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RESEARCH ARTICLE

The launch and operation of the malaria epidemic early warning system in Kenya.

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Abstract

Background

The climate based malaria epidemic early warning system for the western Kenya highlands was developed, tested and validated. During this process, it was critically important to involve key stakeholder to ensure a buy-in and institutionalization of the tool. The performance of the tool during a period of malaria intervention and climate variability was required.

Methods

Three stakeholders' events were held to brief them on the progress of the tool development. *Plasmodium falciparum* prevalence data for Kisii and Kakamega, two highland sites were extracted for the period 2002-17. Laboratory confirmed malaria case data were obtained for Mukumu hospital, Kakamega County. The malaria epidemic predictions were compared to the malaria prevalence and clinical case data.

Results

The involvement of the stakeholders resulted in their full support and institutionalization of the epidemic prediction system at the Kenya Department of Meteorology. The tool identified 8 epidemic events between 2011-18 in Kisii and 27 in Kakamega Counties. The malaria interventions prevented epidemics between 2011-14, However, an El Niño event in 2015-17 caused several epidemics in Kakamega and Kisii.

Conclusions

Due to the stakeholders' confidence in the tool, its predictions have consistently been used for determining if epidemic interventions are required. The epidemic early warning system indicates that climate variability is a threat to malaria control.

Introduction

Malaria in the East African Highlands occurs in endemic and epidemic forms while its transmission varies from hypo-hyper endemicity¹⁻³. The disease profile ranges from uncomplicated to complicated severe malaria⁴⁻⁶. During periods of epidemics, the disease incidence can escalate from 100-700% accompanied by high morbidity and mortality⁷.

The highlands of East Africa are highly populated and rich in agriculture thus forming an important economic zone in the region^{8,9}.

From the late 1900s until mid-2000 severe malaria epidemics occurred in the East African Highlands, often catching the health authorities by surprise¹⁰⁻¹². Many of the epidemics occurred during the short rainy season when they were unexpected. Later, the epidemics were associated with the El Niño weather phenomenon¹³⁻¹⁵. It was critically important to develop early warning systems so that the transmission risks could be identified before the epidemics evolved¹⁶⁻¹⁸. While the anomalous weather initiated the hyper-transmission, drug resistance and lack of vector control failed to prevent the evolution of malaria epidemics^{6, 19-21}. Later, the use of effective chemotherapy and vector control reduced the incidence of the epidemics although the climate risk remained. Afterwards, the 1997/8 El Niño event studies were initiated to develop a model for the western Kenya highlands. A model was developed for a site in the highlands and with a potential for application in other sites. The model showed that the epidemics were driven by anomalous temperatures and rainfall¹³.

In order for the tool to be used in the public health system it had to be tested in different ecosystems, further developed and validated. During this phase of the model development, it was discovered that the model performance was dependent on the drainage efficiency of the different ecosystems^{7, 22}. The models were tested and validated. They were found to have high sensitivity, specificity and positive predictive power⁷.

Experience has shown that stakeholder involvement is critical during the development and testing of the models. This gives the stakeholder a sense of ownership of the final product, failure to which major obstruction could occur at the launching stages of the product. It is important that the concept and function of the model is demystified to the end users of the product. Furthermore, this process promotes the institutionalization of the new tool^{23, 24}. To achieve this objective three events were organized to update the stakeholders including health experts, meteorologists, researchers, policy advisors and the print and electronic media.

The final stage of the development was to transfer the models from the research domain to the end users. While the models were domiciled and operated by the Kenya Meteorology Department, the main end user is the malaria control division in the Ministry of Health.

In this paper the results of the malaria epidemic early warning system's predictions and data interpretations from sites in western Kenya highlands are presented. The analytical framework includes the assessment of the implementation of the tool and the output of its application.

Methodology

Stakeholder engagement during the model development

Key stakeholders were identified from the Ministry of Health, World Health Organization (WHO) Country Offices, Departments of Meteorology, representative from Kenya Medical Research Institute, National Institute for Medical Research, Tanzania (NIMR), Ministry of Health Uganda, the International Centre for Insect Physiology and Ecology *ICIPE* and print and electronic media.

The first brief was held after 50% of the model development had been completed. The second brief was held after 100% of the development had been completed and the third brief after the models had been validated. Finally the models were automated and launched at the Kenya Meteorological Department in 2010.

Meteorological data collection

In Kenya, the models were designed to use weather data from Kericho, Kisii and Kakamega meteorological stations (Figure 1). Data were collected daily and electronically transmitted to the headquarters in Nairobi where they were validated. Monthly mean values of temperature and rainfall are calculated and fed into the models for the calculation of the risk of an epidemic. The threshold risk values for the results are checked for errors before they are disseminated by email to the end users.

Figure 1: Map of the study sites

***Plasmodium falciparum* malaria prevalence data collection.**

Long-term malaria parasitological data collection in some sites in the western Kenya highlands was in progress. Data from 2011–2018 was retrieved from the Ecology of African highland malaria project (University of California, Irvine) database.

