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An Integrated Modelling Approach to Climate Change and Malaria Vulnerability Assessments

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Abstract: Malaria is one of the key research concerns in climate change-health relationships. Numerous risk assessments and modelling studies providing evidence that the transmission range of malaria will expand with rising temperatures resulting in adverse impacts on vulnerable communities. This risk is significant in East Africa whereby current research shows an expansion of malaria into the highland areas due to changes in temperature and rainfall. While there exist multiple lines of evidence for the influence of climate change on malaria and the risk posed to vulnerable communities, there is insufficient understanding of the complexity of factors influencing the spread of the disease at the community level. This paper considers assessment of risk of malaria infection due to climate change, from systems perspective. Drawing upon published literature, we apply systems approach to propose a detailed conceptual model that illustrates causal relationships between the multiple drivers of malaria transmission in line with the current Intergovernmental Panel on Climate Change recommendations for risk and vulnerability assessments. We suggest that this framework can be applied at a community level using both quantitative and qualitative methods with stakeholder engagement and in conjunction with Bayesian Belief Network to models to: explore how policy and management interventions can reduce the risk of malaria infection and; provide targeted adaptation strategies that incorporates both the scientific and the community perspectives.

Keywords*:* integrated modelling; vulnerability and risk assessment; climate change and malaria transmission; systems approach

1 INTRODUCTION

Malaria kills over 500,000 people each year, mostly children in sub-Saharan Africa. The disease is very sensitive to climate change and climate variability, particularly in East Africa, where future changes in climate are projected to increase its spread (Caminade et al., 2014; Tonnang et al., 2014). Also, other important ecological, socioeconomic and sociodemographic factors, such as land use change, gender, age, human immunity, population growth, migration and transportation and levels of economic development have an influence on risk of malaria infection. A sufficiently accurate determination of risk must include the relative contribution this array of influences at multiple scales including those operating at the local level. It is also important to understand the extent to which affected communities are exposed to this risk and how well they are able to cope i.e. their vulnerability. Vulnerability is determined in part by human activities or interventions at the local level, which may far outweigh the negative impacts of climate change. Therefore a robust vulnerability assessment must not only take into account the impact of the climate-induced hazard to the population, but also the heterogeneity of the population and in malaria transmission, the differences in topography and hydrological characteristics of the landscape and other biological and socio-economic influences of transmission (Alonso et al., 2011; Paaijmans et al., 2014). Although there are general guidelines on vulnerability assessments, there is not one accepted method and there are few vulnerability assessments on climate change and malaria in East Africa in published literature (Bizimana et al., 2015, 2016; Hagenlocher and Castro, 2015; Kienberger and Hagenlocher, 2014). While these studies provide useful tools for decision-making, they do have some limitations; There is an assumption of homogeneity of the population and landscape, which suggests uniformity of indicators while the reality is that there are differences in population and possibly even topography that will have an impact on the influence of indicators (Bizimana et al., 2015; Hagenlocher and Castro, 2015; Kienberger and Hagenlocher, 2014). Other limitations included incompatibility of models with data that was not available in a spatially disaggregated format such as acquired immunity to malaria, availability of malaria drugs, migration patterns, quality of the healthcare system, personal beliefs, behaviours and social networks (Bizimana et al., 2016; Hagenlocher and Castro, 2015). Furthermore, these studies only provided an assessment of social vulnerability to malaria and none considered climate change/variability and related uncertainties as well as biophysical and social vulnerability at the same time. These factors are interdependent in driving malaria transmission risk therefore they must be considered as a system. This paper addresses some of the limitations of this previous research by using systems dynamics approach for assessment of vulnerability and exposure of societies from climate change and malaria impacts. We developed a detailed conceptual systems model of climate change and malaria transmission. The conceptual model represents the complementarity of sociological and ecological systems in influencing diseases, and conforms to the current IPCC framework for risk and vulnerability, which recognises that risk of climate hazards can occur due to many influences (IPCC, 2014a, 2014b). This framework can be operationalised using Bayesian Belief Network (BBN) models to develop simulations of how the different variables interact under different future scenarios for policy and management intervention.

