Epidemic Malaria Dynamics in Eastern Africa Highlands: The Role of Climate Change and Human Population Growth

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Abstract: During the last two decades, researchers have suggested that the increase of the malaria incidence rate in tea plantations in the Kericho district in Kenya was driven by climate change. Critics suggested that other variables could be involved in the increase of the malaria burden, such as HIV and human population size. Population ecologists have developed a simple framework which helps to explore the contributions of endogenous (density-dependency) and exogenous processes on population dynamics. Both processes may operate to determine the dynamic behavior of a particular population through time. Briefly, density-dependency (endogenous process) occurs when the per capita population growth rate (R) is determined by its previous population sizes. An exogenous process occurs when some variable affects another but is not affected by the changes it causes. In this study we re-explore the dynamics of the malaria incidence rate in Kericho tea plantations taking into account the HIV incidence rate, rural population size, temperature and rainfall. We found that malaria dynamics showed signs of a negative endogenous process between R and malaria infectious class. We found that there was weak evidence to support the climate change hypothesis and that rural population size and the HIV incidence could interact to positively force malaria models parameters explaining the positive malaria trend observed at Kericho tea plantations in Kenya from 1979 to 2002.

Keywords: Malaria Dynamics, Climate, HIV, Population Size

1. Introduction

During the last two decades, researchers have suggested that the increase of the malaria incidence rate in tea plantations in the Kericho district in Kenya was driven by climate change [1-10]. These studies gave way to extensive debates about the importance of climate in the malaria burden in these locations. Critics suggested that despite the relationship between malaria and climate is evident, principally between seasons, other variables could be involved in the increase of the malaria incidence in Kericho tea plantations [11-13]. Globally, malaria literature suggests that the positive trends in malaria could be also affected by HIV [14, 15], climate [1-10, 16], poverty level [16], health campaigns [16- 18] and human population size [19]. In this study we re-analyze the data from period 1979 to 2002 (resurgence period) from Pascual el al study [4-6] and discuss the role of climate change, and other potential drivers for malaria dynamics in Kericho tea plantations.

Malaria endemcity and the burden of this disease have increased at the global level during the last centuries until 1955, when countries joined in a global effort to eradicate malaria [16, 17]. The use of quinine, chloroquine and indoor DDT reduced the malaria burden in many countries [14- 16]. After three decades of decline, around 1980, malaria started to rise and once again became a major health problem, principally in Sub-Saharan Africa [16, 20, 21].

During the same period (1980’s decade), the Human Immunodeficiency Virus (HIV) started to spread globally [14, 15]. Kenya ranks in the top six HIV High Burden Countries [14]. HIV may increase malaria contagion,
progression rates from latent to infectious stage and may delay the recovery of infected individuals, which increases the period in which an infected individual may transmit malaria. In addition, individuals only acquire malaria immunological defenses following several episodes. By affecting the immunological system, HIV removes the acquired defenses increasing the susceptible pool (the population at risk) [22-26]. Additionally, studies already showed that prevalence of HIV in tea plantations could reach almost 40% of the workers [26], suggesting that HIV increase could be involved on the increase of the malaria burden during the period ranging from 1979 to 2002 (Figure 1).

Malaria is a disease linked to climatological variables due to the aquatic life cycle of the Anopheles sp. larvae. Studies have pointed out that extreme climatological events (El Niño and La Niña) could affect malaria levels [27-29]. High temperatures accelerate larval development rate and the total number of eggs, boosting total mosquito biomass per season. Additionally, rain positively affects Anopheles sp. carrying capacity [30, 31]. Many studies have suggested that climate explains malaria seasonal fluctuations and anomalous outbreaks. Studies have shown an increase of temperature levels during the last decades in Kenya and suggested that temperature was the main driver of the increase of the malaria burden in the Kericho tea plantation (Figure 1) [1-10].

Kenya is a middle-income rural country [16]. The increase of human density in rural areas (i.e Kericho district) has many potential ecological effects that could increase the malaria burden. Increase of rural population size expands agriculture frontiers and in cities grow over natural rural areas. This expansion requires deforestation [16, 32-34]. Deforestation changes the aquatic food web structure where larvae develop part of their life-cycle, usually freeing larvae from predators. Deforestation may also increase the number of mosquito breeding sites and accelerates the mosquito life cycle by means of an increase in local temperature, resulting in high mosquito population biomass and plasmodium transmission in rural areas and small rural cities [4-6, 32, 33], like the Kericho district. Alonso et al [13] suggested that although temperature was the main driver of malaria dynamics in Kericho tea plantations, temperature could interact with rural population size and HIV prevalence, which we will consider in this study.

