk and 4% with high-risk areas. The map depicts that the central and south-west "Bairros" namely Centro Hipico, Trangapsso, Bairro 5 and 1o de Maio have a high-risk, while the rest of the "Bairros" having a moderate risk of malaria.

Conclusion: All the Chimoio population is at risk to contract malaria Precise estimation of malaria risk has important implications in Precision Public Health, and the planning of effective control measures such as right time and place to spray for vector combat, distribution of bed nets and other control measures.

Keywords: Mapping; Malaria Risk; Modelling; Public Precision Health

Background

Malaria is an ancient disease and is a major public health concern in Africa. About 3.2 billion people remain at risk of malaria in the World. It was reported that in 2015, there were 214 million new cases of malaria that resulted in 428000 deaths. Most cases occurred in the WHO African Region (88%), followed by the South-East Region (10%) and the WHO Eastern Mediterranean Region (2%). Approximately 80% occur in just 15 countries, mainly in Africa. Combined together, these high-burden countries recorded a slower than average reduction in malaria incidence and mortality [1] and Mozambique is among them.

Mozambique was recently ranked fifth in Africa for the number of malaria cases [2]. The disease is a major cause of morbidity and mortality, especially among children [3], and the entire population is at risk of contracting the disease since is endemic with seasonal peaks during and after the rainy season, which is between November and March [4].

To eradicate malaria is, therefore, one of Mozambique's main priorities and is recognized as critical to achieve the 2030 Agenda for Sustainable Development [5]. The environment and climate conditions highly influence the malaria transmission, although, their effect is often not linear. It is not expected that the malaria-climate relation keeps the same over areas covered by different agro-ecological zones [6] thus resources for control have to be spread in time and space. An estimated 80 to 90% of malaria cases are related to environmental factors [7-9]. The level of prevalence can be predicted based on the established relationship between malaria prevalence and environmental data.

Temperature affects the development of malaria and below 18°C and over 40°C the parasite does not develop [10,11]. The highest proportion of vectors surviving the incubation period is observed at temperatures between 28° - 32°C [12].

Precipitation is another key player in malaria occurrence; increased precipitation can provide more breeding sites for mosquitoes, but, excess rain can also destroy breeding sites [13,14]. There is an influence of altitude in the distribution and spread of malaria indirectly, via its effect on temperature. For every 200-meter increase in altitude, the temperature decreases by 1°C [15]. Highlands are colder and lowlands are warmer, at certain altitudes malaria transmission does not occur due to the extreme temperatures that are not favourable to the mosquito and parasite life-cycle [10]. For smaller regions, topography remains a single most important aspect that defines large scale differences in malaria risk, because climate variables change little over the limited range of latitude [16]. In Malawi elevation was associated with malaria prevalence and at an elevation of < 650 m, Odd Ratio (OR) was 1.32, between 650 and 1100 the OR was 1.89 [17].

Slope together with precipitation amounts received at a certain location may influence the dispersion of malaria. Flat areas on the ground are more prone to accumulate water, creating dam rain water, increasing the risk of malaria [18]. In Ghana, swampy areas and banana production in the proximity of villages were strong predictors of a high malaria incidence [19]. Land cover is another player in malaria occurrence. In Kenya, the association between land cover type and the presence of anopheline larvae was found to be statistically significant and overall, the highest proportions of anopheline-positive habitats occurred in pastures (33%) and farmlands (32%) followed by swamp habitats (23%), [20] and in Ghana an increase in a forested area of 10% was associated with a 47% decrease of malaria incidence. Different cultivations in the vicinity of homesteads were related to childhood malaria in rural areas [18].

The effectiveness of intervention measures against malaria can be determined by the Euclidian distance of a place from roads. In Zambia it was reported that for every 500 meters increase in distance from the road, there was a corresponding 5% increase in positive malaria in households [21] and, in Kenya roads was found to have the least number of anopheline habitats, 15%, whereas habitats in forests had an 18% rate [22].