2 METHODS

Building the systems conceptual model is an iterative process. While there isn't a set standard for this type of modelling, there are some common steps as described by Sterman (2000), and Voinov (2010), which we adapted for our modelling process (Figure 1). This approach captures our contextual and expert knowledge of the system and then subjects the information to a structural analysis, which was then used to formulate a conceptual model in the form of a causal-loop diagram (CLD).

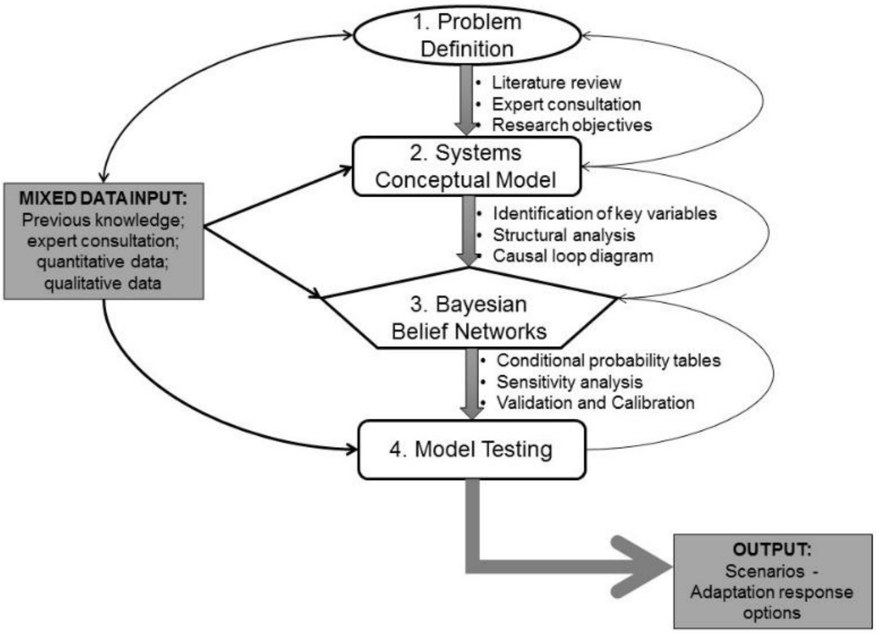

Figure 1. A flow chart showing the systems modelling process adapted from Sterman (2000) and Voinov (2010)

2.1 Problem Definition

Comprehensive reviews of climate change and malaria transmission have been covered in other papers (Martens and Thomas, 2004; Protopopoff et al., 2009; Sutherst, 2004). Other studies have developed suitable environmental, socio-demographic and behavioural indicators of malaria risk at regional, community and household levels (Bates et al., 2004a, 2004b; Ernst et al., 2009; Protopopoff et al., 2009; Sutherst, 2004; Wandiga et al., 2009). The experts selected were three key academics well versed in climate change, malaria transmission and climate change-malaria research in East Africa. They were provided with contextual information regarding the research and were interviewed on their knowledge of the connections between climate change and malaria transmission. We used this previous knowledge and expert consultation to capture relevant knowledge about the system and to identify variables influencing risk of malaria infection in East Africa and the relationships between them. The experts were also involved in the structural analysis phase as described in the next section.

2.2 Structural analysis

The malaria transmission cycle is a complex system with multiple non-linear and often interacting variables of climate change, environmental, biological and socio-economic influences. Conceptualising such a system can be a challenging process however; there are tools such as the Cross-Impact Multiplication Method (CiMMM) (Godet, 2001) that are useful for structural analysis and conceptual modelling. The structural analysis method followed a multi-phase participatory process to generate ideas among the research team and experts on how the system works in order to identify and rank key influential variables. The structural analysis process followed a four step method: a) Identification of all variables from literature review and expert consultations (Table 1); b) Description and ranking of the relationships between variables based on the degree of direct influence using our previous knowledge and validation of the relationships by the experts; c) Identification of key variables using MICMAC approach i.e. Impact Matrix Cross-reference Multiplication Applied to a Classification, which calculates the intensity of influence and dependency between variables and; d) The MICMAC analysis provides us with the relationships between key variables of the system through an analysis of the impact matrix by generating a map of direct influence, which separates the variables into four types according to degree of influence: i) Influential variables i.e. variables that influence the system, but are not dependent on other variables; ii) Relay variables, which influence the system and are dependent on influential variables; iii) Dependant variables, which represent the system's output variables and; iv) Autonomous variables, which are neither influential nor dependent and do not significantly affect the system.

