Social vulnerability to malaria in Rwanda: comparison of two spatial assessment approaches

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Abstract

Since 2005, the Government of Rwanda initiated malaria interventions leading to substantial decline in malaria transmission. However, this achievement is fragile as potentials for malaria transmissions remain. In line with an ambitious goal of eliminating malaria in Rwanda by 2018, an integrated malaria vectors management strategy was adopted as a framework for interventions based on local ecology, malaria epidemiological and social factors of vulnerable host populations. While vulnerability to malaria is a multidimensional concept, its complexity cannot be measured by a single indicator value. This applied existing spatial assessment approaches to vulnerability to bring the attention of decision-makers on relative levels of social vulnerability to malaria in Rwanda. A composite indicator approach highlighted the social vulnerability to malaria at district level. An integrated regionalization based on integrated geons was applied for explicitly modeling homogeneous and vulnerable regions to malaria infection. Both approaches exhibit some similarities. Higher values of social vulnerability to malaria are mainly found in highlands where local communities are more susceptible, lacking capacity to a anticipate mosquito bites or not resilient enough to cope malaria infection. However, many discrepancies between both approaches also exist. By decomposing social vulnerability into its underlying factors, the applied approaches indicate which indicators need to be addressed and where appropriate interventions are most needed. The study results are salient for decision-makers who need to prioritize appropriate interventions to reduce the population susceptibility while increase their resilience to malaria.

Key words: Malaria, vulnerability, composite indicator, integrated geon, regionalization, Rwanda

1. Background

Malaria has been a serious public health problem in Rwanda for many years and great efforts have been made to address the problem. Since 2005, the Government of Rwanda benefited from US Presidential Malaria Initiative to reduce malaria (USAID, 2014). Despite a remarkable decline, malaria has re-emerged in some areas where it was previously reduced. After falling down between 2006 and 2008 owing to an increase, malaria increased again in 2009 due to a short delay in bed nets distribution (WHO, 2011). Malaria declined again in 2010 following the campaign for bed nets distribution (Karema et al., 2012). This achievement is, however, fragile as potentials for local malaria transmissions remain. The entire population is at risk particularly children aged under five years and pregnant women (Government of Rwanda, 2013). Highland communities suffer from epidemic malaria due to low immunity (Government of Rwanda, 2008). High population pressure and environmental changes also increase exposure to malaria vectors where interventions are not sustained (Himeidan and Kweka, 2012).

The declining malaria transmission in Rwanda brings also new challenges for its elimination (Cotter et al., 2013). These challenges include for example the resistance of malaria vectors to insecticides and human activities that increase exposure to mosquito bites (Mboera et al., 2013). With intensive use of bed nets, immunity to malaria develop slowly under the reduced transmission, leading to a longer period of population susceptibility (Lengeler, 2004) which may result in severe malaria cases where interventions are not maintained (Githeko et al., 2012). Malaria is being imported from endemic areas through population movements and migrations. Land use and land cover changes are clustering malaria where populations share the same socio-economic and environmental factors (Bizimana et al., 2015; Gahutu et al., 2011; Kateera et al., 2015) that increase malaria mosquito breeding sites.

As response, an Integrated Vectors Management (IVM) strategy was adopted as a framework for interventions based on local ecology, malaria epidemiology and socioeconomic factors of vulnerable population (USAID, 2014). This strategy encompasses environmental modifications through infrastructural development and sanitation services to regulate not only the vectors, but also the populations’ exposure. It also aims at improving public health and quality of life while minimizing the social disparities (Lizzi et al., 2014). Spatially assessing the social vulnerability to malaria can timely thus support the existing integrated malaria initiatives to improve the efficacy, effectiveness and sustainability of malaria interventions in Rwanda (USAID, 2014).
Public health approach to malaria in Rwanda is yet based on Global Health Initiative strategy which concentrates on reducing malaria burden by only focusing interventions on health care (USAID, 2014). These malaria interventions may be ineffective and unsustainable to addressing proximate and ultimate causes of malaria transmission under social structure and agro-ecological changes induce by demographic pressures (Packard, 2007). Additionally, if efforts to malaria reduction are solely concentrated in health care, they may fail to address other factors that shape individuals’ health such as housing condition, access to food and employment (Morgan, 2001). Malaria reduction requires therefore an integrated approach that is placed within the broader environmental and socio-economic context of malaria incidence. The inclusion of social factors in malaria vulnerability assessment informs decision-makers on social inequalities that might influence vulnerability to infection.

