Modelling Sociodemographic Factors That Affect Malaria Prevalence in Sussundenga, Mozambique.

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Modelling sociodemographic factors that affect malaria prevalence in Sussundenga, Mozambique.

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Abstract

Background

Malaria is still one of the leading causes of mortality and morbidity in Mozambique with little progress in malaria control over the past 20 years. Sussundenga is one of most affected areas. Malaria transmission has a strong association with environmental and socio-demographic factors. The knowledge of sociodemographic factors that affects malaria, may be used to improve the strategic planning for its control and, such studies do not exist in Sussundenga. Hence, the objective of this study is to model the relationship between malaria and sociodemographic factors in Sussundenga, Mozambique.

Methods

Houses in the study area were digitalized and enumerated using GoogleEarth ProTM. Hundred houses were randomly selected to conduct a community survey of P. falciparum parasite prevalence using rapid diagnostic test (RDT). During the survey, a questionnaire was conducted to assess the socio-demographic factors of the participants. Descriptive statistics were analyzed and backward stepwise logistic regression was performed establishing a relationship between positive cases and the factors. The analysis was carried out using SPSS version 20 package.

Results

The overall P. falciparum prevalence was 31.6 %. Half of the malaria positive cases occurred in age group 5 to 14 years. Previous malaria treatment, population density and age group were significant predictors for the model. The model explained 13.5 % of the variance in malaria positive cases and sensitivity of the final model was 73.3 %.

Conclusion

In this area the highest burden of P. falciparum infection was among those t5-14 years old. Malaria infection was related to socio-demographic factors. Targeting malaria control at community level can contributed better than waiting for cases at health centers. These finding can be used to guide more effective interventions in this region.

Trial registration

Review Board (IRB) at the University of Minnesota STUDY00007184

CNBS [IRB00002657]

Keywords: sociodemographic; malaria; prevalence; Sussundenga

Modelling sociodemographic factors that affect malaria prevalence in Sussundenga, Mozambique.

1. Background

Malaria is a serious and sometimes fatal disease caused by a *Plasmodium* parasite that commonly infects *Anopheles* mosquitos which feeds on humans. Although malaria can be a deadly disease, infection and death can be prevented[1]. Almost half of the world's population lives in areas at risk of malaria transmission. Six countries account for more than half of all malaria cases worldwide and Mozambique is among them[2].

In Mozambique, a country in sub-Saharan Africa, with a population of over 30 million inhabitants, malaria is one of the leading causes of mortality and morbidity. In 2018, Mozambique recorded the third largest number of malaria cases in the world, that is, 5 % of all cases[3].

The country has made little progress in malaria control. Indoor residual spraying (IRS), insecticide treated bed nets (ITNs), and parasitological diagnosis in health facilities using rapid diagnostic test (RDTs) with effective artemisinin combination therapy (ACT) are the malaria intervention currently being used. The entire country uses RDTs with ACT as the standard of care in public health facilities and ITNs are only available at antenatal clinics, indicated for pregnant women and children under 5[4].

Manica Province in central Mozambique has the second highest malaria incidence in the country. In the first quarter of 2020, recorded 1,039,283 cases with an incidence of 371 per 1000 inhabitants[5]. Sussundenga village, in Manica Province is one of most affected areas, with 31,397 malaria cases reported in 2019.

Malaria risk, disease severity, and clinical outcome depend on environmental, socio-demographic, economic, and behavioral factors[6,7,8,9]. A study in Chimoio, the Provincial

capital of Manica, close to Sussundenga Village, modelled the influence of climate on malaria occurrence and indicated that selected environmental characteristics accounted for malaria incidence by 72.5% implying that non-environmental factors such as sociodemographic, economic, cultural and behavioral traits would account for the res[10].

While Mozambique has one of the highest incidences and prevalence of malaria in the region and, it accounts for nearly half of childhood deaths, little is known about the epidemiology to inform appropriate and effective interventions. This is one of two major barriers to expanding control measures in the country with the other being limited funding.

In the country, malaria transmission occurs all year round and, the knowledge of sociodemographic factors that affect malaria is crucial for informing the implementation of the most appropriate and effective malaria interventions to achieve control. In Sussundenga no studies are known in this field. Therefore, the objective of this study was to model the relationship between malaria and sociodemographic factors in Sussundenga Rural Municipality.