2.3 Construction of the Systems Conceptual Model Using Causal Loop Diagrams (CLD)

After the structural analysis phase, we designed a CLD to map and visualise the nature of the relationships among key variables in the systems. This allows us to understand the relationships between the system's components and the system's dynamics. In a CLD, the variables are connected or linked by arrows that indicate a causal relationship. The direction of the arrow indicates the direction of causality while the polarity sign at the tip of the arrow (+ or -) indicates whether the relationship between the two variables is positive or negative. The CLD was visualized using the free software Vensim PLE for Windows Version 6.3D.

3 RESULTS

3.1 Identification of variables

Based on our contextual knowledge, key insights from expert interviews and key literature, a list of 34 variables in the climate change and malaria transmission cycle were identified and grouped in biophysical and socio-economic indicators (Table 1).

Table 1. Variables in climate change and malaria transmission identified from literature review and expert consultation.

Biophysical Variables			
Nº	**Variables**	**Description**	**Source**
1.	Transmission temperature (air)	Temperatures suitable for malaria transmission i.e. between 16 °C to 34 °C	Protopopoff et al., 2009; Sutherst, 2004
2.	Water temperature	Suitable breeding temperature for mosquito habitat	Sutherst, 2004
3.	Precipitation	Average monthly rainfall; rainy season	Protopopoff et al., 2009; Wandiga et al., 2009
4.	El Nino	Periods of extreme rainfall	Protopopoff et al., 2009; Wandiga et al., 2009
5.	Altitude	Height/distance above sea level	Protopopoff et al., 2009