Climate change, HIV dispersion, rural population size are regional and global processes that could interact to explain the malaria dynamics in Kericho tea plantations [31]. Our main goal is to explore the potential interactions between climate, the HIV burden and rural population on the increase of the malaria burden in the period ranging from 1979 to 2002 in Kericho tea plantations.

Figure 1. Location of Kenya Kericho district showing the degree of deforestation (rural land, light green) and shows a degree of urbanization in rural areas at Kericho district. We present the Pascual data of malaria incidence rate, rainfall and temperature during the years at Kericho tea plantations. The HIV incidence rate and rural population size at Kenya national level, as alternative drivers of malaria dynamics at Kericho tea plantations.
2. Methods

Population ecologists have developed a simple framework, which helps to explore the contributions of endogenous and exogenous processes on populations. Briefly, density-dependency (endogenous process) occurs when the per capita population growth rate (R) is determined by its previous population sizes. An exogenous process occurs when some variable affects another but is not affected by the changes it causes. Climate variables and governmental disease control policies are known examples of exogenous pulse/press perturbations with relation to diseases. Both processes may operate to determine the dynamic behavior of a particular population through time [34-36]. Therefore, a more complete understanding of the dynamics of a population is achieved when both endogenous and exogenous processes are considered. Using this framework, recent studies have captured the trends of measles, tuberculosis and pertussis at city, country and global scales [37-39].

The ecological principles mentioned above have analogies in epidemiological processes. Following the introduction of an infected individual in a naïve population, the infected class is expected to grow exponentially driven by $R_0$, the basic reproductive number, since there are almost unlimited susceptible individuals (resources). Nevertheless, as the infected class grows, the susceptible pool is depleted and per infected transmission rate declines ($R_0$ becomes $R_S$, the realized reproductive number), a process known as self-limiting, analogous to the principle of intra-specific competition [37-39]. Higher infected class may increase contact rate enhancing transmission rate, analogous to the intra-specific cooperation principle. The realized that the per capita population rate of change ($R$) is the cornerstone of the framework adopted in this study [36-43]. $R$ can be estimated by the natural log differences between actual and past numbers of infected individuals, which are adopted in this work.

We used a simple linear regression between the malaria infectious class incidence rate and its rate of change to detect the sign and significance of the slope parameter, which suggest the principle; exponential (non-significant slope), cooperation (positive slope) and competition (significant negative slope). This exploratory process will suggest the basic model which could capture the general positive trend of malaria incidence rate in the Kericho tea plantations (from 1969 to 2002).

$$R_{II} = R_{max} - b \times I_{s,1} \tag{1}$$

where $R_{II}$ is the per capita growth rate, $R_{max}$ is maximum population rate of change (analogous to $R_0$), $b$ measures the impact of increasing incidence rate ($I_{s,1}$) on $R_{max}$. In advance, we found a negative correlation between $R_{II}$ and $I_{s,1}$, which can be capture by the following Ricker model:

$$R_{II} = R_{max} \left(1 - \frac{I_{s,1}}{K} \right)Q \tag{2}$$

where $R_{II} \text{, } R_{max} \text{, } I_{s,1}$ are as above and $K$ is the stable malaria incidence carrying capacity. $Q$ measures the degree of self-limiting around $K$. We also present the data from Pascual study using 4-month intervals. The goal is to identify distinct domain periods between $RI$ and $I_{s,1}$ to help to interpret non-linear regression results.

The effect of exogenous variables on malaria dynamics will be assessed using Royama methodology [40], whom classified three basic exogenous effects on the logistic model (Eq.2): vertical, lateral and non-linear effects. Vertical effects occur when the exogenous variable affects proportionally both $R_{max}$ and $K$, changing the intercepts (Eq. 3). Lateral effects occur when only the K is affected (Eq. 4), and the non-linear effects when the variable affects both $R_{max}$ and $K$, but disproportionally (Eq. 5). These three types of exogenous effects can be tested as follows [34]:

$$R = R_{max} \left(1 - \frac{I_{s,1}}{K + g + V} \right) \tag{3}$$

$$R = R_{max} \left(1 - \frac{I_{s,1}}{K} \right)^{Q + g + V} \tag{4}$$

$$R = R_{max} \left(1 - \frac{I_{s,1}}{Q + g + V} \right) \tag{5}$$

where $g$ is the linear coefficient that measures the effect of any exogenous variable on the self-limiting model parameters.