The complexity of vulnerability concept cannot be measured by a single indicator value. Vulnerability assessment uses a set of indicators to simplify the complex information into aggregated measure relevant for decision-making (Dickin et al., 2013). While most composite indicator approaches are based on administrative boundaries (Borderon, 2013); malaria transmission does not however respect the artificial boundaries which may be inappropriate for targeting interventions (Rytkönen, 2004). This was also supported by Hongoh et al. (2011) who advocated for a spatial explicit modelling of vulnerability to disease.

In East Africa, an integrated framework for modelling the social vulnerability to vector-borne diseases was proposed by Kienberger and Hagenlocher (2014). This study spatially delineated homogeneous regions of social vulnerability to malaria in explicit manner in order to inform decision-makers for targeting interventions to most vulnerable populations. Nevertheless, its macro-level analyses focusing regional scale may not perform well in representing social vulnerability to malaria at national level and local capacities to adapt. The country and sub-administrative units’ sizes vary significantly across the countries, which make difficult to compare these units. This regional modelling was not able to provide detailed information on local heterogeneity of social vulnerability which is particularly relevant for small countries like Rwanda. Consequently, the aim of this paper was consequently to benchmark two different spatial modelling approaches to draw the attention of decision makers on relative levels of hidden and heterogeneous vulnerability to malaria in Rwanda from social perspective.

2. Methods
2.1. Conceptual setting
There is huge interest in the concept of vulnerability and different associated conceptual frameworks (Birkmann et al., 2013; Kienberger and Hagenlocher, 2014; Kienberger et al., 2009). Although approaches are still evolving, the concept of vulnerability is well rooted in climate change risk adaptations (Birkmann, 2006). Attempts to understand the vulnerability have focused on exposure to a hazard; susceptibility of exposed elements; and adaptive capacity of affected communities (Birkmann et al., 2013).

From epidemiological perspective, socioeconomic factors significantly influence malaria incidence (Heggenhougen, 2000). Malaria reduction strategies are expanding approach to malaria because existing tools may lead to limited outcomes due to socioeconomic barriers (Packard and Brown, 2010). Moreover, ignoring socioeconomic determinants of malaria incidence encourage decision-makers to only concentrate on malaria mosquitoes rather than on its key drivers such poverty, inequalities in health facilities, access to health treatment, access to land and resources (Brown, 1997). It is almost impossible to eradicate malaria by only distributing bed nets and attacking malaria vectors and parasites, while sanitation and housing facilities are not ensured. Removing barriers that prevent people from achieving health services and treatment is imperative for tackling malaria from multiple fronts (Packard, 2007). Consequently, there is a need to move away from a narrow biomedical approach which viewed malaria as a problem of mosquitoes, parasites and vectors, towards an integrated perspective which is tied to socioeconomic conditions that influence malaria incidence (Brown, 1997). This was supported by Jones and Williams (2004), when advocating for a comprehensive approach for diseases control.

The vulnerability to malaria can be defined as the predisposition of the society to malaria burden, considering spatial and temporal differences in susceptibility and lack of resilience (Hagenlocher et al., 2014; Kienberger and Hagenlocher, 2014). Drivers of vulnerability to malaria range from biological, social, economic, and demographic to institutional factors. There are complex interactions between these factors and unraveling their individual roles is difficult (Bates et al., 2004). This study is drawn on a holistic vulnerability framework developed by Kienberger and Hagenlocher (2014).
Figure 1 shows the adopted framework of social vulnerability to malaria.

We consider the susceptibility and lack of resilience as key elements of social vulnerability to malaria. Susceptibility is determined by individual’s lacking ability to withstand malaria infection. Generic susceptibility is the predisposition of individuals to be affected by malaria. Biological susceptibility reflects the efficiency of a mosquito to infect humans. This latter is a function of immunity which depends on age, pregnancy or co-infection with other diseases (Bates et al., 2004). Lack of resilience is the limited capacity to anticipate the exposure to mosquito bites or to recover from malaria infection (Hagenlocher et al., 2014). The capacity to anticipate the mosquito biting exposure may be influenced by education, knowledge about malaria transmission, protection measures and housing conditions (Ricci, 2012). A resilient community has many opportunities to cope with or recover from malaria infection. This resilience is influenced by access to health facilities, access to effective and appropriate medical treatment.

