Socioeconomic factors, climate change and malaria prevalence in Sub Saharan Africa

Abstract: This project analyzes how malaria prevalence is influenced by socioeconomic factors, climate anomalies, deforestation, and access to treatment in Sub Saharan Africa. Biomarkers of malaria prevalence, treatment availability and socio-economic data are measured at two points in time, from cross sectional, nationally representative biomarkers and social data covering 350 million people in Sub Saharan Africa. These health data (together with demographic, social and economic information) will be further linked to high-resolution precipitation, temperature and deforestation information. Spatial regression models will then be employed to analyze the effects these covariates have on malaria prevalence.

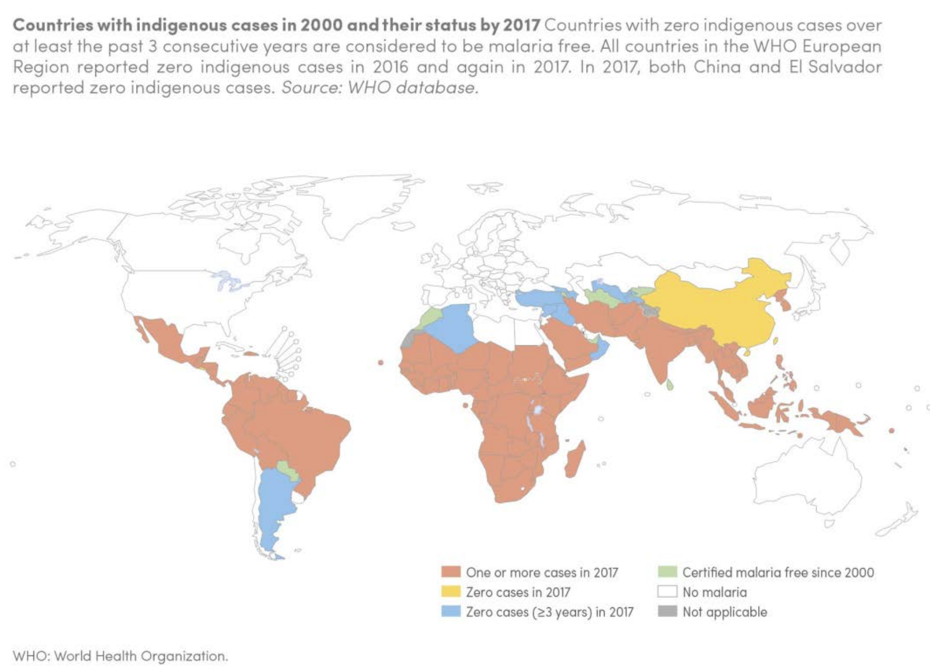
The research will advance the understanding of the connections between malaria prevalence and socio-economic factors/ access to treatment. While there is a wealth of literature focused on the climate- malaria link, there is no large-scale study in which all the most relevant factors (climate, land changes, socio-economic characteristics and access to treatment) are studied together on a large, nationally representative, scale.

Extended abstract

Introduction

Over the past decade significant advances have been achieved in the fight against malaria. Since 2010, there has been an 18% decrease in malaria incidence and 28% decrease in mortality worldwide. However, the number of malaria cases is still high (219 million in 2017), malaria parasites are increasingly resistant to artemisinin (a core compound in the most common antimalarial medicine), and malaria mosquitoes have developed insecticide resistance (WHO, 2019). 90% of malaria cases occur in Sub Saharan Africa and the decrease in incidence is not spatially homogeneous as some areas (in particular, highlands in Africa and Asia) have seen an increase in the number of cases (Chavez and Koenraadt, 2010). As a vector borne disease, malaria is affected both by environmental changes (rainfall, temperature, humidity, land cover) and socioeconomic factors. Environmental factors affect the density and development of the virus and vector population while the socio economic variables have an influence human susceptibility to the disease.