6.	Micro-habitat changes	Changes in mosquito habitat micro-climate due to loss of forest cover or other environmental controls such as clearing of bushes.	Sutherst 2004
7.	Topography	Physical land surface including hills and valleys	Ernst et al., 2009; Protopopoff et al., 2009
8.	Wetlands and water bodies	Proximity to swamps or other stagnant water bodies	Ernst et al., 2009
9.	Bare areas	Land without forest cover or other vegetation	Ernst et al. 2009
10.	Forest edge	Human proximity to forest boundaries and potential exposure to exposed mosquito breeding sites due to deforestation	Ernst et al., 2009
11.	Agriculture	livestock and maize farming, swamp drainage and farming and small-scale irrigation	Bates et al., 2004a; Ernst et al., 2009; Protopopoff et al., 2009
12.	Vector abundance	Increase in numbers of malaria mosquitoes	Sutherst 2004
13.	Vector biting	Chances of an infective bite from mosquito	Protopopoff et al., 2009
14.	Vector infection rate	Efficiency of transmission and infection with the malaria parasite by the mosquito	Protopopoff et al., 2009
15.	Vector adaptive behaviour	Changes in mosquito vector behaviour such as early biting or indoor resting	Expert input
16.	Population under 5 years	Number of individuals under five years old	Bates et al., 2004a; Protopopoff et al., 2009
17.	Immune status	Lowered immunity to malaria due to pregnancy; acquired immunity to malaria from long term exposure	Bates et al., 2004a; Protopopoff et al. 2009
18.	Interactions	Coinfections with other diseases such as HIV increase likelihood and severity of infection	Bates et al., 2004b; Protopopoff et al., 2009
19.	Drug resistance	Resistance of the malaria parasite to drugs/ parasite evolution	Bates et al., 2004b; Protopopoff et al., 2009; Wandiga et al., 2009
Socio-economic Variables			
20.	Urbanisation	Expansion of urban areas and overcrowding in cities	Bates et al., 2004a; Sutherst, 2004
21.	Population Migration / travel	Movement of people from low risk areas to malaria endemic or epidemic-prone areas and vice versa	Bates et al., 2004a; Protopopoff et al., 2009
22.	Nutritional status	Poor health as a result of undernutrition or malnutrition	Bates et al. 2004a; Protopopoff et al. 2009
23.	Gender	Gender roles, expectations and cultural customs	Bates et al. 2004a; Protopopoff et al. 2009
24.	Poverty	Socio-economic conditions; household income, food and household assets	Bates et al., 2004a; Protopopoff et al., 2009; Sutherst, 2004
25.	Religious beliefs	Religion or superstitions in managing malaria and/or climate change impacts	Bates et al., 2004a; Wandiga et al., 2009
26.	Perception	Knowledge and understanding of disease	Bates et al., 2004a; Ernst et al., 2009; Wandiga et al., 2009
27.	Type of house	House with grass-thatched roof and mud walls, brick house with tiled or aluminium roof; house with separate kitchen, house with ceiling and house with open eaves	Bates et al. 2004a; Ernst et al. 2009; Protopopoff et al. 2009
28.	Education level of household head	Education level of male or female head of household	Ernst et al. 2009
29.	Health-seeking behaviour	Willingness to seek treatment for malaria; households with malaria medicine in stock, self-medication, traditional treatments	Bates et al. 2004a; Protopopoff et al. 2009
30.	Mosquito net use	Use of insecticide-treated bed nets to prevent malaria infection	Ernst et al., 2009; Wandiga et al., 2009
31.	Environmental controls	Clearing bushes around households, safe disposal of plastics and other water-retaining containers	Ernst et al. 2009; Wandiga et al., 2009
32.	Quality of health systems	Health services and policy; availability of health facilities; access to healthcare; quality of healthcare and capacity for malaria treatment	Bates et al., 2004b; Protopopoff et al., 2009; Wandiga et al. 2009
33.	Malaria vector control	Distribution and coverage of insecticide-treated bed nets by the government; Coverage of households sprayed with malaria insecticide (indoor residual spraying)	Protopopoff et al. 2009; Wandiga et al. 2009
34.	Quality of information	Reliable and easy to understand information systems for communicating weather and climate information or early warning systems for malaria epidemics; outreach and education for malaria prevention	Wandiga et al. 2009; Bates et al., 2004b

3.2 Structural Analysis – Cross matrix multiplication methods (CiM3)

Structural analysis revealed the relationships between variables ranging from strong to weak. The strongest influential variable identified from the structural analysis were El Niño, agriculture and air temperature; relay variables were vector biting and vector abundance and the main dependent variable was vector infection rate while the rest of the variables were autonomous (Figure 2).