Data reported here was collected at Marani, Kisii County (0.35° S, 34.48° E and 1,520–1,700m asl) and Iguhu, Kakamega County (0.10° N, 34.45° E and 1,430–1,580 m asl) as previously described^{22, 25}. Kisii has hypoendemic transmission while Kakamega County varied from hypo-hyper endemic transmission. Both Counties have a history of epidemic malaria. No malaria data was available for the Kericho (0.58°S, 35.19°E and 1,900 m asl) and Nandi sites (0.13°N, 35.10°E and 2,047m asl).

An epidemic is defined as an increase in malaria case or prevalence of greater than 100% in a month.

The proportional departure from the long-term monthly mean malaria prevalence was calculated. Values above 100% were classified as epidemics. However, in areas of very low transmission the outbreaks do not develop into true epidemics because the increased cases can be managed by the health system.

Clinical malaria data; St Elizabeth Mukumu Mission Hospital, Kakamega.

Laboratory confirmed malaria cases of all age groups collected monthly, 2011–2018, were obtained from the Nation health information system database, Ministry of Health Nairobi.

The long-term mean of the malaria cases was calculated from the data set. Thereafter the percent departure of the monthly total number of cases from the long-term mean was calculated as the monthly anomaly.

A value of >100% was classified as an epidemic.

Model operation, prediction and communication

Details of the model construction have been described^{7, 13}. Briefly, the model identifies anomalous temperatures occurring one month ahead of rains >150mm/month. In a poor drainage ecosystem, the rainfall threshold for hyper transmission is 200mm and 250mm in a well-drained ecosystem. The epidemic occurs 1–3 months after the rains. The model lags the temperature signal one month before the rainfall signal. This is a process based model that uses signal filters and logic statements to undertake the epidemic risk calculations.

Daily meteorological data were collected at Kericho, Kisii, and Kakamega stations. The data were transmitted to the Kenya Meteorological data center in Nairobi. Data were checked for errors before use.

Daily data from the three stations were aggregated and the monthly means calculated. The temperature and rainfall data were then fed into the models and the epidemic risk for each

site calculated. The Kakamega model has a threshold of 30% for the risk to be declared an epidemic while the Kisii and the Kericho/Nandi models have a value of 20% ⁷. The results were checked for errors before they were disseminated to the end-users in the Ministry of Health. The predictions were checked before action on interventions were undertaken.

Results

Launch of the models

When the final product was ready for launching, its approval and acceptance was over 95%. Following the testing and sharing of the performance results with the stakeholder, the models were put into operation at the beginning of 2011 at the Kenya Meteorological department, Nairobi. A meteorologist was assigned to run the models and communicate the results at the end of every month. The data were assessed by the malaria control division at the Ministry of Health. Where the risk of an epidemic was expected, extra drugs and diagnostic supplies were restocked. Extra insecticide treated nets were also supplied.

The model operations were occasionally affected by the breakdown of equipment. For example, no temperature data was available for the Kakamega station Sep 2016-Feb 2017. An epidemic signal was not detected (Figure 2).

Figure 2: Predicted epidemic risk in Kakamega, Kericho and Kisii from 2011-2018

Malaria prevalence

The National Malaria control program started the universal ITN program in 2011²⁶. Every two persons per house were supplied with an ITN following which malaria prevalence significantly decreased by 50-90% ²⁷. The old nets were replaced with new ones in 2014.

The mean *Plasmodium falciparum* malaria prevalence for 6-15 years old in Marani, Kisii was 3.3% and 13.2% for Iguhu, Kakamega after the ITN intervention in 2011.

Prior to the intervention, the mean *P. falciparum* prevalence was 21.4% for Iguhu and 4.9% for Marani.

Prior to the intervention, the 95% confidence interval for Marani was 3.5-6.2% Iguhu was 18.6-24.3%, while post intervention, the 95% CI for Marani was 2.5-4.2% and for Iguhu 11.9-14.5% (Figure 3).

Figure 3: Malaria prevalence in Iguhu and Marani from 2002-2017

Malaria infections in Marani have significantly declined and so has the deviation around the mean prevalence. The site is less susceptible to epidemics. Iguhu still has moderate prevalence and seasonal variability leaving it more susceptible to serious malaria out-breaks.

Active surveillance of malaria prevalence studies using school going children has a bias towards asymptomatic cases in contrast to passive hospital based surveillance.

Epidemics are characterized by a significant surge in clinical malaria cases.

Seasonal variation in clinical malaria cases, 2011-2018: Mukumu hospital.

The frequency of malaria epidemic signals predicted by the tool varies among the three sites with Kisii having 8, Kericho 13, and Kakamega 27.

It should be noted that 2014-16 were El Niño years with 2015-16 classified as a very strong event. Furthermore, 2016-17 had a weak event. Thereafter, 2018 was impacted by a positive Indian Ocean dipole resulting in severe flooding in Kenya, in April and May.