Figure 1. Malaria in the world



A number of studies have explained the spatially fine changes in malaria incidence as being a result of large scale variations in the atmosphere (Bouma 2003; Gagnon et al. 2002; Kovats et al. 2003), in particular through the changes induced by the El Niño–Southern Oscillation (ENSO) phenomenon. *Anopheles gambiae* - the major vector for *Plasmodium falciparum* in Africa – needs a temperature of 16°C -32°C (61° F - 90° F) in order to develop into an adult and thrive (Jepsonetal. 1947) with small amplitude variations in mosquito population between 20°C -26°C (68° F -79° F) (Beck-Johnson et al., 2013). The amount of rainfall has been shown to affect the abundance of larval habitats (Koenraadt et al. 2004), while rainfall anomalies was shown to influence the mosquitoes density (Lindblade et al. 1999; Chavez and Koenraadt, 2010). Humidity – a result of temperature and rainfall – affects the lifespan of the mosquito (Clements 1999) but its influence seems to be strongly spatially connected. Within African contexts, relative humidity levels were associated with malaria incidence in Burkina Faso (Ye et al. 2007) although they were not correlated to vector density in Uganda at high altitude (Lindblade et al., 2000). Proximity of water bodies increases mosquitoes' densities and , as such, malaria incidence (Bøgh et al., 2007; Lautze et al., 2007; Oesterholt et al., 2006; Staedke et al., 2003; Minakawa et al., 2004)). Vegetation creates microhabitats in which conditions are better for mosquitoes than in areas without vegetation and, as such, it might increase their life span (Clements 1999; Chavez and Koenraadt, 2010). Deforestation reduces shade and alters rainfall patterns and "increases surface water availability through the loss of topsoil and vegetation root systems that absorb rain water" (Yasuoka and Levins, 2007). In East Africa, deforestation has been shown to increase significantly mean temperature and variability which, in turn, affect the survival of the malaria vectors (Afrane et al. 2006; Lindblade et al. 2000).

A comprehensive literature review of the articles published in English between1990-2009 (Mbaso and Ndlovu, 2011) on the topic of malaria and climate records no study in which also accounts for socioeconomic factors relevant to malaria incidence or mortality. Overlooking socioeconomic factors is likely due to the data used in prior work; the great majority of data on malaria cases come from hospital/clinics data and this data is not generally attached to any socioeconomic. However, socioeconomic factors including housing conditions, poverty, agricultural development, population movement, and urbanization affect malaria transmission. For example, poverty is associated with malaria incidence as : children of the poorest households tend to have higher incidence of malaria than do children from more advantaged households (Clarke et al. 2001). Though socioeconomic conditions like poverty have long been considered fundamental causes of disease (Link and Phelan 1995), mechanisms such as malnourishment and malnutrition (in particular, lack of vitamin A, zinc, iron, folate, and other micronutrients) demonstrate pathways linking poverty and malaria morbidity or mortality (Caulfield et al., 2004). Similarly, accesses to health services, high education, and socioeconomic development have been shown to decrease malaria incidence in communities around the world (Bouma, 2003, Yasuoka et al. 2006; Lindsay and Birley, 2004).

In this paper, we add to the existing literature by analyzing how climate, socioeconomic variables, access to treatment and landscape changes jointly affect malaria prevalence in Sub Saharan Africa.

Data and methods

For this research we combine three types of datasets: socio-economic and health datasets, climate data and deforestation information. These datasets will be linked through the GPS information. We will use spatial regressions and spatial correlations to analyze these connections.

Socio-economic and health datasets

We use the Demographic and Health Surveys (DHS) to gather the socio-economic and health information. The DHS use nationally representative samples of at least 8,000 households and implements a standardized questionnaire that can include, for some countries and in certain years, information on malaria prevalence (through biomarker testing), availability of malaria treatment as well as GPS information for the households included in the sample. Given our research interests, we will use the following DHS datasets (the only ones surveys for Sub Saharan Africa that contains all the information mentioned above):

Angola: 2011, 2016
Burkina Faso: 2014, 2017
Mali 2010, 2015
Mozambique 2011, 2015
Nigeria 2010, 2015
Rwanda 2013, 2017

Senegal 2008, 2016

Uganda 2009, 2016

DHS employ clustered stratified samples of population: they use the most recent available census framework to divide the population into sectors (based on census tracts) and then select a representative bi-stratified sample of households from within these areas. This results in around 1000 clusters with up to 30 households each; the GPS information made available gives the latitude and longitude of the cluster center.

Climate Data

High density and comprehensive observational networks of meteorological data or high spatial resolution gridded data would have facilitated our analyses, but these data are not available for all countries of interest. Therefore, in this study we used relatively coarse resolution gridded (0.5° by 0.5° latitude and longitude; ~ 53 kms) monthly total precipitation, average temperature, and maximum temperature data for 19811981–2018 period from the Climate Research Unit[1] (CRU TS v.4.03; Harris, et al., 2014). The gridded dataset is generated from monthly observations at meteorological stations covering the global land surface. CRU data have been widely used in a variety of climate and public health related studies (e.g., Karmalkar, et al., 2011; Lehmann, et al., 2015; Swain and Hayhoe, 2015; Colón-González, et al., 2018). For this analysis, we performed a bilinear interpolation on the original data (0.5° by 0.5° grids) to develop a re-gridded CRU database at a resolution of 0.025° by 0.025° latitude and longitude (~ 3-km).