2. Methods

2.1. Study area.

The village of Sussundenga is a rural, agrarian community 40 Km from the Zimbabwe border, and is 40 kilometers from the provincial capital of Chimoio (Figure 1).

Sussundenga has an estimated population of 31,429 inhabitants, 47% males and 53% females. The age distribution is: 19.5% from 0 to 4 years old, 29.9% from 5 to 14-year-old, 20.5% from 15 to 24 years old and 30.1% with over 24 years old [11].

The climate is tropical with an average annual precipitation of 1,200 mm. The rainy season occurs from November to April. The average minimum temperature is 6.3ºC in the month of July and the average maximum temperature is 38.9ºC in the month of January and the annual average is 21.2ºC[12]. The village is divided administratively in 17 residential areas called “Bairros”.

2.2. Data collection

GoogleEarth Pro™ satellite imagery was used to digitize and enumerate all household structures in the village of Sussundenga. A random sampling of 125 households was taken; 100 households for enrollment in the study and 25 households as backup for refusals and errors in the digitizing process (misclassified non-household structures).

Coordinates of the households were extracted using a GPS device and maps of the selected households to conduct study visits. The study involved two visits to the selected households. The first was a notification visit where the study team introduced themselves to the head of the household and explained the objectives and procedures of the study. It is customary for the head of household to provide permission to the study team before any activities take place at the household involving other household members. Once the head of household gave permission, the study team conducted a household census with the head of household and begin the process of individual informed consent with the household residents, for all adult (18+ years) residents and parental permission and assent from minors.

After obtaining consent from the household residents, the study team informed participants when they will return the following day to conduct the study activities. The only eligibility requirement was that the residents live in household full time. Data

collectors verbally administered a questionnaire to collect the basic demographics. The field study was carried out from December 2019 to January 2020.

The study nurse collected current malaria specific symptoms by self-report and will took participant's temperature using a digital thermometer (Mebaline). They then collected a finger prick blood sample to administer a Rapid Diagnostic Test (RDT), RightSign Biotest ^{R} (Biotest, Hangzhou Biotest Biotech Co, China). According to the manufacture, this test captures the HRP2 antigen on the strip and its sensitivity is >99.0%. The results were recorded and, in the event, that a participant was positive for malaria, the study nurse referred them to the Sussundenga rural health center (RHC) for diagnosis confirmation and treatment. The questionnaire was conducted using tablet computers with the REDCap (Research Electronic Data Capture, USA) a secure, web-based data capture tool. Data was stored in a secure REDCap server hosted by the University of Minnesota.

2.3. Data Analysis

This study was a cross-sectional community-based survey. The analyses were conducted on datasets downloaded from REDCap to excel spread sheet **(additional file 1)**. As variables, a binary variable as the dependent variable malaria infection, that is whether malaria was present (positive) to RDT or absent (negative) was used.

The explanatory variables analyzed were the following sociodemographic factors: age, if the person was an adult or child, age category, sex, history of malaria treatment, paid employment, cell phone ownership, education level, population density, location (Bairro), household category and household size.

The malaria prevalence, was calculated dividing positive cases of malaria by the study population tested at the time multiplied by 100[13].

$$Prevalence\ (\%) \frac{Persons\ having\ malaria}{Tested\ \ during\ the\ period}\ x\ 100 \quad (1)$$

Chi-square for proportion of age group and sex was tested. To establish the relationship between malaria prevalence and socio-demographic factors, logistic backward stepwise logistic regression was used with the following model:

$$X_i : g(Pi) = ß_0 + ß_1x_1 + ß_2x_2 + \ldots ßix_i \quad (2)$$

Where:

$G(P_{i)}$ = link function

P_i = likelihood of response for the -ith factor

$ß_0$ = intercept

$ß_1$ = coefficient

x_1 = independent variable.

This method starts with a full (saturated) model and at each step gradually eliminates variables that do not contribute for the model to find a reduced model that best explains the data. This method is useful since, it reduces the number of predictors, reducing multicollinearity and resolves overfitting[14].