We include HIV incidence rate, Temperature ($^\circ$C), rain (mm) and rural population size as exogenous variables in Eq. 3, 4 and 5. We used the HIV national incidence rate and national rural population size from World Bank and World Health Organization websites, because there are no time series for these variables for Kericho area. We assumed that national trends are a proxy to what occurs at a smaller scale (Kericho tea plantation). We used Temperature and rain data from a Pascual study [4, 5].

In advance, using data from a period of four months between observations, we found three distinct logistic growth periods (see Figure 2). We also chose to analyze a shorter period (1978 to 1994), which corresponds to the second chronological logistic growth rate, avoiding the noise at the end of time series (1995-2002). We compared the results from both approaches (cut and uncut time series) looking for consistency between results. To address the effects of climate variables versus HIV and Human population size, we first analyzed models with and without climate variables. Secondly, we analyzed the effects of human population size and HIV without climate variables, and last, we analyzed the interaction of all variables on the logistic model parameters. The best model was selected based on the Akaike information criteria and $R^2$ (Coefficient of determination). Eqs. 1 to 5 were fitted using the nls library in R through non-linear regression analysis.

3. Results

We found that the malaria increase incidence rate could be capture by the logistic growth model (Table 1).
Table 1. The linear regression between the malaria incidence rate (It-1) and the per capita rate of change (RI). The malaria dynamics showed signs of the self-limiting process during the study period (negative slope).

| Response variable | Intercept (Rmax) | Pendent | Independent variable | P-value | R2 |
|-------------------|------------------|---------|----------------------|---------|----|
| RI                | 0.488            | -0.003  | I_{t-1}              | 0.0028  | 0.307 |

Table 2. The logistic model parameter estimations using four-months interval data from period 1969 to 2002. It shows an almost vertical dynamical change from 1979-1994 to 1994-2002 (Figure 1). Bold faces are for significant results.

| Parameters | Model | Variable | Period | Rmax | K  | Q  | R2   |
|------------|-------|----------|--------|------|----|----|------|
| Logistic   | Malaria| 1969-1979| 0.639  | 107.57| 0.876| 0.549|
| Logistic   | Malaria| 1979-1994| 0.734  | 295  | 1.085| 0.693|
| Logistic   | Malaria| 1994-2002| 2.793  | 755  | 0.52 | 0.861|

Models only including the interaction between rain and temperature had lower predictability and were less parsimonious than models with the interaction between climate variables and other variables, suggesting that climate had a low contribution to the increase of the malaria incidence rate in Kericho tea plantations from 1979 to 1994 and in 2002 (Table 3). Uncut and cut time series had similar results. Models with the interaction (lateral and vertical) between rural population size and HIV incidence rate performed better than models with climate variables and the model without exogenous variables (Table 3). These results suggest that these variables could be involved in the malaria increase burden as exogenous forcing on malaria endogenous model parameters leading to an increase in the malaria burden. These results are consistent with regards to the graphical R behavior changes with infectious class (Figure 2, 3 and 4). The models with non-linear effects (Eq. 5) delivered worse results (R^2 and AIC) than vertical and lateral logistic models (not shown here).
4. Discussion

The results suggest that other variables were more important than climate change in terms of the increase of malaria burden in Kericho tea plantations, as initially proposed in many studies from Kericho. In this study, we will discuss the manner in which the effects of HIV and rural population size could interact to explain the changes in model parameters.

Perhaps human population size could be the most important variable, because of its many effects. Rural population size increases the contact rate between infected and susceptible individuals by adding individuals inside the natural flying range of mosquitoes in households, villages and small rural cities (such as the Kericho district); creates mosquitoes breeding sites; leads to higher transport of individuals between localities dispersing and amplifying the geographical range of malaria endemicity and increases pollution (favoring mosquito abundance) in rural areas [13, 16, 19, 31-34, 40-44]. All these effects could increase malaria transmission and burden in Kericho tea plantations.

The HIV spread completes the scenario. HIV grew exponentially for most part of the study period at the country level in Kenya. One potential effect of a higher malaria burden is that individuals only acquire malaria immunological defenses following several episodes of re-infection. The spread of HIV incidence in rural populations could remove this potential positive effect (i.e. herd immunity). The interaction between malaria and HIV is suspected to be synergistic, because malaria-infected individuals show an increase of the HIV host cells in the immunological system. This could produce a longer period of the acute phase of HIV, increasing infectivity between
individuals and susceptibility to future malaria infections. Besides the synergy, the effects of HIV seem to be greater than the effects of malaria on the spread of HIV, because the infection period and AIDS stage may last for years reducing the immune defense efficiency [24, 25]. The spread of HIV expands the population at risk of contracting malaria [13-16, 21-26]. The effects of HIV could aggravate the effects of increasing rural population size and regional ecological changes affecting the model parameters of malaria.

