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# Malaria in Kenya during 2020: malaria indicator survey and suitability mapping for understanding spatial variations in prevalence and risk

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**Abstract.** Despite the availability of effective interventions malaria continues to be a major public health issue in Kenya, where young children and pregnant women are particularly vulnerable. In this study we examined the spatial distribution of malaria incidence and how this relates to the environmental conditions required for malaria in 2020. The Kenya Malaria Indicator Survey (N=11,549) for 2020 was used with the Local Indicators of Spatial Autocorrelation (LISA) method to determine spatial clusters of malaria and assess their significance as well as interventions in use. Climate data was used with a Fuzzy Overlay method to create malaria risk maps. The findings suggest that malaria incidence is not evenly distributed across Kenya, with some regions having higher rates of transmission and others having lower rates. High-rate clusters of malaria and high-risk areas of malaria transmission could benefit from increased vector control measures.

**Keywords.** Suitability mapping, prevalence, malaria, malaria indicator survey, spatial variation

## 1 Introduction

Malaria continues to be a major public health issue in many countries (Girum et al., 2019), including Kenya, where young children and pregnant women are particularly vulnerable (Girum et al., 2019). Despite the availability of effective interventions, such as indoor spraying and bed nets, malaria continues to pose a significant threat in many areas of Kenya, such as Western Kenya and the Coastal region. Kenya aims to reduce malaria mortality by 75% of 2016 levels by 2023 (Githure et al., 2022). If this is to be achieved, understanding the distribution of malaria and current control efforts are needed.

### 1.1 Malaria Survey

Malaria indicator surveys (MIS) provides valuable data on the current situation of malaria in the country (Guerra et al., 2019) as well as interventions that are in use (Guerra et al., 2019). The survey was designed to collect data on various socio-economic and demographic factors at a household level. MIS uses a two-stage stratified clustering sampling strategy to select county representative samples for accurate estimation of malaria prevalence, with a sample size of between 5,000 and 30,000 households. In 2020, surveys were geolocated.

### 1.2 Spatial Analysis of Malaria

Geographic information system (GIS), statistical and spatial analysis methods have been widely used to map malaria. For example, (Craig et al., 1999) used a fuzzy logic model and (Blanford et al., 2013) used geocomputational methods with host-pathogen-environment models to map areas suitable for malaria transmission to occur using temperature and rainfall information. (Hay et al., 2009) used Bayesian geostatistical methods with parasite prevalence information to map *Plasmodium falciparum* malaria endemicity while (Giardina et al., 2014) used similar methods to examine the effects of vector-control interventions on changes in risk of malaria parasitemia in sub-Saharan Africa. When risk surfaces are combined with population information, they are useful for assessing populations at risk. For example, in Africa it was determined that 53% of population live in high endemicity areas, 30% live in intermediate risk areas and 17% live in low stable risk areas (Hay et al., 2009). (Giardina et al., 2014) used Bayesian geostatistical methods to examine the effects of vector-control interventions on changes in risk of malaria parasitemia in sub-Saharan Africa. Lastly, (Warkaw et al., 2022) used Global and Local Moran's I, and auto logistic spatial binary regression model to determine spatial patterns and predictors of malaria in Ethiopia. They found that house characteristics (e.g., floor and roof-type) was important in determining malaria risk (Warkaw et al., 2022). However, according to our knowledge no studies have used the 2020 Kenya MIS data to study malaria clusters and how this relates to environmental drivers of malaria. Thus, the purpose of this study was to examine the distribution of malaria in Kenya and how malaria prevalence from the surveys relates to the environmental conditions required for malaria.

### 1.3 Study Area

Kenya, a country in East Africa with a population of 47,564,296 and has five malaria zones. The zones include coastal endemic along the East Coast (Mombasa and Taita Taveta), lake endemic region (Kisumu, Busia, Homa Bay, Bungoma and Kakamega), highland epidemic (Baringo, Trans-Nzoia, Uasin Gishu, and West Pokot), low risk areas (Nairobi, Nakuru, Nyandarua, Nyeri, and Turkana) and semi-arid and seasonal risk (Garissa, Mandera, Marsabit, Wajir, Bungoma, and Kakamega) (Gopal et al., 2019).