To evaluate potential confounders and, effect modifiers between the final model variables, Hosmer -Lemeshow (1989) test was performed[15]. To build the final model, the independent variables $p < 0.05$ were included. Outcomes such as Scores statistic's, regression coefficient's, significance levels of variable coefficients and, overall classification accuracy were performed

The model sensitivity (conditional probability of a positive test given that the patient has malaria) of the final model measures the proportion of positive that were correctly identified and, was calculated as[16]:

$$Sensitivity(\%) = \frac{Number\ of\ true\ malaria\ positive}{Number\ of\ true\ malaria\ positive + Number\ of\ false\ malaria\ negative)}\ x\ 100 \quad (3.1)$$

The model specificity (conditional probability of a negative test given that the patient is well) of the final model measures the proportion of negative case correctly identified and was calculated as[16]:

$$Specificity(\%) = \frac{Number\ of\ true\ \ negatives}{Number\ of\ true\ \ malaria\ negatives + Number\ of\ false\ malaria\ positives)}\ x\ 100 \quad (3.2)$$

Positive Predictive Value (PPV) that is, the conditional probability, whether the screened people who tested positive do or do not actually have malaria was calculated as[16]:

$$PPV(\%) = \frac{Number\ of\ true\ \ malaria\ positive}{Number\ of\ true\ malaria\ positive + Number\ of\ false\ malaria\ positive)}\ x\ 100 \quad (3.3)$$

Negative Predicted Value (NPV) that is, the conditional probability that an individual with a test indicative of No malaria is actually disease free, was calculated as[16]:

$$NPV(\%) = \frac{Number\ of\ true\ malaria\ negatives}{Number\ of\ true\ malaria\ negatives + Number\ of\ false\ malaria\ negative)}\ x\ 100 \quad (3.4)$$

All tests were carried out using SPSS IBM version 20.

Ethical consideration

This study is part of the Malaria Risk, Prevention, and Health Seeking Behaviors in Sussundenga, Mozambique Project. All participants, or the guardians provided informed written assent and consent prior to participation. Ethical review and approval for the study was completed by the Institutional Review Board (IRB) at the University of Minnesota [STUDY00007184] and from A Comissão Nacional de Bioética em Saúde (CNBS) at the Ministry of Health of Mozambique [IRB00002657].

3. Results

3.1. Malaria prevalence, sex, age and, age group and education level of participants.

From 125 selected households 100 were visited Figure 2 presents the positive and negative cases per visited site. Of the 358 participants tested and, interviewed 108 (31.6 %) tested positive for malaria. There was an equal distribution of the enrolled participants among sex, 55% were female and 45% males, Chi-square = 0.081, P = 0.8872, DF = 1. No difference was found between female and male positive cases, 53 and 47% respectively, Chi-square = 0.180, P = 07772, DF = 1.

The age of participants varied from 1 to 80 years old, with a median of 17 years and an average of 21 standard deviation (SD), 16.2 years old. For the participants' education level (n = 302), 35.1% had no education or less than primary (5 grades), 47.4% had primary or basic school (grades 5 to 10) and 17.5 % had secondary and higher education.

3.4. Malaria prevalence by age category

Figure 3 presents the malaria positivity results for age categories. Half of the malaria positive cases occurred among those 5 to 14 years age category. This category comprises has 32.7 % of the Sussundenga population according to the National Institute of statistics (INE). Age category over 24 years presented 17.6% the malaria This age category comprises 30.4 % of the Sussundenga population according to INE. There was a statistically significant difference in positive malaria cases among groups, Chi-square = 17.527, P = 0.0075, Df = 6.

3.5. Association between malaria infection and sociodemographic factors.

The backward stepwise regression selection of predictors into the binary logistic model produced a series of model and, in this study, we only present the relevant, initial models and other outputs can be found in appendix 1.

Table 1 presents the backward stepwise (Wald) model summary and the Nagelkeke's R^2 in final step is 0.135 suggesting that malaria presence explained variation in the dependent variable in this model is approximately13.5%.

Table 1. Backward stepwise model summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	408.482[a]	.109	.151
9	413.304[b]	.096	.135
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			
b. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.			

Table 2 presents the Hosmer and Lemeshow test, indicating that this model fit the data.