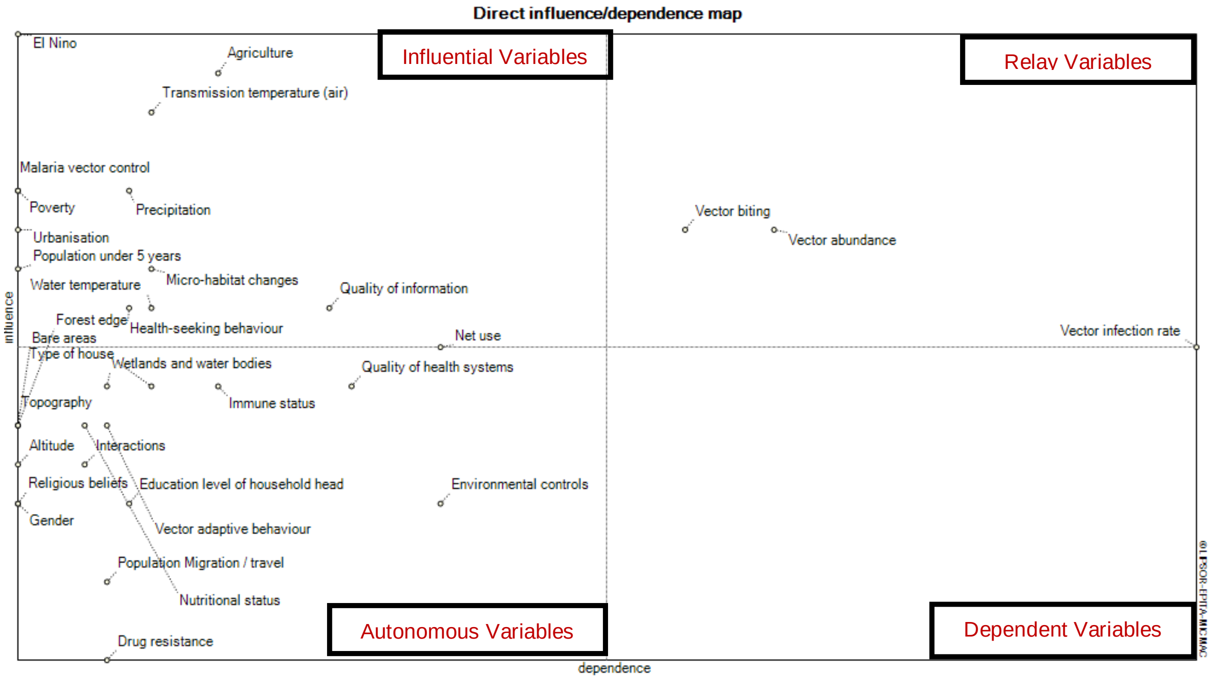

Figure 2. Direct influence-dependence map of variables of the climate change and malaria transmission system.

3.3 Conceptual model of climate change and malaria transmission using CLD

Knowing the relationships between variables influencing the climate change-malaria transmission system helps us to construct a conceptual model of the system using CLD (Figure 3). By eliminating the autonomous variables, we can focus on the influential variables driving the systems as well as the relay and dependent variables. The variables are colour coded according to the relevant systems i.e. Blue = climate, climate change and variability; green = land use and land use; pink = malaria vector attributes; orange = susceptibility and yellow = adaptive capacity. The thicker arrows represent strong pathways of direct influence between variables, while the dashed arrows represent weaker pathways of influence between variables. The red arrows represent a negative relationship while blue arrows represent a positive relationship. These relationships are also indicated by the polarity signs "+" or "- "at the arrow tip. Lack of a polarity sign (black arrow) indicates that the relationship can be either positive or negative or that the relationship has not been determined. The conceptual model represents the complementarity of sociological and ecological systems in influencing diseases and can be used to guide an integrated approach for assessing vulnerability and exposure of human societies from climate related impacts on malaria.