## 2 Methods

### 2.1 Data

### 2.1.1 Malaria Indicator Surveys (MIS)

MIS was obtained from Demographic and Health Survey (Kenya, 2021). Kenya MIS uses a two-stage stratified clustering sampling strategy to select county representative samples for accurate estimation of malaria prevalence, with a sample size of between 5,000 and 30,000 households (Figure 1). In each sampled household, children were tested for malaria using a rapid malaria diagnostic test (RDT), and RDTs is one of the initial malaria tests performed during the survey as it offers the possibility to expand the arrangement of exact malaria diagnosis to the region where microscopy services are not accessible (Gaston & Ramroop, 2020). GPS technology was used to record the geographical coordinates of each sample unit. The survey focused on school-aged children below 15 years old and interviewed women aged 15 to 49 years old in each household. The survey also included questions about use of mosquito nets and knowledge about malaria.

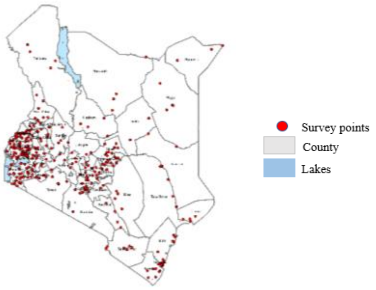



**Figure 1.** Spatial distribution of MIS household surveys conducted in 2020.

### 2.1.2 Climate data

Climate data for Kenya was obtained from the National Centres for Environmental Information (NOAA, 2020) for the months of August, September, and October 2020. These months coincided with when the MIS was conducted. Climatic variables included daily total precipitation (mm) and daily average temperature in degrees Celsius. Simple ordinary kriging method was used to create continuous temperature surfaces and rainfall surfaces. Surfaces were created for each month.

### 2.2 Spatial distribution of malaria

Rapid Diagnostic Test (RDT) result with categorical response "Positive" or "Negative" was used to map and measure malaria prevalence in Kenya. Prevalence for each geographical zone was calculated using the formula (*Prevalence = Positive cases/Total number of children*), and empirical Bayesian kriging (EBK) interpolation method was used to obtain continuous surface. EBK method performs better prediction than other interpolation methods (Krivoruchko & Gribov, 2019). ArcGIS Pro version 3.0 software was used to create malaria risk surfaces.

### 2.3 Spatial clustering of malaria

ArcGIS pro version 3.0 was used to perform cluster and outlier analysis (Anselin Local Moran's I). This method was used to identify statistically significant hotspots (high-high clusters), cold spots (low-low clusters), and outliers (high-low or low-high clusters) (Anselin et al., 2010). In summary, this method assess the malaria prevalence rates for each area with rates in surrounding areas at a fixed distance. In addition, the same method has been applied by (Fatima et al., 2021) to examine spatial clustering and outlier's detection of Covid-19 incidence in 2020.

### 2.4 Malaria Suitability Risk Analysis

A fuzzy overlay method was used to create a malaria risk map for 2020. This method includes both 'fuzzy membership functions' tool which allocates respective ratings for attribute values in a given thematic layer between 0 (unsuitable) and 1 (most suitable), and 'fuzzy overlay' tool, that merges multiple fuzzy membership results into the final map (Raines et al., 2010), (Joss et al., 2007). To do so, the average temperature for each month and total precipitation (August, September, October) were first reclassified into malaria suitability layers. Temperature raster was reclassified into 4 categories where 1 = unsuitable; 2 and 3 = somewhat suitable; and 4 as the most suitable. Precipitation greater or equal to 81 mm was assigned suitable (4) and anything below was assigned unsuitable (1). The risk categories used for temperature and precipitation are summarized in Table 1. These are based on the host-pathogen-environment relationship of malaria as described in (Blanford et al., 2013; Craig et al., 1999). Once each layer was classified, they were combined using the fuzzy overlay method (And) to create a malaria suitability risk map for Kenya for 2020. Thus, a spatial distribution malaria risk map was created by combining the temperature and precipitation map using the fuzzy AND operator.