Table 2. Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	8.558	8	.381
9	5.990	8	.648

Table 3 presents the classification table of the final model, that is, the model capability to predict malaria positive cases, indicating a model accuracy of 71.6%. The sensitivity of the final model in classifying malaria positive cases is 73.3 % and specificity of the final model to classify malaria negative cases is 93.3 %. The positive predictive value is 66 % and, the Negative Predictive Value is 72.5 % meaning that, the final model is able to predict 66 % of malaria positive tests and, 72.5 % negative malaria tests.

Table 3. Final backward stepwise (Wald) model classification table

Observed			Predicted		
			Malaria results		Percentage Correct
			Negative	Positive	
Step 1	Malaria result	Negative	218	22	90.8
		Positive	77	39	33.6
	Overall Percentage				72.2

Step 9	Malaria result	Negative	224	16	93.3
		Positive	85	31	26.7
	Overall Percentage				71.6
a. The cut value is .500					

Table 4 presents the Wald's test of significance and the odds ratio predictors variables in the final model. From the results, pervious malaria treatment ($p = 0.15$), population density ($p = 0.05$) and, age group ($p = 0.00$) were significant predictors while, household category did not add significantly to the model. The table indicates that the age category 0 to 4 years old as almost three times chance to test positive for malaria (OR 2.829, 95 % CI 1.153 – 6.944), 3.6 times (OR 3.61, 95 % CI 1.952 – 6.755) for age group 5 to 14 years and, 1.6 times (OR 1.603, 95 % CI 0.824 – 3.117).

Table 4. Final model Wald's of significance and odds ratio of predictor variables

		Constant (B)	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 9[a]	Previous malaria treatment	-.607	.249	5.941	1	.015	.545	.335	.888
	Population density	.000	.000	3.830	1	.050	1.000	1.000	1.000
	Household category	-.601	.315	3.651	1	.056	.548	.296	1.016
	Age category			18.890	3	.000			
	Age category (0 to 4 years)	1.040	.458	5.155	1	.023	2.829	1.153	6.944
	Age category (5 to 14 years)	1.289	.317	16.573	1	.000	3.631	1.952	6.755
	Age category (> 14 years)	.472	.339	1.934	1	.164	1.603	.824	3.117
	Constant	-.821	.305	7.232	1	.007	.440		

a. Variable(s) entered on step 1: Adult or child, Sex, Previous malaria treatment, Employment, Age, Cell phone, Education, Population density, Household size, HH category, Age category, Location

***B* = regression coefficients, S.E = standard errors, Wald = Wald test, Df = degrees of freedom, Sig. = Wald's significance, *Exp(B) (OR* = odds ratio, 95 % CI = confidence interval of the odds ratio**

The built model is:

g(Pi) = -.821 -.607 Previous malaria treatment + 1.040 Age category (0 to 4 years) + 1.289 + Age category (5 to 14 years).

Discussion

In this study, malaria prevalence was 31.6% for Sussundenga Village, much higher than the prevalence recorded in Chimoio city[17] of 20.1%. In the neighboring Zimbabwe, malaria prevalence was 19.5% in Mutare and 50.9% in Mutasa districts in 2016[18]. In southern Zambia a study in 2020, reported parasite prevalence between 0.7 and 1.8%[19] and, 34% in Malawi in 2016[20].

No difference was found between sex in this study. Similar results were reported in Chimoio, Mozambique in 2018[17], in Malawi in 2020[21] and in Zimbabwe[22] in 2021.

This study recorded half malaria prevalence in the 5 to 14 years age category and, OR of 3.61. In Ghana it was recorded 43.3 % and, in Rwanda the odds of infection by malaria were reported to be 1.817 times for this age category[23, 24]. Studies in Kenya indicated that highest malaria prevalence occurs in children between ages of 11 to 14 and, children from 5 to 18 years as the most at-risk age category[25,26]. Contrarily, in Chimoio, Mozambique it was reported 52% of malaria cases in children under five[17] and, the discrepancy may due to the fact that the present study was carried out at community level while, the Chimoio study was carried out from health center data.