2.2. Composite indicator approach

2.2.1. Indicators and data sources
Guided by the adopted social vulnerability framework, 19 relevant to influence malaria incidence indicators have been identified from literature review. A composite index was constructed by integrating indicator values through normalization, weighting and aggregation. Table 1 shows the vulnerability domains, indicators and weights derived from Principal Component Analysis (PCA). A positive sign indicates that the high indicator values increase the social vulnerability to malaria, while a negative sign means that high indicator values result in low social vulnerability and vice versa.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Sub-domains</th>
<th>Indicators</th>
<th>Proxies</th>
<th>Sign</th>
<th>Source</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generic</td>
<td>Population</td>
<td>Population density in sq km</td>
<td>+</td>
<td>NISR 2012</td>
<td>0.087</td>
<td></td>
</tr>
</tbody>
</table>
### Biological susceptibility

<table>
<thead>
<tr>
<th>Susceptibility</th>
<th>Variables</th>
<th>Source</th>
<th>Year</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population pressures</td>
<td>Population change 2002-2012</td>
<td>NISR, 2012</td>
<td>0.056</td>
<td></td>
</tr>
<tr>
<td>Population of arriving populations</td>
<td>+</td>
<td>EICV 2011</td>
<td>0.126</td>
<td></td>
</tr>
<tr>
<td>Households size</td>
<td>Average number of persons per bedroom</td>
<td>EICV 2011</td>
<td>0.050</td>
<td></td>
</tr>
<tr>
<td>Livelihoods</td>
<td>Land area used for irrigation</td>
<td>EICV 2011</td>
<td>0.081</td>
<td></td>
</tr>
<tr>
<td>Poverty index</td>
<td># of poor populations</td>
<td>DHS 2010</td>
<td>0.134</td>
<td></td>
</tr>
<tr>
<td>Pregnancy</td>
<td>Women of child-bearing age</td>
<td>NISR 2012</td>
<td>0.110</td>
<td></td>
</tr>
</tbody>
</table>

### Capacity to anticipate

<table>
<thead>
<tr>
<th>Vulnerability</th>
<th>Variables</th>
<th>Source</th>
<th>Year</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td># of children under five years</td>
<td>NISR, 2012</td>
<td>0.113</td>
<td></td>
</tr>
<tr>
<td># of population above 65 years</td>
<td>-</td>
<td>NISR, 2012</td>
<td>0.060</td>
<td></td>
</tr>
<tr>
<td>HIV</td>
<td>HIV prevalence in adults aged 15-49</td>
<td>DHS2010</td>
<td>0.120</td>
<td></td>
</tr>
<tr>
<td>Malnutrition</td>
<td>% of households affected by drought and famines</td>
<td>EICV 2011</td>
<td>0.064</td>
<td></td>
</tr>
<tr>
<td>Education level</td>
<td>Low literacy rate</td>
<td>DHS, 2010</td>
<td>0.133</td>
<td></td>
</tr>
<tr>
<td>Housing condition</td>
<td># of households in poor housing walls</td>
<td>DHS2010</td>
<td>0.162</td>
<td></td>
</tr>
<tr>
<td># of households in poor housing roofs</td>
<td>+</td>
<td>DHS2010</td>
<td>0.200</td>
<td></td>
</tr>
<tr>
<td>Access to media</td>
<td># of households without radio</td>
<td>DHS2010</td>
<td>0.113</td>
<td></td>
</tr>
</tbody>
</table>

### Lack of resilience

<table>
<thead>
<tr>
<th>Vulnerability</th>
<th>Variables</th>
<th>Source</th>
<th>Year</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Access to health services</td>
<td>Nurse ratio to population</td>
<td>MoH</td>
<td>0.085</td>
<td></td>
</tr>
</tbody>
</table>

**NISR=National Institute of Statistics of Rwanda; EICV= Integrated Household Living Conditions Survey; DHS=Demographic and Health Survey; MoH: Ministry of Health.**

