COMMUNITY VULNERABILITY TO MALARIA IN MADRE DE DIOS, PERU

by

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Abstract

Construction of a highway and artisanal gold mining have contributed to population and land use changes within the department of Madre de Dios, Peru. Such changes are expected to alter malaria rates due to impacts on vector habitat and human exposure. Vulnerability, as defined by the possibility of bereavement of a physical good or abstract state, is useful for understanding which communities are most likely to be adversely impacted by hazards such as malaria. A model defining susceptibility (SUS) and lack of resilience (LOR) was used to create an index of vulnerability to malaria for 40 communities in Madre de Dios. Indicators of SUS and LOR were developed from household and community data and combined into a final vulnerability index score. Vulnerability scores ranged between 0.13 and 0.31 with a mean of 0.21. Communities were grouped according to standard deviations from the mean. The most vulnerable communities (>1.5 standard deviations from mean) were located in the southern portion of the study area. When the dimension scores were compared for all communities, scores were generally higher in the susceptibility dimension than in the lack of resilience dimension. Examination of the indicator scores of individual communities revealed that drivers of vulnerability vary across the department. Therefore, targeted interventions addressing specific aspects of vulnerability may be useful. Finally, a predicted vulnerability surface was created for a 10 km buffer surrounding the Interoceanic Highway in Madre de Dios.

Figure 1. Location of Madre de Dios Department, Peru.

Introduction

Change in Madre de Dios, Peru

The department of Madre de Dios is located in the southeastern portion of the Peruvian Amazon (Figure 1). Rich in biodiversity and natural resources such as valuable timber and gold rich sediments, the department is undergoing a number of rapid changes (Asner et al. 2013). Gold mining has taken hold in the region due to the offer of a lucrative option for households seeking to diversify their incomes (Skeldon 2012). Madre de Dios is responsible for 70% of the gold mined in Peru (reported in Asner et al. 2013). Probably the most obvious environmental impact of the mining is the massive deforestation that has taken place. Asner et al. (2013) found that the mining extent, which has been deforested, had increased by 50,000 hectares from 1999 to 2012. Similar to mining, the construction of the Interoceanic Highway, a large infrastructure project, has also caused change. It has increased mobility, in terms of both permanent migration and temporary travel, throughout the department (Perz et al. 2010, Perz et al. 2013). In addition, the construction of the IOH is also a driver of deforestation. Southworth et al. (2011) found that the presence of the road increased the rate of deforestation and that the rate was highest within the nearest 18 km.

Connections to Infectious Disease

The deforestation and increased movement of individuals throughout the region have implications for infectious disease dynamics. The change in land use from heavy forest cover to deforested mining or urban roadside areas is likely to impact the transmission of malaria in the department due to the habitat preferences of the primary vector, the mosquito *Anopheles darlingi. An. darlingi* are more likely to be found in areas disturbed by human activity (da Silva-Nunes et al. 2012). This is likely due to creation of areas suitable for larval habitat (Charlwood 1996). Vittor et al. (2006) found that areas with less than 20% forest cover and more than 30% grass or crops, representing human activity, had a 278 times higher biting rate than areas with 70% forest cover. A department located in the northern Amazonian region of Peru, Loreto, underwent similar deforestation in the 1990s which resulted in the influx of *An. darlingi* and an increase in malaria cases (da Silva-Nunes et al. 2012).

Increased mobility is also expected to alter the transmission of malaria in Madre de Dios. In Loreto, the travel of individuals between farms in which they worked and the communities in which they lived is thought to have provided an opportunity for different malaria parasites to be transmitted between communities, contributing to the severity of the epidemic (da Silva-Nunes et al. 2012). The

Naya basin, a region in Colombia, has seasonal migration of farm workers from highland areas of low malaria to lowland agricultural areas with high malaria occurrence which has greatly increased transmission in the region (Martens and Hall 2000). The presence of the IOH has been shown to increase movement between urban areas and small communities and from small community to small community (Perz et al. 2010, Perz et al. 2013). If individuals utilize the road for temporary movement between deforested areas where malaria rates are high (eg. mining camps, agricultural fields, logging operations) and their home communities, an increased number of malaria cases can be expected.

Permanent migration is also important in the incidence and transmission of disease. The gold mining in Madre de Dios has drawn people both from the department and from the poorer Andean region of Peru to work (da Silva-Nunes et al. 2012). A gold rush in Brazil in the 1980s resulted in a similar movement of people into the region and an over 10 fold increase in the number of malaria cases between 1970 and 1990 (Marten and Hall 2010). Migrants from the Andean highlands are unlikely to have been exposed prior and therefore are not immune, making them particularly susceptible (da Silva-Nunes et al. 2012).

Why is the potential increase in malaria transmission and incidence important? In terms of the global burden of disease, approximately 90% of deaths due to malaria occur in Africa (WHO 2013). However, malaria's impact is not restricted to mortality. It is a costly disease due both to medical costs and lost days of work (Sachs and Malaney 2002). These costs and other impacts of the disease can result in changes in household behavior such as preventing financial saving or migration, potentially decreasing the quality of life (Sachs and Malaney 2002). Furthermore, future human capital can be degraded due to impacts of early life malaria episodes. Lee et al. (2012) assessed the impact of malaria in the first 72 months of life on children's growth in Loreto, Peru. Weight gain was significantly reduced in children who had an episode of malaria at 2, 4, and 6 months (last time point measured) post episode (Lee et al. 2012). Height gain was also reduced at 4 and 6 months post episode (Lee et al. 2012). The results of Lee et al. (2012) indicate long term negative effects as children who become stunted (short for age) will not catch up to their peers in height as they age. Reduced growth has been associated with reduced cognitive and work abilities (Grantham-McGregor et al. 1995, Haas et al. 1995). As transmission of malaria is expected to increase in Madre de Dios, it is important to understand which communities are most vulnerable to the disease so that targeted interventions can be made.