This study suggests that recent diagnosis and treatment for malaria infection reduces the odds of subsequent infection approximately by 54.5 %. Similar results were reported in Mozambique, Ghana, Comoros, Kenya, Indonesia and India[27, 28, 29, 30, 31, 32, 33]. This reduction in odds is likely due to prophylactic effect of ACT. It provides protection usually 2 weeks to 1 month after completion. After repeated infections, the individual develops a certain degree of immunity. Also, when re-infected, patients present a mild form of the diseases without symptoms. Natural active immunity is established after ten or more *P. falciparum* infections, which can be sufficient to suppress symptoms and clinical signs[34].

Different results were reported in Angola where women who had a previous malaria infection during pregnancy also had a higher risk to contract malaria[35]. This is likely because pregnant women may take SP rather than ACT.

In this study population density was found as a significant predictor for an individual to test positive for malaria. Similar results were reported in Chimoio[17] in 2016, in a study in 14 endemic African countries[36] in 2017 and in Ethiopia[37] in 2015.

The variables age, if the person was an adult or child, sex, paid employment, cell phone ownership, education level, location (Bairro) and household size were removed from the model due to redundancy and for not adding significance to the model.

Age category is a good proxy for age group and, household size for household category. Paid employment ant cell phone ownership variables were included in this study, as rural wealth indicators and, were not found significant predators contrary to study in Mozambique that indicated that, Children from higher income families (58%) tend to be at lower risk for malaria compared to children from lower income families (43%)[38] and, in Sub-Saharan Africa[39] that, find malaria prevalence increases with decrease in income in 2018.

Education level was not finding significant predictor in this study. Similar results were reported in Malawi in 2018[40], Indonesia and India[32,33]. Different results were reported in Mozambique[38] in 2011, in Ghana in 2014 and in Sub-Saharan Africa[39] in 2018.

In this study it is suggested that approximately 13.5 % of the variation in malaria infection can be attributed to sociodemographic and economic traits. Previous study modelled the influence of climate on malaria occurrence in Chimoio and indicated that environmental traits accounted for malaria occurrence by 72.5%[7], implying that non-environmental

281 factors such as sociodemographic, economic, cultural and behavioral traits could partially
282 account for the remaining percentage, consistent with this result.
283 The Model using social, economic, and demographic variables capability to predict
284 malaria positive cases (model accuracy), was 72.3% in this study. A logistic regression
285 model analyzing hematological parameter and age in Ghana reported 77.4%[23]. The
286 sensitivity of the final model in classifying malaria positive cases was 73.3 % and the final
287 model was able to predict 66 % (positive predictive value) meaning that the model is very
288 effective in predicting malaria infection using socio demographic characteristics. In Iran a
289 model predicting malaria re-introduction reported 81.8% positive predictive value [40] and
290 52.72 % in Ghana in a model analyzing hematological parameter and age[26].

291 **5. Limitations of the study**

292 Data collection for this study was conducted in December and January during the rainy
293 and wet season which is also the peak malaria transmission season. Because of this, it
294 is likely that we detected a large number of infections and results reflect this season and
295 my not be representative of malaria dynamics in the dry season. The RightSign Biotest ^{R}
296 test detects the histidine rich protein 2 antigen of the *Plasmodim falciparum* parasite
297 which can last over a month in the blood among patients recently treated with malaria.

298 **6. Conclusion**

299 This study evaluated the sociodemographic factors that affect malaria prevalence in
300 Sussundenga Village, Mozambique. Recent diagnosis and treatment, population density
301 age category was found to be significant predators. The model accuracy was 72.3% and
302 implying that the model is robust. Targeting malaria control at the community level can
303 contribute to decreased transmission that may be more impactful than passive case

detection and treatment alone. This model indicates that 13.5% of malaria cases can be attributed to sociodemographic factors while previous studied indicated that environmental conditions are attributed to approximately 73 % of malaria cases. Further studies are needed specially in dry season and in other areas of the district to fully understand the malaria transmission dynamics in this region and inform efficient control measures.

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Figure Legends

Figure 1. Study area. **A.** Map of Mozambique, Manica Province and Sussundenga District: adapted from CENACARTA, Public, https://www.mozgis.gov.mz. **B.** High resolution imagery of Sussundenga village from Google Earth Pro™ **C.** Sampled site in Sussundenga Village: adapted from CENACARTA,Public, https://www.mozgis.gov.mz. **D.** Selected households from Google Earth Pro™.