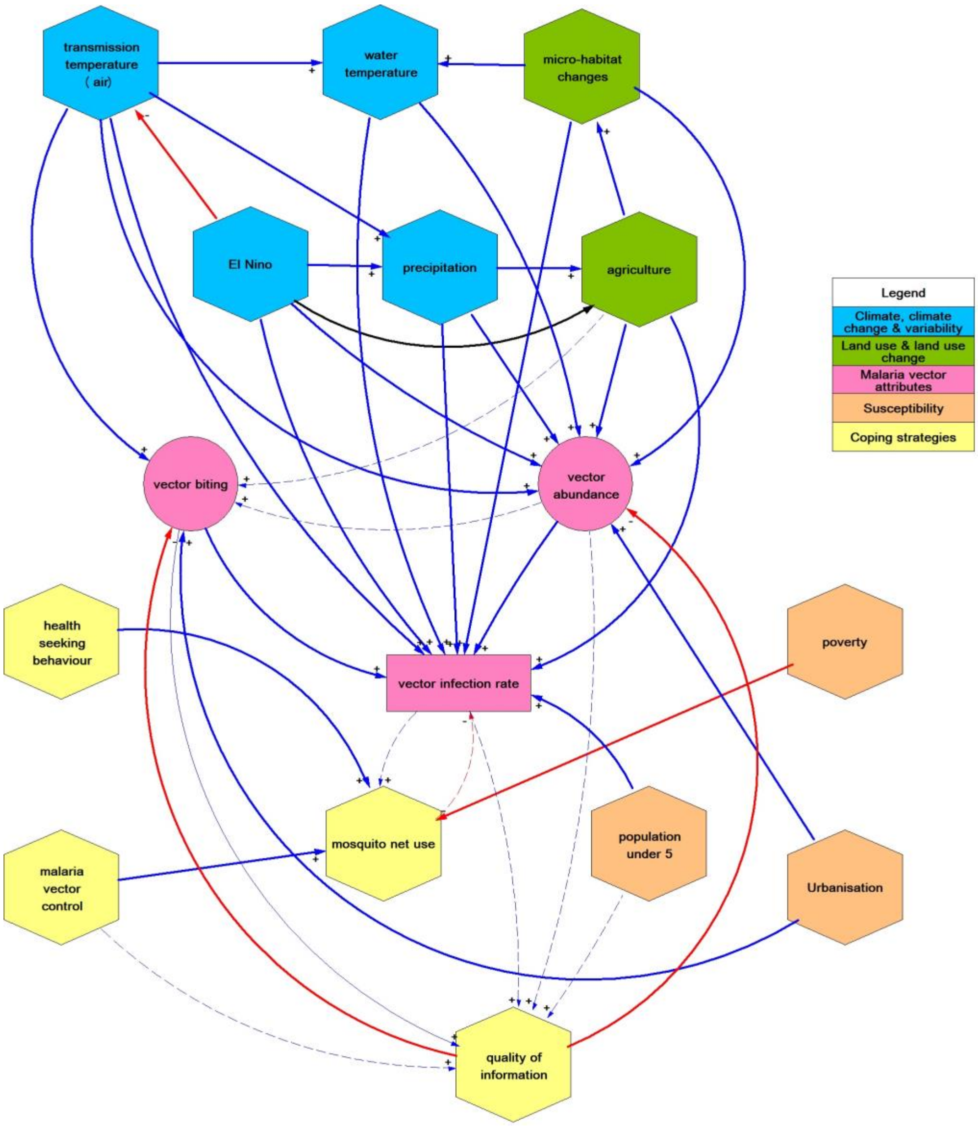

Figure 3. A systems conceptual model detailing the connections between climate change, land use and land use change, other biological and socio-economic factors and malaria transmission.

4 CONCLUSIONS AND RECOMMENDATIONS

We have presented an integrated modelling approach for assessment of the vulnerability and exposure of societies from climate related impacts on malaria, which conforms the IPCC framework on risk and vulnerability and we suggest that the generated systems conceptual model to be operationalised using BBN models preferably over a systems dynamics model to explore how policy and management interventions can reduce the risk of malaria infection. Use of BBN models allows us to address some of the previous limitations of climate change and malaria research: mainly with the lack of reliable and quality data and; the relative exclusion of socio-economic and socio-cultural influences in climate change and malaria risk assessment studies. Data acquisition can be from a range of quantitative and qualitative sources including literature reviews, secondary data, community surveys and stakeholder interviews. Expert stakeholders will provide the necessary contextual knowledge while empirical knowledge from local stakeholders and the general community will be important in identifying specific determinants of vulnerability. In this manner, BBN models useful as they are capable of incorporating a range of quantitative and qualitative sources and can adequately capture qualitative knowledge from stakeholders thus resulting in a more robust model incorporating both the scientific and community perspectives. Conversion from CLD to a BBN model also makes the relationships between models easier for stakeholders to understand and to give their input on the degree of influence between variables. Transitioning from CLD to BBN model does have its limitations, primarily in the inability of

BBN models to capture feedback loops therefore the full suite of variables identified from our structural analysis cannot be represented in a single BBN model. The resultant CLD includes a few feedback loops e.g. between vector infection rate and use of mosquito nets (balancing loop); vector biting, vector infection and quality of information (reinforcing loop) among others. This limitation can be addressed by constructing multiple BBN models if needed to capture feedbacks. Other limitations include the subjective nature of the modelling process; however, this can be overcome through the iterative cycle by which results of the structural analysis can be used to provide feedback to stakeholders for further refinement of the model.

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