#### 2.2.2. Constructing the composite indicator

To construct a composite index, a methodology developed by Nardo *et al.* (2005) was adopted (Figure 2). The main steps were indicators selection, identification of appropriate datasets, imputation of missing data, descriptive statistics (distribution, multicollinearity analysis and outliers’ detection); data transformation, normalization and correlation analysis. PCA was performed to weight indicators for further aggregation into a composite index of social vulnerability for each district.
Since indicators were at different measurement scales, standardization was required before aggregation (Malczewski, 1999). Sometimes high indicator values mean low vulnerability to malaria. Therefore, these indicators have been transformed to have the high values for high vulnerability. Minimum-maximum transformation method was used by accounting for the direction of indicators (Munda and Saisana, 2011) and using the following formula:

\[ VI = \frac{Xi - \text{min}Xi}{\text{max}Xi - \text{min}Xi} \cdot 0.5 \cdot (1 - \text{direction}) \]  

Where \( VI \) is the standardized indicator \( i \); \( Xi \) represents the indicator value before its transformation; \( Xi, \text{min} \) is as minimum score of indicator \( i \) before transformation; and \( Xi, \text{max} \) as maximum score of indicator \( i \) before its transformation. All indicator values were transformed into a relative score ranging from 0 to 1, where higher values imply high vulnerability (Saisana, 2012).

Prior to PCA, the correlation coefficient matrix was scanned to check for the values greater than 0.92 as indication of collinearity (Field, 2005). After scanning the matrix of correlation coefficient, no value greater than the above threshold was found, meaning that PCA would yield the acceptable results (Tabachnick and Fidell, 2001). Kaiser-Meyer-Olkin (KMO) criteria and Bartlett’s test were performed to examine the suitability of used data for PCA. Generally, KMO value should be 0.60 or higher to
proceed with PCA. Overall KMO values for susceptibility and lack of resilience domains were 0.655 and 0.615 respectively, implying that they were suitable for PCA.

2.2.3. PCA for weighting indicators

PCA was used to weight indicators based on their variance. Using a varimax orthogonal rotation, components with eigenvalues larger than one; which contribute individually to overall variance by more than 10%; and cumulatively to more than 60% were chosen (OECD, 2008). Two extracted principle components explained 64.54 % of total variance for lack of resilience domain. The highest indicator scores and their weights are highlighted in Table 2.

Table 2: Squared loadings of extracted components for lack of resilience indicators

<table>
<thead>
<tr>
<th>LoR indicators</th>
<th>Components</th>
<th>Weights</th>
<th>Scaled weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poor housing roof materials</td>
<td>0.808</td>
<td>0.000</td>
<td>0.428</td>
</tr>
<tr>
<td>Poor housing walls materials</td>
<td>0.656</td>
<td>0.043</td>
<td>0.347</td>
</tr>
<tr>
<td>Low literacy rate</td>
<td>0.536</td>
<td>0.104</td>
<td>0.283</td>
</tr>
<tr>
<td>Nurse ratio to populations</td>
<td>0.343</td>
<td>0.193</td>
<td>0.182</td>
</tr>
<tr>
<td>Households without mobile phone</td>
<td>0.209</td>
<td>0.634</td>
<td>0.272</td>
</tr>
<tr>
<td>Households without radio</td>
<td>0.167</td>
<td>0.563</td>
<td>0.242</td>
</tr>
<tr>
<td>Households without bed nets</td>
<td>0.011</td>
<td>0.466</td>
<td>0.201</td>
</tr>
<tr>
<td>Number of health facilities</td>
<td>0.003</td>
<td>0.428</td>
<td>0.184</td>
</tr>
<tr>
<td>Sums of squared loadings (VE)</td>
<td>2.733</td>
<td>2.430</td>
<td>2.139</td>
</tr>
<tr>
<td>Total variance</td>
<td>5.164</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VE/Total variance</td>
<td>0.529</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For susceptibility domain, 3 extracted components explained 73.04 % of total variance. The highest indicator scores and their weights are highlighted in Table 3. The susceptibility indicators with highest squared loadings include the number of poor populations, number of arriving populations, HIV prevalence and population density. Most of the highest scored indicators in first principal component are related to generic susceptibility sub-domain. The biological susceptibility sub-domain dominates the second principal component. The land area used for irrigation and population change between 2002 and 2012 have an excessive influence in last principal component.