Distribution of water bodies is a major factor that influences the malaria occurrence and malaria case distributions. Water bodies play a very important role as larval breeding sites for malaria mosquitoes. Therefore, the identification of water body sites is then a direct indicator for malaria risk occurrences. The Euclidian distance to a water body is a determinant of the malaria risk incidence [23]. A study carried out in China indicated that population living within 60 meters of water bodies had a higher risk of contracting malaria [24].In terms of malaria breeding in 1934 the following statement was stated: "it may safely be inferred that the influence of any production from breeding place within 0.81 kilometres radius will be felt there in, at radii of 1.61 kilometres the influence may be doubtful, and ordinarily at radii of more than 1.61 kilometres the influence may be expected to be nil" [25]. Recent studies indicate that the mosquitoes flew no more than 170 metres after taking a blood meal [26] and, that a hungry mosquito will fly up to 1.5 kilometres [27].

In Chimoio a positive correlation, r = 0.407 between malaria cases and population density and the r^2 value indicates 0.165, was found [28]. The mosquito breeding, feeding, and resting behaviour is often associated with vegetation [28]. There are a number of vegetation indices that have been used in remote sensing, but the most used index to enhance the vegetation areas is the Normalized Difference Vegetation Index (NDVI). The measurement of NDVI is from -1 to 1 and, if a value is close to 0 means that there is little vegetation in the area. When the value is close to 1, means that there is more vegetation in the region [29]. In Brazil, most domiciles with more than five notified cases were located near areas with high NDVI values [30].

Chimoio is the capital of Manica Province in the Centre of Mozambique. Very little research on malaria was carried out in Chimoio. Malaria is increasing in the suburbs, urban areas present fewer malaria cases than rural areas. The annual overall average of malaria incidence is 20.1 % and the Attributable Fraction (AF) of malaria is 16%. Children under five are three times more prone to malaria than adults and 11.7% of the total annual deaths were due to malaria [31]. The two most important climate factors that influence malaria in Chimoio were found to be relative humidity and, minimum temperature and they show positive high correlation with climate [8]. In the spatial epidemiology of malaria, recent studies benefited from the huge progress in the development of Geographic Information Systems (GIS). The health practitioner, and/or researcher's ability to locate the precise position of a disease in their area allows for the creation of maps of the spatial variability and incorporate many variables as can be measured [32].

Precision public health strategy is based on a specific site by observing, measuring and responding to inter and intra-region variability in malaria trends. That makes statistical and computational treatments quite involved and, can lead to decision support systems to help in malaria eradication, optimizing the resources and minimize the impact on the environment [33]. The decisions can be in areas such as the right time and place for spraying, the correct site to build a water body, the correct time and place for drainage and other relevant activities for malaria control and eradication.

Target vector control in high-risk areas, focus on asymptomatic and symptomatic infections and manage importation risk are needed to control and eradicate the disease. High spatial and temporal resolution maps of malaria risk can support all of these activities [34]. Risk maps can be used for Precision Public Health but, the maps available for malaria were produced at national, regional or continental magnitude, such as MARA [35], and they have a limited operational use to support local program activities.

Malaria risk maps of the country, especially for Chimoio, have not been produced and it is urgent to have them in order to identify areas at risk the Public Precision Health approach. By using spatial modelling techniques with GIS, the research goal is to map and model malaria risk areas, using socio-demographic, climate, and clinical variables in Chimoio, Mozambique.

Materials and Methods

Study area

Chimoio is a municipality located in Manica Province in the central region of Mozambique (-19º6´59S, 33º28´59E). The population of Chimoio is presently estimated to be 324816 [36]. The area is 174 km² at an altitude that varies between 513 and 786 meters. The Chimoio climate has a warm temperature with dry winters from April to July, hot and dry summer from August to October and, hot and humid summer from November to April. The major economic activities are: agriculture production, livestock, general trading, metallurgical industry, food industry, tourism, telecommunication, banking and insurances and energy supply [37].

Material

For the study the following material was used:

a) 30m×30m Landsat image.

b) ArcGis 10.2.

c) Bioclimatic (1950 to 2000) [38].

Methods

Figure 1 presents the schematic representation of data flow and analysis for malaria risk map for Chimoio.