Figure 2. Malaria positive and negative cases in Sussundenga Village

Figire 3. Malaria prevalence by age group in Sussundenga Village, INE = National Institute of Statistics

Figures

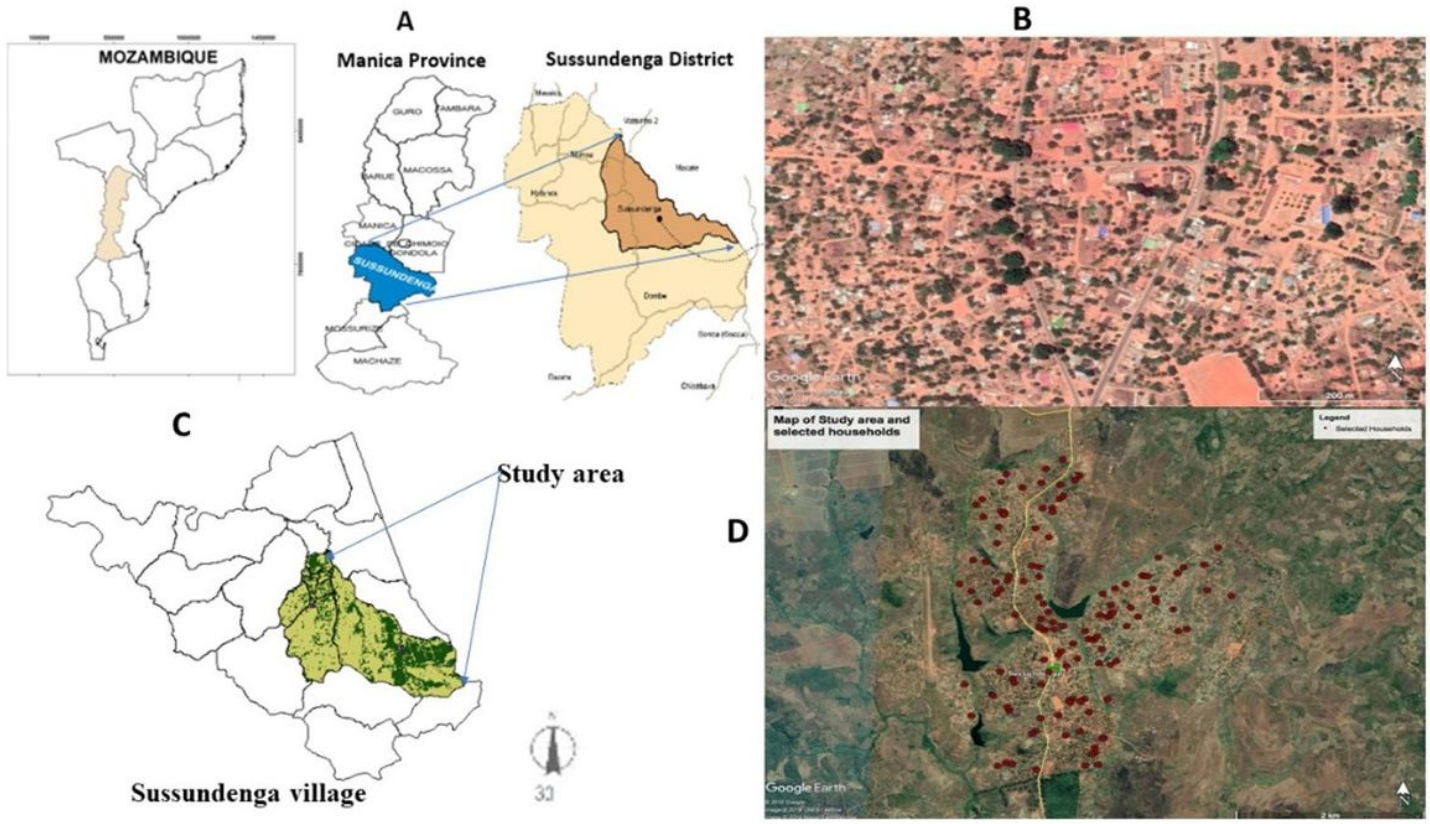

Figure 1

Study area. A. Map of Mozambique, Manica Province and Sussundenga District: adapted from CENACARTA, Public, https://www.mozgis.gov.mz. B. High resolution imagery of Sussundenga village from Google Earth ProTM C. Sampled site in Sussundenga Village: adapted from CENACARTA,Public, https://www.mozgis.gov.mz. D. Selected households from Google Earth ProTM. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