Table 3: Squared loadings of extracted components for susceptibility indicators

<table>
<thead>
<tr>
<th>Susceptibility indicators</th>
<th>Component</th>
<th>Weights</th>
<th>Scaled weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of poor populations</td>
<td>0.776</td>
<td>0.000</td>
<td>0.320</td>
</tr>
<tr>
<td>Number of arriving populations</td>
<td>0.732</td>
<td>0.001</td>
<td>0.301</td>
</tr>
<tr>
<td>HIV prevalence</td>
<td>0.695</td>
<td>0.000</td>
<td>0.286</td>
</tr>
<tr>
<td>Population density</td>
<td>0.505</td>
<td>0.024</td>
<td>0.208</td>
</tr>
<tr>
<td>Children under five years of age</td>
<td>0.072</td>
<td>0.756</td>
<td>0.271</td>
</tr>
<tr>
<td>Women of child-bearing age</td>
<td>0.000</td>
<td>0.735</td>
<td>0.263</td>
</tr>
<tr>
<td>Households affected by droughts and famines</td>
<td>0.151</td>
<td>0.427</td>
<td>0.153</td>
</tr>
</tbody>
</table>
2.2.4. Aggregating indicators

Approaches to indicators weights and aggregation are subject to debate and no approach is without limitations (Giné and Pérez-Foguet, 2010). Some approaches use equal weights to ensure transparency, but they are criticized for implicitly assigning equal weights (Nardo et al., 2005). Hagenlocher et al. (2013) concluded that in absence of local expertise, statistical approaches could be used to weight indicators. PCA was therefore used to determine weights based largest variation in original indicators (Slottje, 1991). Weighted indicators were then aggregated based domains where the weighted indicators for each domain were summed using the following formula:

\[
\text{SUS} = \sum_{i=1}^{n} W_{im} \cdot I
\]  

(2)

SUS represent the value of susceptibility domains; \( W \) refers to weight of indicator in each domain; and \( I \) is the normalized value of indicator. The final composite index was calculated by aggregating two domains and taking into account the number of indicators in each domain in order to assign higher weights to a domain with high number of indicators as follow:

\[
\text{VI} = \frac{n \cdot d}{N}
\]  

(3)

The vulnerability index (VI) is equal to \( n \) which represents the number of indicators for a given domain; times the value of each vulnerability domain (\( d \)) and divide by the total number of indicators (\( N \)). From nineteen indicators that have been identified, eleven indicators were assigned to susceptibility domain and eight indicators to lack of resilience domain. To visualize the results, the composite index values were normalized within a new range from zero to one, where zero reflects a very low and one a very high vulnerability. The final vulnerability index for each district was translated into ArcGIS10.2 software for mapping and visualization.

2.3. Vulnerable regions from “integrated geons”

The composite index based on administrative boundaries may not appropriate for explicitly showing social vulnerability as boundaries rarely correspond to varying vulnerabilities (Larmarange et al., 2011). Boundaries are defined based on natural geographic or physical features seen as barriers to continuing social vulnerability (King and Blackmore, 2013). Besides, spatial scale is determined by what is collected rather than what is appropriate (Meade, 1986). Spatial scale is therefore important because indicators at national or district level may not be as important for the smallest reporting units (Kienberger et al., 2013a).

To overcome scale related challenges, a spatial regionalization based on “integrated geon” was applied. Geons concept was initially introduced by Lang et al. (2008). Geons are constructed spatial objects, whereby a geon refers to a unit based on its Greek etymology: \( \text{ge} = \text{Earth} \) and \( \text{on} = \text{part} \). It is a type of region delineated with expert knowledge incorporated, scaled with uniform response to a phenomenon under space-related policy concern. Recently, Lang et al. (2014) developed an “integrated geon” approach which address abstract, yet policy-relevant phenomena such as societal vulnerability to hazards (e.g malaria as biological hazard). Geons are defined as spatial objects delineated by regionalizing continuous spatial data sets using different indicators. By applying an integrated geon, we created spatial units showing the social vulnerability to malaria, scalable to policy intervention level; and homogenous in their domain-specific response and independent of district boundaries (Lang et al., 2014). Figure 3 shows the workflow for modelling the vulnerability to malaria using integrated geons.
Geons transform continuous spatial information into discrete objects by interpolation, segmentation, regionalization and generalization (Lang et al., 2014) based not only on administrative units but also on characteristics of phenomena under investigation. (Kienberger, 2012).