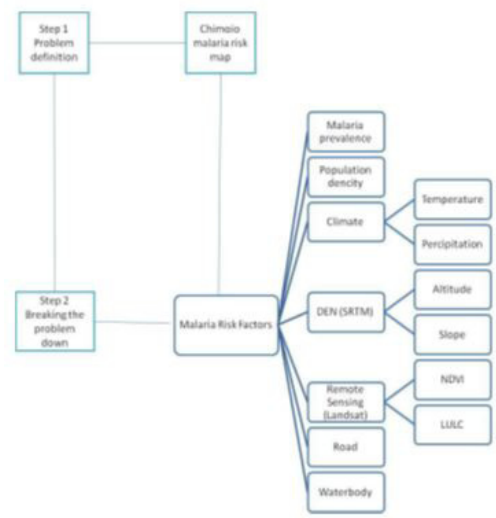
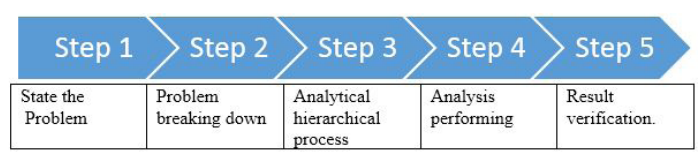


Figure 1: Schematic representation of data flow and analysis for malaria risk map for Chimoio.

The conceptual model to solve spatial problems was used to create the Chimoio Map risk [39]. The process involved the following steps:



- **Step 1:** In this stage the problem was stated and was: Mapping malaria risk for chimoio
- **Step 2:** Problem breaking down

Table 1 presents the malaria factors, their weight, classification and the rationale for the classification adapted from literature from Zimbabwe, Tanzania and Latin America [16,40-42].

Factor	Weight	Class	Influence	Rationale
T mean	0.224	< 22^{o}C	Low	Bellow 22^{o}C sporogony is not completed
		> 28 ^{o}C	Moderate	Over 28^{o}C sporogony is affected
		22 - 28^{o}C	High	22 - 28^{o}C ideal for incubation
Precipit	0.208	<450 mm	Low	< 450 mm is arid, and mosquitoes will have
		450 – 700 mm	Moderate	difficulties to survive > 700 mm is wet and.
		> 1000 mm	Low	inappropriate for mosquitoes breeding
Altitude	0.123	< 200 m	High	< 200 m low land and high risk of vector
		200 – 500 m	Moderate	proliferation, 200 to 500 m upland
		>500 m	Low	>1000 m highlands and low risk of mosquitoes' survival
Slope	0.082	0 – 5^o	High	Appropriate conditions for water stagnation
		5 – 15^o	Moderate	
		>15^o	Low	>15^o inappropriate for water stagnation
LULC	0.082	crop, grass and water bodies	High	Suitable for mosquitoes' proliferation
		shrubs and mosaic vegetation	Moderate	
		forest, bare, urban	Low	Not suitable for mosquitoes breeding
DTWB	0.123	< 500 m	High	The mosquito fly range is 1500 m.
		500 – 1500 m	Moderate	Less than 500 m from WTBD
		>1500m	Low	the risk of malaria is high
DTR	0.038	< 2.5 Km	Lowe	< 2.5 km walking distance to clinic
		2.5 – 5 Km	Moderate	2.5 to 5 km clinic can be reached by bicycle
		> 5 Km	High	< 5 Km interventions are difficult
Pop dens	0.051	< 6000 pers/Km^2	Low	High populated area has higher risk
		6000 – 9000pers/m^2	Moderate	since mosquitoes have abundant
		>9000 pers/km^2	High	blood meal close by.
Malar prev	0.051	< 14%	Low	High prevalence areas have higher
		14 – 21%	Moderate	risk since mosquitoes do not have
		> 21%	High	to travel long for blood meal
NDVI	0.047	-0.2777 – 0	Low	
		0 – 0.255	Moderate	
		0.255 – 1	High	High NDVI is related to high malaria risk

Table 1: Classification, weighing and rationale of malaria risk factors.

For this stage the input data set or malaria risk factors were the following: average Temperature (Tmean), Precipitation (PP), Altitude (Alt), Slope (SLP), Distance to water body (DTWB), Distance to road (DTR), Normalised Difference Index (NDVI), Land use and land cover (LULC), Malaria prevalence (Mal prev) and Population density (pop dens).