In terms of climate measures, we use indicators such as anomalies in monthly precipitation, maximum temperature, and average temperature to analyze the impacts of temperature and precipitation on malaria prevalence in the study area. We first calculated three climate indicators such as anomalies in precipitation, maximum temperature, and average temperature using the CRU data corresponding to the months of survey data collection. We then overlaid the GPS points on the climate indicator maps and extracted the grid cell values corresponding to the GPS points. So only the GPS points (within same month of data collection) that fall on the same 3-km grid would have the same climate data. Precipitation anomalies were

[1] https://climatedataguide.ucar.edu/climate-data/cru-ts321-gridded-precipitation-and-other-meteorological-variables-1901

calculated as the current month's total precipitation minus the average total precipitation for that month for a 30-year historical period (1981-2010), divided by the current month's total precipitation. Temperature anomalies were calculated as current month's maximum and average temperatures minus their respective 1981-2010 monthly averages. We then calculated the climate indicators at the cluster level

Deforestation data

We will use a high-resolution global forest change (GFC) dataset to derive deforestation information for the study area and time period (Hansen et al. 2013). GFC characterizes forest cover loss, defined as a complete removal of tree stands, at 0.00025° × 0.00025° spatial resolution (~28 × 28 meters at the equator) for every year from 2001 to 2018. This satellite-based high-resolution dataset is globally consistent and thereby allows local-scale analysis across the study area. For each centroid of the clustered DHS sample, we will create a buffer circle around the centroid with a 10-km radius. We will match the exact beginning and ending years of the DHS data for each country and compute the total area and percentage of forest loss within each buffer.

Preliminary results

One of the most debated topics nowadays is whether or not climate change is the main factor that accounts for the changes in the distribution of malaria cases as the incidence is increasing in the highlands while decreasing everywhere else. Our preliminary results suggest that, while changes in climate made possible the spread of the *Anopheles gambiae* at higher altitudes than before, socioeconomic factors (high poverty and restricted access to treatment in the highlands of Africa) play a significant role as well. This suggests that when malaria evolution is modeled within the context of climate change, there are direct effects that the Shared Socio Economic Pathway have on malaria and they need to be taken into account.

Selected References

Beck-Johnson, Lindsay M., William A. Nelson, Krijn P. Paaijmans, Andrew F. Read, Matthew B. Thomas, Ottar N. Bjørnstad. 2013. The Effect of Temperature on *Anopheles* Mosquito Population Dynamics and the Potential for Malaria Transmission. PLoS One. 2013 Nov 14;8(11):e79276. doi: 10.1371/journal.pone.0079276. eCollection 2013

Breman, Joel G., Martin S. Alilio, and Anne Mills. 2004. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. *Am. J. Trop. Med. Hyg.,* 71(2): 1–15

Caulfield L, Richard SA, Black R. 2004. Undernutrition as an underlying cause of malaria morbidity and mortality. *Am J Trop Med Hyg* 71(2): 55–63

Chaves, Luis Fernando and Constantianus J. M. Koenraadt. 2010. Climate Change and Highland Malaria: Fresh Air for a Hot Debate, The Quarterly Review of Biology , Vol. 85(1):27-55

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., & Townshend, J.R.G. 2013. High-resolution global maps of 21st-centry forest cover change. Science, 342, 850-853

Karmalkar, A. V., Bradley, R. S., & Diaz, H. F. (2011). Climate change in Central America and Mexico: regional climate model validation and climate change projections. Climate dynamics, 37(3-4), 605.

Link BG and Phelan J. 1995. Social conditions as fundamental causes of disease, J Health Soc Behav. Spec No:80-94

Patz, J.A., Daszak, P., Tabor, G.M., Aguirre, A.A., Pearl, M., Epstein, J., Wolfe, N.D., Kilpatrick, A.M., Foufopoulos, J., Molyneaux, D., Bradley, D.J., and Members of the Working Group on Land Use Change Disease Emergence. (2004). Unhealthy landscapes: Policy recommendations on land use change and infectious disease emergence. Environmental Health Perspectives, 112(10), 1092-1098.

Patz JA, Graczyk TK, Gellera N, Vittor AY, 2000. Effects of environmental change on emerging parasitic diseases. Int J Parasitol 30: 1395–1405

Smith, K.R., A.Woodward, D. Campbell-Lendrum, D.D. Chadee, Y. Honda, Q. Liu, J.M. Olwoch, B. Revich, and R. Sauerborn, 2014: Human health: impacts, adaptation, and co-benefits. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel,A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 709-754.

Swain, S. and Hayhoe, K. (2015). CMIP5 projected changes in spring and summer drought and wet conditions over North America. Climate Dynamics, 44(9-10), 2737-2750.

Wyndham, C.H. (1969) Adaptation to heat and cold. Environmental Research, 2(5), 442-469

Yasuoka J., Levins R. 2007. Impact of deforestation and agricultural development on anopheline ecology and malaria epidemiology. *American Journal of Tropical Medicine and Hygiene* 76(3): 450 – 460