2.3.1. From databases to spatial layers
The data used in spatial explicit modelling of social vulnerability have been collected from Rwanda 2010 DHS database, and from different data sources in Rwanda. Although DHS data can be geo-referenced, the sampling method was however not appropriate for spatial interpolation. Accordingly, a spatial
interpolation methodology developed by Larmarange et al. (2011) was adopted to estimate regional variations of DHS data in accordance with data accuracy using R statistical software. Other spatial gridded data (child-bearing age women, population under five years, and elderly populations) have been downloaded from WorldPop Project database. The raster population data for Rwanda was acquired from the US Census Bureau (2011). Kernel density estimation was then applied using ArcGIS 10.2 software to generate the intensity of population change.

Spatial data for irrigated lands was collected from Rwanda Natural Resources Authority. The assumption was that vulnerability to malaria may be higher near irrigated farming communities than in populations far away from irrigated lands. Kernel density was applied to estimate the clinics density using health centers geographic coordinates collected from Rwandan Ministry of Health. A distance layer from main roads was also computed using road network for Rwanda.

### 2.3.2. Normalization of indicators

To integrate indicator layers, a normalization was applied using min-max normalization method (Nardo et al., 2005):

\[
V = \frac{\nu - \text{min}}{\text{max} - \text{min}} \times 255 \tag{4}
\]

\(V\) indicates the normalized indicator; \(\nu\) is the value of indicator; \(\text{max}\) and \(\text{min}\) are derived from the value range. For this study, an 8-bits value range (0-255) was applied to make use of the full radiometric spectrum of raster datasets. To detect multicollinearity among datasets, correlation coefficients and Variance Inflation Factors (VIF) were computed (OECD, 2008). When scanning the correlation coefficient matrix and looking for values greater than 0.92 as indication of collinearity (Field, 2005), no value above this threshold was found. The highest VIF value was 4.987 which is below the threshold for multicollinearity (OECD, 2008).

### 2.3.3. Indicators weighting

A PCA was used to weight indicators (Pattanaik et al., 2008). Prior to PCA, Kaiser-Meyer-Olkin (KMO) statistics and Bartlett’s test were also performed to examine the data suitability for PCA. High KMO values (> 0.60) indicate that PCA may be useful for weighting indicators (Vines, 2000), as it is the case in this study (KMO=0.727). Two extracted components were able to describe 91.5% of cumulative variance of raster input layers. Indicators have been weighed using the variance explained by components and accounting for the total variance of the component in which indicator is heavily loaded (Abson et al., 2012). Weight for each indicator was calculated using the method described in section 2.2.3.

### 2.3.4. Delineating homogeneous regions of vulnerability

After rasterizing all indicator datasets on the same cell size, indicator datasets were integrated into Trimble eCognition Developer software for delineating homogeneous regions of vulnerability through the process of regionalization. The multiresolution segmentation (Baatz and Schäpe, 2000) was used for regionalizing spectral reflectance of indicators. To parameterize the segmentation, the estimation of scale parameter tool (ESP2) was used. This tool iteratively generated the image-objects at multiple scale levels to calculate local variance for each scale (Drãgut et al., 2014). For each delineated region, a vulnerability domain value was calculated by multiplying squared indicator value by its respective weight and summed as follow:

\[
\text{GenSUS} = \sqrt{W_1I_1^2 + W_2I_2^2 + W_3I_3^2 + W_4I_4^2} \tag{5}
\]

GenSUS refers to generic susceptibility domain. The domain value is equal to square root of the summed weighted and squared indicator values (Kienberger et al., 2009). \(W\) represents indicator weight, and \(I\) represents indicator value. The relative share of indicator for each delineated unit was calculated to evaluate the composition of delineated regions of vulnerability by decomposing them into underlying indicators (Kienberger et al., 2013b). The aggregation of vulnerability domains into final index was calculated by summing vulnerability domain values by accounting for the number of indicators in each domain as follow:

\[
VU = \frac{1}{N} \sum_{i=1}^{D} n_i \tag{6}
\]

\(VU\) represents the vulnerability index value; \(n\) is the number of indicators for a given domain; \(D\) is equal to the value of vulnerability domain and \(N\) refers is the total number of indicators.

### 3. Results and discussions

#### 3.1. Social vulnerability to malaria in Rwanda

The vulnerability index reflects the relative levels of social vulnerability to malaria, which means that the value of 0.00 does not mean the absence of vulnerability to malaria within the district.
Figure 4: Levels of social vulnerability to malaria at district level in Rwanda

Figure 4 shows the high values of social vulnerability to malaria in Gicumbi (1.00), Rusizi (0.81), Nyaruguru (0.79), Gisagara (0.71), and Burera (0.67), and districts, and low values of vulnerability index in Muhanga (0.00), Nyarugenge (0.10), Kicukiro (0.13), and Nyanza (0.17).