Average temperature (Tmean)

Long-term minimum and maximum temperature was extracted from the Bioclim [38] and the average temperature calculated. In this study average temperature below 22˚C were classified as low risk for malaria transmission, while those from 22˚C-28˚C were classified as high-risk for malaria transmission and temperatures above 32°C were classified as of moderate risk.

Precipitation (Prec)

Precipitation data were extracted from the Bioclim Data. In the study, areas that received the precipitation less than 450 millimetres were classified as low risk, those that received a precipitation between 450 to 700 millimetres were classified as a moderate risk, and the ones over 700 millimetres were classified as having high-risk.

Altitude (Alt)

A digital elevation model at 30×30 m resolution was used to estimate the altitude. Areas below 200 m (lowlands) were classified as being the highest risks for malaria occurrence, areas between 201 to 500 metres (uplands) were classified as having moderate risk and over 500 m (midlands) were classified as having the least risk of malaria exposure.

Slope (SLP)

The slope was derived from the 30m×30m digital elevation model, obtained from the spatial analysis tool from ArcGis. In the study, areas of from 0 to 5 degrees were classified as being high-risk, those from 5 to 15 degrees were classified as of moderate risk, while those over 15 degrees were classified as having the lowest risk.

Land cover and Land-use (LCLU)

Land-use and land cover data were retrieved from the most recent (April 2016) the 30m×30m Landsat satellite image (GIS Geography, 2016). The image was reclassified into different LULC classes. Areas with crops, grass and water bodies were classified as having the high-risk of malaria. Areas such as shrubs and mosaic cover vegetation were classified has having a moderate risk of malaria, while the areas with forest, bare, and urban settlements were classified as having the lowest risk of malaria.

Distance from Roads (DTR)

Euclidean distance to nearest road was calculated using ArcGIS, classifying a 2016, 30m ×30m Landsat image. Distances of places from the road were then calculated using the measuring distance function in ArcGIS software. In the study, places over 5 km from the roads were classified to be at highest risks to malaria, those between 2.6 km and 5 km from roads were classified to be of moderate risk and those less than 2.5 km from the roads were classified as having the lowest risk of malaria infection.

Distance to Water Bodies (DTWB)

Distance to the nearest water body were calculated with ArcGIS, classifying a 2016, 30m×30m Landsat image for water and undefined. Distance from water bodies were then calculated using the measurement distance function in ArcGIS software. In this study, areas with less than 500 metres from a water source were classified as being a high-risk area, those between 501 to 1500 metres were classified as moderate risk areas while those above 1500 metres from water bodies were classified as being of low risk to malaria.

Population density (pop dens)

Data on population density were calculated from the National census population projections for 2014. In the study places over 9000 people/ km^2 were classified to be at highest risks to malaria, those between 6001 to 9000 people/ km^2, were classified to be of moderate risk, and those less than 6000 person/ km^2 were classified to be as low risk of malaria infections.

Malaria Prevalence (Mal prev)

Malaria cases diagnosed by health personnel as described elsewhere Ferrão et al. (2016) were used. In the study over 21% prevalence were classified as being the highest malaria risk areas, between 14 and 21% were classified as being of moderate malaria risk and, less than 14% were classified as having the lowest risk of malaria occurrence.

Normalized Difference Vegetation Index (NDVI)

The NDVI was extracted from a Landsat image. The NDVI map has been grouped into three principal categories: -0.288 to 0, and classified as moderate risk, 0 to 0.255 classified as moderate risk and 0.255 to 0.986 classified as high risk was classified as being of high malaria risk [43].

- **Step 3: Analytical hierarchical process (AHP)**

The analytical hierarchical process is a method that uses hierarchical structures to represent a problem and makes judgments based on expert panels to derive priority scales [44]. In this step, the input datasets were explored to understand their content and attributes within and between data sets are more important for solving the stated problem and searching for trends in the dataset[45].