(<http://www.icpac.net/index.php/component/osdownloads/routedownload/monthly-bulletin-2018/june-2018-bulletin.html?Itemid=622>)

In Kakamega, the epidemic risks were identified in April between 2011-13. In contrast, the second half of 2014 was at high risk. Similarly, in 2015 the risk was high from February-November in 2016. The risk occurred after the long rains in April, while in 2017 the risk extended to the second half of the year. In 2018, the epidemic risks were identified in the first quarter of the year. It should be noted that extreme rains destroyed most of the mosquito breeding habitats.

In the Nandi/Kericho region, almost all the epidemic signals were detected in April and May.

The Kisii events were less consistent, however signals were more common in April but in some cases signals occurred in the second half of the year e.g. 2015.

In some years, cold temperatures suppressed the epidemic potential that were supported by heavy rains.

In Mukumu hospital, the mean number of confirmed malaria cases was 76.6/month between 2011-2018. Between 2011-2014, no epidemics occurred in Kakamega. In June 2015, the first epidemic occurred and the second one in October. In 2016, an unusual epidemic occurred between January and March which is normally the dry season. Serious epidemics were observed in the long rain season of 2017, and peaking at 879% departure from the long-term mean. An unusual epidemic occurred in September 2017, which is a normally dry period. The epidemics were associated with the El Niño event. Although for 2018 data was available up to June, a minor epidemic occurred in May but decayed in June after record rains in April (540mm) (Figure 4).

Figure 4: Malaria cases anomaly compared to the predicted epidemic risk from 2011-2018

Discussion

Following the malaria epidemics in East African highlands in the 1990s, it became clear that the epidemics were associated with climate variability and in particular the El Niño phenomena. The challenge was to develop a climate based malaria epidemic early warning system (MEWS) as a tool for managing this public health threat¹⁶. While the formulation of MEWS was a primary challenge, the institutionalization of the tool was quite another challenge^{13, 28, 29}. During this period, a divergent opinion was that epidemics were caused by lack of vector control and drug resistance. Data from this study indicates that despite the optimized distribution of insecticide impregnated bed nets and the use of effective antimalarial drugs, climate variability still generated epidemics.

Traditionally, most malaria transmission models are either statistical or dynamical. These two approaches have not been very successful as predictive tools for malaria epidemics and this has led to a degree of skepticism as to whether malaria epidemics are predictable in the modelling community³⁰. The problem in the models has been the failure to include environmental attributes that modify vector breeding habitats such as topography and hydrology⁷. Our models were developed to address the different ecosystems^{22, 31}.

Previous studies³²⁻³⁴ have shown that sea surface temperature anomalies are predictive of malaria epidemics in the African highlands and elsewhere. However, these predictive systems have not been implemented as a tool as public health utilities.

For the models to be accepted and adopted in the public health sector, it was necessary to involve key stakeholders at all critical stages of the development of the tool including its validation and launching. This procedure was implemented ensuring support and use of the tool. The media played a very big role in disseminating the development of the tool to the general public.

Coincidental with the launching of the MEWS was the launching of the universal distribution of the long lasting insecticide impregnated bed nets in malaria endemic areas in Kenya. This intervention lead to a significant reduction in malaria prevalence³⁵. The impact included a reduction of the frequency and intensity of malaria epidemics. In Kisii, the baseline prevalence was very low for the evolution of epidemics. However, there was a significant surge in malaria prevalence between 2014-17, an El Niño period. In Kakamega, the baseline prevalence was 4-fold that of Kisii, thus making this site more vulnerable to epidemics. Between 2014-17, epidemics occurred in Kakamega increasing the confirmed malaria cases by 100-800%.

The models identified several epidemic signals with Kakamega having the most and Kisii having the least. In general, the ongoing interventions prevented the epidemics between 2011-14. El Niño years were characterized by warmer temperatures, that accelerate mosquito and parasite development¹³.

The models indicated that climate variability remains a major driver of malaria epidemics in the western Kenya highlands. While the current interventions have reduced the frequency of the epidemics, the El Niño weather phenomenon can still generate malaria epidemics.

Apart from equipment failure, the models have performed as expected. In many cases, they have indicated that despite heavy rains, the prevailing temperatures do not support the evolution of epidemics. This has prevented launching of unnecessary and expensive interventions.

Data from this study suggests that a more robust response to climate induced malaria epidemics needs to be developed for the western Kenya highlands.

Conclusion

Due to the stakeholders' confidence in the tool, its predictions have consistently been used for determining if epidemic interventions are required. The epidemic early warning system indicates that climate variability is a threat to malaria control.

The different sites have different sensitivities and vulnerabilities to malaria epidemics depending on their levels of transmission and malaria prevalence. This can explain why epidemics may occur in some sites and not in others despite similar weather

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Authors' contributions

AKG conceived the study and drafted the manuscript. EO compiled the data and participated in the drafting of the MS, PM ran the models and provided the prediction data. GZ and GY provided the prevalence data while JS provided the malaria clinical data. All authors read the manuscript and contributed to the final paper.

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