3.2. Underlying factors of social vulnerability
For lack of resilience (Figure 5), poor housing walls and roofs, and low literacy rate are the main factors that are hampering the capacity of Gicumbi, Ruzizi, Nyaruguru, Gisagara and Nyamagabe districts to anticipate mosquito-biting exposure. The vulnerability of Gicumbi, Nyaruguru and Nyamagabe districts is exacerbated by low rate of bednets ownership. These vulnerable districts are mostly located in remote rural areas near the borders, where limited access to communication amplifies existing vulnerabilities. With regard to coping capacity, the limited number of health facilities and insufficient medical personnel require improved interventions in Gicumbi, Rusizi and Gisagara districts. These districts are already prone to epidemics malaria; and thus climate variability may combine with limited health infrastructure and poverty to result in high malaria incidences.
Gicumbi is more susceptible mainly because of poverty, high number of child-bearing age women, high number of child-bearing age women, and high number of elder populations (Figure 6). The vulnerability of Gicumbi is exacerbated by high number of arriving populations particularly refugees. The vulnerability of Rusizi is largely associated with high number of child-bearing age women, high number of children under five years, and high population density and HIV prevalence. The susceptibility of Nyaruguru is mostly explained by poverty, high number of persons per bedroom, high number households affected by famines, and high number of elder populations. The vulnerability of Gisagara is dominated by poverty, high number of child-bearing age women, irrigated livelihood activities and high population density.
Nyamagabe is more susceptible mainly because of poverty and demographic pressure. Efforts to locally eliminate malaria in most vulnerable districts should focus on alleviating poverty and improving house structures to limit indoor malaria transmission and on an effective implementation of insecticide-treated bed nets and indoor residual spraying (Kateera et al., 2015). The results of the composite indicator are useful because they allow comparison of relative of social vulnerability to malaria among the district of Rwanda. They may be however not appropriate for explicitly displaying vulnerabilities inside the districts as their boundaries do not correspond to spatial variation of vulnerabilities. Moreover, malaria transmission does not respect boundaries which are defined for administrative or political purpose. Homogeneous regions vulnerability in explicit manner can therefore help to overcome these challenges.

3.3. Regions of social vulnerability to malaria
A spatially explicit modelling of social vulnerability to malaria shows heterogeneity in social vulnerability (Figure 7). The areas of high vulnerability are shown in red while the areas of low vulnerability are displayed in blue.
High values of social vulnerability index are found in highlands along the Congo-Nile Crest and Eastern lowlands near the Tanzania border. Other vulnerable regions are located in northern highlands where malaria transmission is unstable. In these areas, epidemic malaria overwhelsms the ability of medical facilities to cope with (Hay et al., 2002). The low values vulnerability concentrate near urban centres especially in Kigali City, in central plateau and in eastern lowlands. This finding is supported by Richmond et al. (2015), whose study on household vulnerability mapping highlighted the capital and major urban center of Kigali with low values of vulnerability in stark contrast to the rest of the country. This concentration of wellbeing in primate city exemplifies the well known geographic concepts of core and periphery and distance decay (Baldwin and Forslid, 2000).

Low values of social vulnerability amplify the susceptibility of low immune populations in highlands which are prone to epidemics malaria. Besides, the remoteness of these areas impedes the provision of health services to local populations. Their vulnerability is exacerbated by cross-border migrations leading to imported malaria from outside (WHO, 2011). Temporary migrations have been reported in the last five years (Blumenstock, 2012); and cross-border movements play a key role in malaria transmission (USAID, 2013). This mobility of populations may result in asymptomatic malaria as reservoir for local transmission. Adequate health facilities and effective malaria treatment should therefore be provided in the most vulnerable areas. Malaria elimination near the borders needs also to identify migrant streams with potentials for spreading malaria and thus target appropriate interventions accordingly.