To obtain the weights for each individual factor for the map the following step was as follows:

a) Formulation of a pair-wise comparison matrix for each of the input variables.

b) Establishment of the relative weights of each input variable.

c) Checking for consistency in the pairing process [16].

a) The fundamental scale to help in, the weighting process was used to develop the pair-wise comparison matrix (Table 2).

b) Establishment of the relative weights of each input variable: Indeed, the malaria risk factors don't have the weight and role in the modelling of the final malaria risk map. Therefore, in order to designate the importance of each variable, they were weighted using a pair-wise comparison method from the AHP template worksheet [45].

c) Checking for consistency: After computing the pair-wise matrix and, to measure if the derived matrix was derived at an acceptable level, a consistency test was calculated. For this study, a consistency index less than 10% was considered good enough [16]. A result above 10%, the matrix was revised until the indication of an acceptable level of acceptance [44].

Extremely less important	1/9
	1/8
Very strong less important	1/7
	1/6
Strongly less important	1/5
	1/4
Moderately less important	1/3
	1/2
Equal importance	1
	2
Moderately more important	3
	4
Strongly more important	5
	6
Very strong more important	7
	8
Extremely more important	9

Table 2: Fundamental scale for pair-wise comparison matrix.

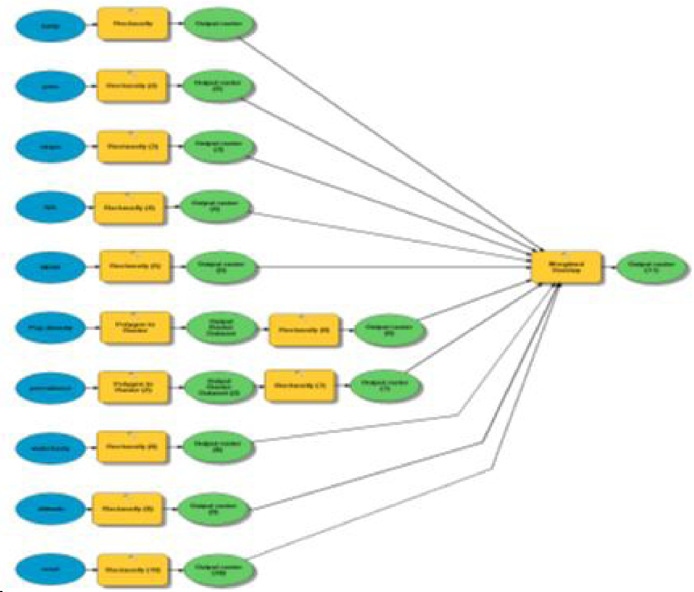


Figure 2: The spatial analysis depicted in (Figure 2) was performed.

- **Step 4: Performing analysis**

Layers for Tmean, PP, Alt,SLP, DTWB, DTR, NDVI, LULC, malaria prevalence (%) and population density (person/ km^2) were created in a raster dataset. To compare the values of the classes between layers, numeric values to classes within each map layer was assigned from 1 to 3 being low, moderate and high-risk respectively. The reclassification was carried out and all measures had the same numeric scale giving them the same level of importance.

For the suitability model, reclassified outputs of Tmean, PP, Alt, SLP, DTWB, DTR, NDVI, LULC, Mal prev, Pop dens were combined. The final suitability map was produced by combining all the maps together. Weights were assigned at the same time as combining the suitability maps [44].

Step 5: Verifying the result

After the result of the spatial analysis the correctness of the findings were discussed with experts and places visited.

Results

Table 3 shows the 10 x 10 comparison matrix of malaria risk factors used in the study and a value of 1 for example, means that factors under comparison have the same weight, and they affect the malaria occurrence equally. A value of five would mean the factor in the column is five times more important in the malaria risk occurrence than the comparison in the row.

	Tmean	Prec	Alt	Slope	LULC	DTWB	DTR	Pop den	Prev	NDVI
Tmean	1.00	1.00	3.00	4.00	4.00	2.00	6.00	4.00	4.00	4.00
Prec	1.00	1.00	3.00	4.00	3.00	1.00	7.00	4.00	4.00	4.00
Alt	0.33	0.33	1.00	3.00	3.00	1.00	4.00	2.00	2.00	3.00
Slope	0.25	0.25	0.33	1.00	1.00	2.00	1.00	3.00	1.00	1.00
LULC	0.25	0.33	0.33	1.00	1.00	2.00	2.00	5.00	1.00	1.00
DTWB	0.50	1.00	1.00	0.50	0.50	1.00	3.00	4.00	4.00	2.00
DTR	0.17	0.25	0.25	1.00	0.50	0.33	1.00	1.00	1.00	2.00
Pop den	0.25	0.50	0.50	0.33	0.20	0.25	1.00	1.00	2.00	4.00
Prev	0.25	0.50	0.50	1.00	1.00	0.25	1.00	0.50	1.00	2.00
NDVI	0.25	0.25	0.33	1.00	1.00	0.50	0.50	0.25	0.50	1.00

Table 3: 10 x 10 Comparison Matrix of Risk Factors used in the study.