We could even propose a simpler model only including rural population size as a vertical effect. The increase of population size could allow the spread of HIV increasing the pool of the susceptible population at risk to contract malaria. Additionally, habitat degradation near Kericho district could favor Anopheles increase. We believe that habitat degradation driven by the mentioned effects of population size had stronger effects than climate change in the malaria dynamics in Kericho tea plantations.

We did not want to rule out climate change. We believe that climate could always provide an initial set of potential variables which could influence the dynamics of malaria. The main factor is probably temperature, which can accelerate larval development rate (including more life-cycles per season) and reduce the differences between seasons. Local rises in temperature could interact with deforestation and the effects of HIV to explain the higher malaria incidence rate peaks at the end of the time series from Kericho tea plantations [1-10]. For example, Alonzo [13] found that rise of temperature in Kericho tea plantations was indeed the main driver behind the rise of malaria burden. But they also suggested that temperature could interact with the increases of the HIV burden and human population size to explain the malaria positive trends, as we tested and confirmed in this study.

Despite the observed increases in temperature, the malaria incidence rate in Kericho tea plantations declined from 2002 to 2010, which is suspected to be related to investments in malaria control programs in Kenya [14-18, 20, 29-31, 43-44]. In 2000, several countries joined in a global effort to halt and begin to reverse the incidence of malaria by 2015 (Millennium Development Goals 6- Target 6C). Kenya received international funding and developed efficient national strategies to achieve the Millennium Development Goals. Kenya invested in Artemisinin-based Combination therapy (ACTs), increased the distribution of insecticide-treated mosquito nets (ITNs), rapid diagnostic tests (RDTs) and the application of Indoor Residual Spraying (IRS). Studies have demonstrated that investments in malaria commodities like ITNs, IRS, ACTs and RDTs reduced the malaria burden in many regions including the Sub-Saharan region. The increase of malaria commodities could explain the decreases of the incidence rate of malaria at district and at regional levels, despite the rises of temperature, population size and regional ecological changes [14-18, 20, 29-31, 43, 44].

Additionally, literature suggests that declining HIV could be also involved in the decrease of the malaria burden. Between 2001 and 2011, HIV incidence was reported to have declined by >50% across 13 countries in sub-Saharan Africa. In 2004, USA made a massive investment to increase ART (Antiretroviral Therapy) coverage in Sub-Saharan Africa [2, 3]. ART is effective in preventing mother-to-child transmission and sexual transmission of HIV within couples. These correlated chronologies (malaria and HIV decline) may suggest that the malaria decline rate could also be related to HIV investments and interventions (ART coverage, education level, prevalence of male circumcision and condom use) along with the ITNs, ACTs and IRSs coverages during this period [14-18]. This suggests that efforts to control two linked diseases could interact in order to achieve the malaria Millennium Development Goals 6- Target 6C.

5. Conclusion

Here, we applied the Population Ecology Theory to re-explore malaria incidence rate dynamics in Kericho tea plantations. We present a distinct scenario to explain that others large-scale phenomena (HIV and rural population size) could have influenced the local malaria dynamics at a higher level than climate change from 1979 to 2002. Despite the many advances in malaria commodities, which could eradicate malaria from Kenya, the deforestation effects and high HIV burden could slow down the malaria burden decline and allow new epidemics episodes, under a potential scenario of any type of failure of the malaria control programs.

The framework employed is based on the realized per capita population rate of change (\(R_0\)), which is surrounded by plausible ecological principles and is hence an advantageous starting point to explore disease dynamics. Any government may disentangle \(R_0\) in its components (new per capita infections and per capita mortality), explore which of them are most important for \(R_0\) trends and explore the contributions of endogenous and exogenous processes. Hence, we suggest that this approach, based on simple principles based on population ecology theory, could be included as a supplement to WHO reports with minimal cost and time-demanding efforts, which could provide insights and hypotheses and may facilitate the testing and estimation of the drivers of disease dynamics.

Data Accessibility Statement

Malaria incidence rate, rain and temperature are available in published studies [4-6]. HIV and human population size data were obtained from World Bank (https://www.worldbank.org/) and WHO (https://www.who.int/) web sites.

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