With regard to underlying indicators of vulnerability in vulnerable regions, the vulnerability of region 1 in North West is associated with the lacking capacity to anticipate and to recover. Region 2 along Congo-Nile Crest needs interventions to reduce the susceptibility to mosquito but also to improve the limited coping capacity. For region 3 near Tanzanian border, more
attention should be paid to generic susceptibility indicators. Although region 1 and 2 are identified in the areas where malaria transmission would be absent or limited by low temperature, 2010 demographic and health survey in Rwanda confirmed some pockets of malaria prevalence in these highlands. This uneven malaria occurrence may be the interplay of both poor socioeconomic conditions of host populations and climate variability in highlands (Henninger, 2013a; Henninger, 2013b). This finding highlights again the importance of including social to reduce malaria in Rwanda.

3.4. “Composite indicator” v “integrated geon”

Figure 8 compares the social vulnerability using the traditional “composite indicator” and homogeneous regions of social vulnerability to malaria as delineating by “integrated geon”. Both approaches reveal higher values of social vulnerability highlands and in remotes rural areas. For instance, the composite indicator approach presents the districts of Nyaruguru, Nyamagabe and Rusizi in Southern West as the most vulnerable districts. The same districts slightly correspond with the highly vulnerable regions delineated by an explicit modelling. These findings are in strong agreement with a recent study by Richmond et al. (2015) who found the high vulnerable areas in the western districts near Gishwati and Nyungwe National Park. These regions frequently affected by food insecure due to soil infertile soil and market access. As such, what emerges in these highland landscapes is rural density where poor households live in small crowded homes on small plots of land and lack income diversification.
Despite few similarities, there are, however, many spatial discrepancies between both approaches. As an example, with Gicumbi district, the composite indicator approach has revealed high levels of social vulnerability, while a spatial explicit modeling using integrated geon has slightly delineated the momentous regions of lower social vulnerability. By displaying the homogeneous regions of vulnerability at domain levels, susceptibility indicators are the most influential in Gicumbi. Conversely, “integrated geon” revealed the high values of vulnerability near the Tanzania border and near Virunga National Park which were not identified by the composite indicator. This difference in spatial pattern can be explained by the fact that some indicators like distance to irrigated lands and access to health infrastructure that were used differently in two assessment approaches. Moreover, the number of households affected by droughts and famines was not integrated in explicitly

Figure 8: Comparison of two spatial assessment approaches
modelling. This study emphasizes that spatially explicit modelling of social vulnerability can better guide the decision-policy makers in identifying the factors of hidden and heterogeneous vulnerability to malaria in specific areas independent of the spatial scale. This holistic assessment approach can empower decision-makers in targeting mitigation efforts in most vulnerable areas and at indicators that mostly impact the vulnerability.

4. Concluding remarks
The results from this study are salient for decision makers in malaria reduction and elimination. By displaying the lack of resilience versus susceptibility to malaria, a composite indicator approach provides useful information for decision-makers and communicates complex interactions between relevant factors of vulnerability to malaria. Squeezing the complex system of socioeconomic conditions into a single vulnerability index, the developed approaches yields a powerful comparative assessment tool capable of capturing societal conditions in a given district that drive people’s vulnerability to malaria infection. This has an important implication as malaria reduction requires combining a set of strategies that address the most important factors of vulnerability in the most vulnerable districts.

The comparative assessment of social vulnerability to malaria is however without limitations and comes along with some challenges. Malaria vulnerability assessment based on administrative boundaries may be incomplete for making decisions in complex situations. The composite indicator approach provides a comparative assessment by presenting the relative levels of social vulnerability among the districts. It does not however provide useful information about what areas within the districts are the most vulnerable to malaria infection. A lack of spatial details in composite indicator approach can result in implementation of the same interventions to differing vulnerabilities.

Explicit modelling using integrated geon” provides spatially explicit information on contious and hidden social vulnerability that can help decision-makers to tackle malaria from social perspective. This explicit modelling emphasizes the importance of moving away from intervention strategies that solely focus on climate and ecological factors of malaria transmission. It is a well-timed support to national malaria initiative which to seeks to improve the efficacy, effectiveness and sustainability of malaria interventions. By integrating multisource indicators, it meaningfully informs decision-makers on social vulnerability to malaria in specific locations. It indicates not only which areas are the most vulnerable, but also what is mostly driving that vulnerability. Interventions to support the socio-economic development are necessary for eliminating malaria through different channels in the identified vulnerable areas. Such interventions could provide effective and sustainable responses for malaria reduction and elimination. Further research opportunity in Rwanda can combine the resulting social vulnerability maps for Rwanda with the probability of an infective mosquito bites from Entomological Inoculation Rates towards malaria risk assessment.

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