The weights of each factor used for the spatial model to produce the malaria risk map are presented in Table 2. Tmean (22.4%) and precipitation (20.8%) presented the highest weights followed by DTWB (12.3%) and altitude (10.4%), LULC (8.2%), slope (7.3%), pop dens and malar prev (5.1%), NDVI (4.7%) and DTR (3.8%). The consistency index for the pair-wise matrix was 9%.

- **The special model to produce the malaria risk map formula was:**

[(Tmin*0.224) + (precipitation*0.208) + (altitude*0.104) + (slope*0.073) + LULC*0.082) + (DTWB*0.123) + (DTR*0.038) + (Pop dens*0.051) + (Mal prev*0.051) + (NDVI*0.047)]

Figure 3 presents the malaria prevalence, slope, temperature, NDVI and LULC. In terms of malaria prevalence, Chimoio presents 42% of the area with low risk, 17 % with moderate risk and, 41% with high-risk areas. It is possible to see that the prevalence risk of malaria varies spatially in the Chimoio Municipality. For slope, Chimoio presents 2% of the area with low risk, 52 % with moderate risk and 46% with high-risk areas. For average temperature, Chimoio presents 100% of moderate risk areas.

For NDVI Chimoio presents 5% of the area with low risk, 12% with moderate risk and 88% with high-risk areas. For LU/LC Chimoio presents 39% of the area with low risk, 4% with moderate risk and 43% with high-risk areas.

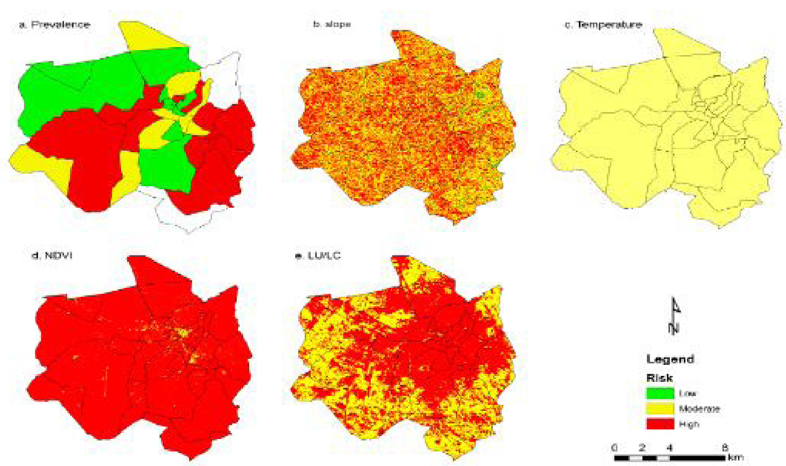


Figure 3: Malaria risk for malaria occurrence. a) Prevalence b) Slope c) Temperature d) NDVI e) LULC Source: (Ferrão et al., 2016).

Figure 4 presents the precipitation, altitude, Distance to a water body (DTWB), Distance to road (DTR), and population density (person/km^2). For precipitation, Chimoio presents 100% moderate risk areas. For altitude, Chimoio presents 34% with moderate risk and, 66% with high-risk areas. For DTWD, Chimoio presents 44% of the area with low risk, 40 % with moderate risk and, 16% with high-risk areas. For DTR, Chimoio presents 40% of the area with low risk, 43% with moderate risk and 17% with high-risk areas. For population density, Chimoio presents 92% of the area with low risk, 5% with moderate risk and 3% with high-risk areas.