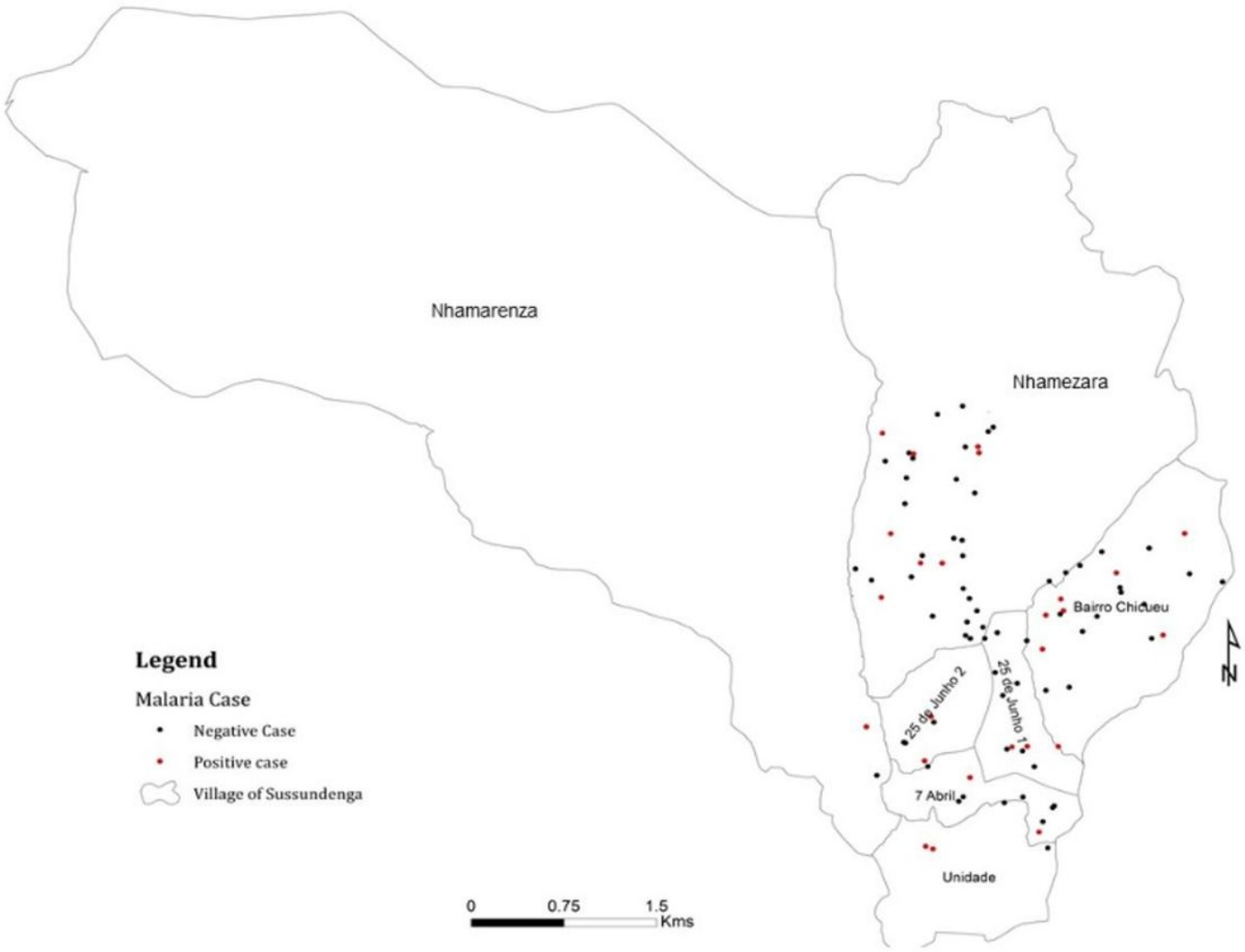

Figure 2

Malaria positive and negative cases in Sussundenga Village. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