**Table 1:** Suitability Categories and associated temperature and precipitation ranges.

| Reclassified group and associated risk | Temperature Range (°C) | Precipitation range (mm) |
|---|---|---|
| 1 (Low risk) | < 17, >30 | < 81 |
| 2 | 18 - 21 | |
| 3 | 26 - 30 | |
| 4 (High risk) | 22 - 25 | ≥ 81 |

## 3 Results

### 3.1 Malaria during 2020 in Kenya

Over 11,549 children were tested for malaria and 10% were positive. Twenty percent of positive cases were from the lake endemic zone, followed by low risk, highland epidemic, coast endemic and seasonal zone (Table 2); whereby twenty two percent of children aged 5 to 14 years and 20.5% of children below 5 years were positive. Twenty one percent of children owning nets tested positive for malaria, while 22.3% of the children without nets tested positive. Twenty-five percent of children living in rural areas were positive compared with 11.3% living in urban areas. Twenty-one percent and 21.4% of male and female children, respectively tested positive for malaria. Twenty-five percent of children from poor family tested positive compared with 21.9% from middle class families and 12% from rich backgrounds (Table 3).

**Table 2:** Proportions of positive cases from each malaria zone

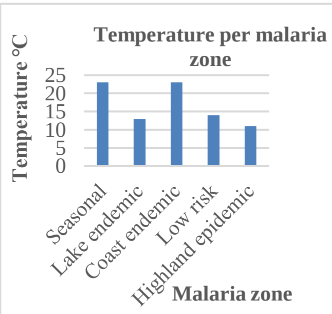
| Malaria zone | Percentage |
|---|---|
| Coast endemic | <1% |
| Lake endemic | 20.3% |
| Highland epidemic | 2.5% |
| Low risk | 4.0% |
| Seasonal | <1% |

Place of residence, and wealth index were significantly associated with malaria test results at 5% level of significance (Table 3).

**Table 3:** Characteristics of children aged 6 months to 14 years from Lake endemic zone (N = 4,664), 2020

| Variable | Categories | Positive (n=984) | P-value |
|---|---|---|---|
| Age | < 5 | 620 (20.5%) | **0.1629** |
| | 5 – 14 | 364 (22.3%) | |
| Ownership of nets | Yes | 808 (20.9%) | **0.3869** |
| | No | 176 (22.3%) | |
| Place of residence | Urban | 145 (11.3% | **< 0.0000*** |
| | Rural | 839 (24.8%) | |
| Gender | Male | 464 (20.8%) | **0.6565** |
| | Female | 520 (21.4%) | |
| Wealth index | Poor | 611 (24.9%) | **< 0.0000*** |
| | Medium | 236 (21.9%) | |
| | Rich | 137 (12%) | |

Monthly average temperature and total precipitation for 3 months (August, September, October) were calculated in each zone. Lake Endemic zone experienced the highest rainfall, and coastal, seasonal had the highest temperature (Figure 2).



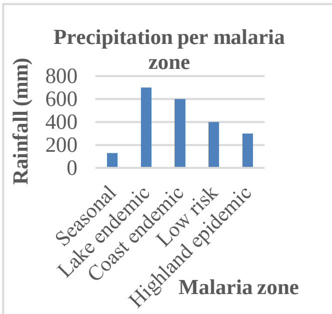




**Figure 2.** Total precipitation (mm) and average temperature (°C) in each of the malaria zones

### 3.2 Spatial distribution and risk of malaria during 2020

Children in the Western region were found to be at high risk of malaria compared to children from the Eastern-

Central region. Results from the survey found that malaria prevalence was highest in the Lake Endemic region (Figure 3a). This coincided with environmental conditions conducive for malaria (Figure 3b). Overall key malaria hotspots were found in the Lake Endemic region (Figure 3c).