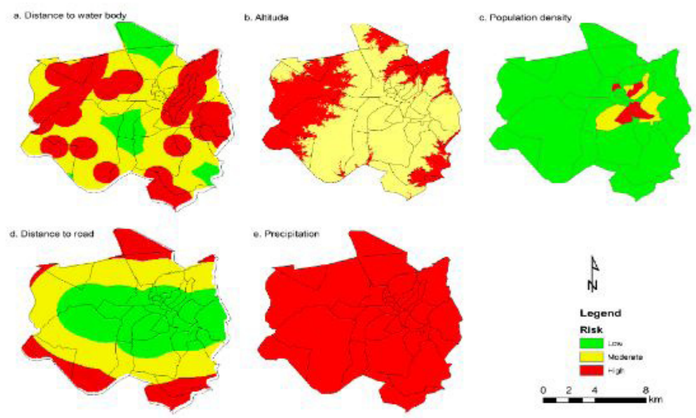


Figure 4: Malaria risk for malaria occurrence. a) DTWB, b) Altitude, c) Population density, d) Distance to road, e) Precipitation.

Figure 4 presents the Chimoio map risk for malaria after the consolidation of the weighted malaria risk factors used in the present study. Chimoio presents 0% of the area with low risk, 96% with moderate risk and 4% with high-risk areas. The Map depicts that the central and south-west "Bairros" namely Centro Hipico, Trangapsso, Bairro 5 and 1o de Maio while the rest of the "Bairros" have a moderate risk of malaria.

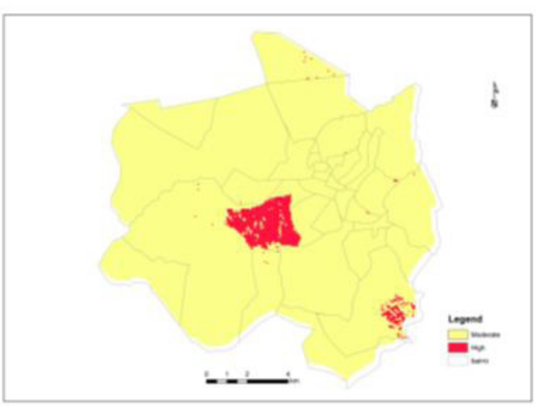


Figure 5: Malaria risk.

Discussion

In this study it was determined that climatic factors mean temperature and precipitation presented the highest weights followed by DTWB, 12.3% and altitude 10.4% and the other climatic factors presented the least weights. The results are similar to other studies in Mozambique and the World [16,41,42,46-48]. The Mozambique risk Map produced by other authors are similar with the findings of this study [49,50]. The malaria risk map produced by the study differs in many ways with other available models. The area is small (174 km^2) and it used ten risk factor variables. It also uses high, sharp and fine spatial and temporal resolutions of risk factors and includes climate variable data that impacts in the factors that affect the mosquito proliferation. It also includes human-induced variables such as distance from roads and LCLU changes and, clinical data. The model is reasonably scaled to present variance in malaria risk at micro-scale level. A relatively small number of studies have included ten risk factor variables in geostatistical models for malaria risk mapping. Similarly, this approach can also be applied for modelling and prediction of other environment driven diseases.

Conclusion

The weights used in this map are consistent with several studies and the map is reliable. The entire population of Chimoio his at a risk to contract malaria and, 96 % have a moderate risk and 4% high-risk. Trees in the Chimoio streets and households are probably resting areas for mosquitoes. Precise estimation of malaria risk has important implications in Precision Public Health, and the planning of effective control measures such as the right time and place to spray for vector combat the right time to prune the trees from the trees and homesteads, distribution of bed nets, correct site to build a water body, the correct time and place for drainage and other relevant activities for malaria control and eradication. The study demonstrated the importance of the possible use of GIS and remote sensing in predicting, mapping and modelling the malaria risk in Chimoio municipality. More studies should be carried out such as bed net usage, the relationship between household presence of trees and malaria and others.

Declarations

Ethic of approval and consent to participate

Non-applicable

Consent for publication

Not applicable

Availability of data and material

The AHP data are included in the attached file. The modeling datasets analyzed during the current study are available from the corresponding author.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

The author JLF was involved in research design, and manuscript writing. SMN was responsible for the mapping, JMM and MP contributed in analysis and manuscript revision analysis and manuscript revision.

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