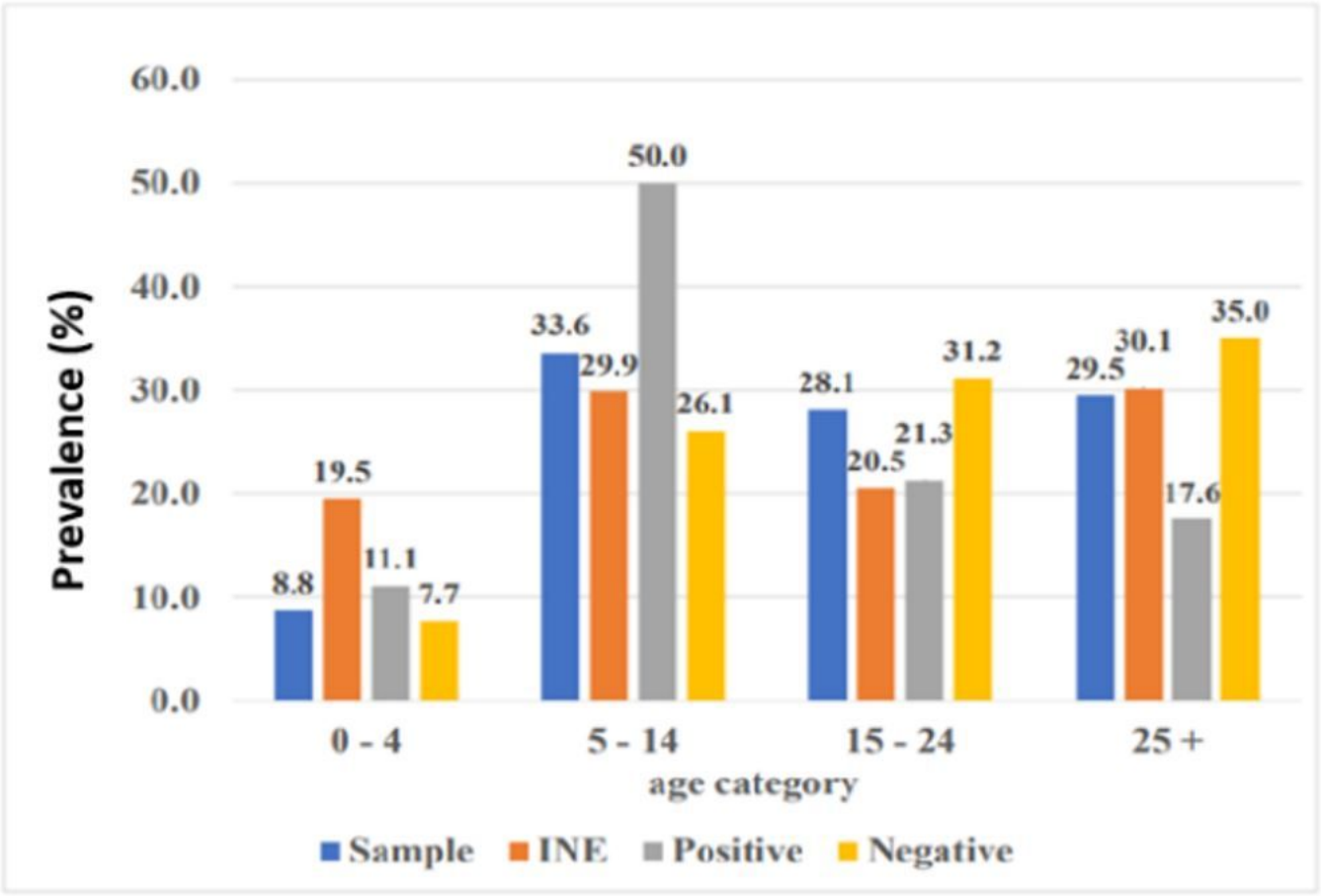

Figure 3

Malaria prevalence by age group in Sussundenga Village, INE = National Institute of Statistics

Supplementary Files

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