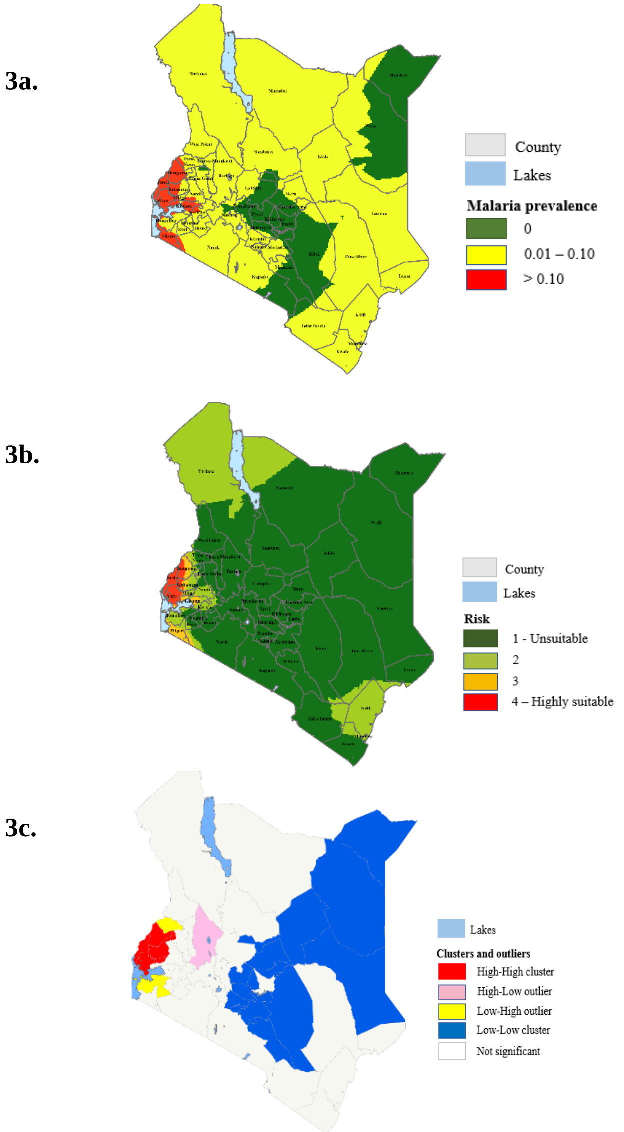



**Figure 3.** (a) shows spatial distribution of malaria in 2020, (b) shows suitable areas of malaria transmission, and (c) shows malaria clusters during 2020.

## 4 Discussion

The results showed spatial variation of malaria across Kenya. High rates were observed in the lake endemic zone, and low rates in the seasonal and low risk zones. The findings in this study were in line with previous findings (Noor et al., 2009) who also found high malaria transmission in lake endemic and coastal endemic zone and low transmission in low risk and seasonal zones. Based on the survey results and the climate risk maps, lake endemic and coastal endemic region climate are more suitable for vector survival resulting in higher risk of transmission. The proximity to Lake Victoria in Western Kenya is also believed to contribute to the high transmission risk. On the other hand, elevated temperatures experienced in Northern and Eastern regions are not suitable for vector development and transmission of malaria (Blanford et al., 2013). In addition, human mobility across the border may also be the reason for higher transmission in lake endemic zone (Wesolowski et al., 2012).

According to this study, prevention programmes should target counties of highest risk, and people should be informed of the risk and ways to reduce the transmission before the next survey. For example, in Western Kenya, increased resources for vector control, malaria testing, and treatment can be directed to those areas to reduce the burden of malaria. On the other hand, areas at low risk, it may be necessary to maintain ongoing monitoring and control efforts to prevent an increase in malaria transmission.

### 4.1 Limitation

The survey was conducted after the rainy season; therefore, malaria risk estimates may not be accurate during the highest transmission period.

### 4.2 Future research

This study only examined one year of survey data. Future work will examine multiple layers of information to explore how risk changes each year. In addition, to environmental factors, the use of mosquito nets, mother's malaria knowledge, the presence of mosquito species and the availability of health care services need to be examined further to ascertain the underlying causes of the spatial variation in malaria incidence in Kenya and determine what interventions measures are needed to help further reduce malaria.

### 4.3 Conclusion

The methods used here demonstrate how environmental data can be used to create real-time local seasonal risk maps. The maps can be used by government and malaria control programs to prioritize targeted intervention strategies in areas where high malaria transmission is likely.

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