Vulnerability

At the most basic level, vulnerability is the possibility of bereavement of something, which may range from physical possessions to good health to more abstract ideas such as positive social interactions (Cutter 1996, Cutter et al. 2003). The study of vulnerability has been approached from many perspectives which emphasize different aspects such as the hazard, the societal determinants of exposure and impact, and the ability of a system to resume normal function as summarized in Eakin and Luers (2006). The political-ecology approach addresses both aspects of human society that increase and decrease vulnerability as well as the biophysical factors that contribute to vulnerability (Eakin and Luers 2006). Utilizing a similar approach, Parkins and MacKendrick (2007) defined four components of vulnerability (physical, social, political, and economic) in their assessment of Canadian communities' vulnerability to outbreaks of mountain pine beetles.

Similar to the variety in approaches to vulnerability, a number of different frameworks have been developed for the assessment of vulnerability. A particular example is the MOVE framework, created out of the Methods for the Improvement of Vulnerability Assessment in Europe project (Birkmann et al. 2013). This framework defines risk as the interaction of hazards and a society's vulnerability which in turn is composed of exposure, susceptibility and fragility, and lack of resilience (Birkmann et al. 2013). The framework overlaps with the political-ecology approach in that the susceptibility and fragility component is defined both by biophysical and societal factors (Birkmann et al. 2013). In addition, the ability (or lack thereof) of a society to respond to a hazard is explicitly taken into account in the lack of resilience component (Birkmann et al. 2013).

While vulnerability assessments have typically focused on vulnerability to natural disasters such as earth quakes (e.g. Basaran-Uysal et al. 2013) or more recently on climate change associated events (e.g. Parkins and MacKendrick 2007), there is a growing body of literature addressing vulnerability to infectious diseases. Bates et al. (2004) reviewed determinants of vulnerability to malaria, HIV, and tuberculosis at both a household and an individual level, but did not assess any particular place. Dickin et al. (2013) employed the water-associated disease index to determine vulnerability to dengue across the country of Malaysia. The index was mapped using ArcGIS to visualize how vulnerability varied across the country both spatially and temporally (Dickin et al. 2013). A similar project was performed at a finer scale in Cali, Colombia (Hagenlocher et al. 2013). Hagenlocher et al. (2013) utilized a modification of the MOVE framework to determine socioeconomic vulnerability to dengue in the city. Working at the neighborhood level, they also created a continuous mapped surface of vulnerability in ArcGIS

(Hagenlocher et al. 2013). Both sets of authors emphasized the utility of their work in targeting interventions rather than applying them across an entire area with varying levels of need due to varying levels of vulnerability (Dickin et al. 2013, Hagenlocher et al. 2013). Furthermore, Hagenlocher et al. (2013) emphasized how the drivers of vulnerability varied across the city and that these could be teased out by exploring the different indicators making up the vulnerability index score.

Objectives

Due to such changes as deforestation and migration, transmission and incidence of malaria is expected to increase in Madre de Dios. The implications of malaria on health and economic well being make interventions for the control of malaria important. Identification of which communities are most vulnerable to the disease in both a societal and biophysical context is therefore important. An index of community vulnerability to malaria was created and applied to communities located in Madre de Dios. Examination of vulnerability index scores was used to determine which communities are most vulnerable while exploration of the separate indicator scores was used to understand the drivers of vulnerability.

Methods

Description of the Data

Both household level and community level data were used in development of the individual indicators of the vulnerability index. Forty-six communities were selected for inclusion in a larger study assessing the impacts of the Interoceanic Highway. Selection was limited to communities within 10km of the road and was stratified by urban-rural designation. Participation at the community level was elicited by approaching key community leaders. Within each community, households were randomly selected and informed consent was obtained from all members of the household. Data collection at both levels was performed using a structured, primarily close-ended survey instrument. For the community survey, one to two important or longstanding members of the community (assumed to be most knowledgeable about the community) were selected. For the household survey, a single informant (typically the head of the household or the spouse of the household head) provided information. Trained fieldworkers conducted in person interviews in both cases. Questions covered a wide variety of topics related to the community, including infrastructure, services, population, and health status.

Several sets of geospatial data were used as well. Latitude and longitude of each household was obtained from the household surveys. ArcGIS shapefiles detailing land use of the department of Madre de Dios were obtained from the Amazon Conservation Association. Shapefiles of the department of Madre de Dios, districts of Madre de Dios, and the Interoceanic Highway were provided by the Peruvian Amazon Research Institute (IIAP). Finally, the district shapefiles were merged with malaria case data provided by the health directorate in Madre de Dios (Epidemiologia DIRESA, MDD) and population data from the Instituto Nacional de Estadistica E Informatica (downloaded from http://www.inei.gob.pe/estadisticas/indice-tematico/poblacion-y-vivienda/).

Establishing the Framework

The MOVE framework was modified for use as the working foundation (Figure 2) (Birkmann et al. 2013). Specifically, in this study, exposure is separated from vulnerability whereas in the original framework it is a component of vulnerability (Birkmann et al. 2013). In the current study, vulnerability is defined as being comprised of two dimensions: lack of resilience (LOR) and susceptibility (SUS) (Birkmann et al. 2013). Borrowing from the political-ecology theory of vulnerability, there are physical, social, economic, and political aspects of each component (Eakin and Luers 2006; Parkins and MacKendrick 2007). Vulnerability interacts with hazards, in both the original framework and the current modification, and with exposure, in the current modification, to produce risk (Birkmann et al. 2013).

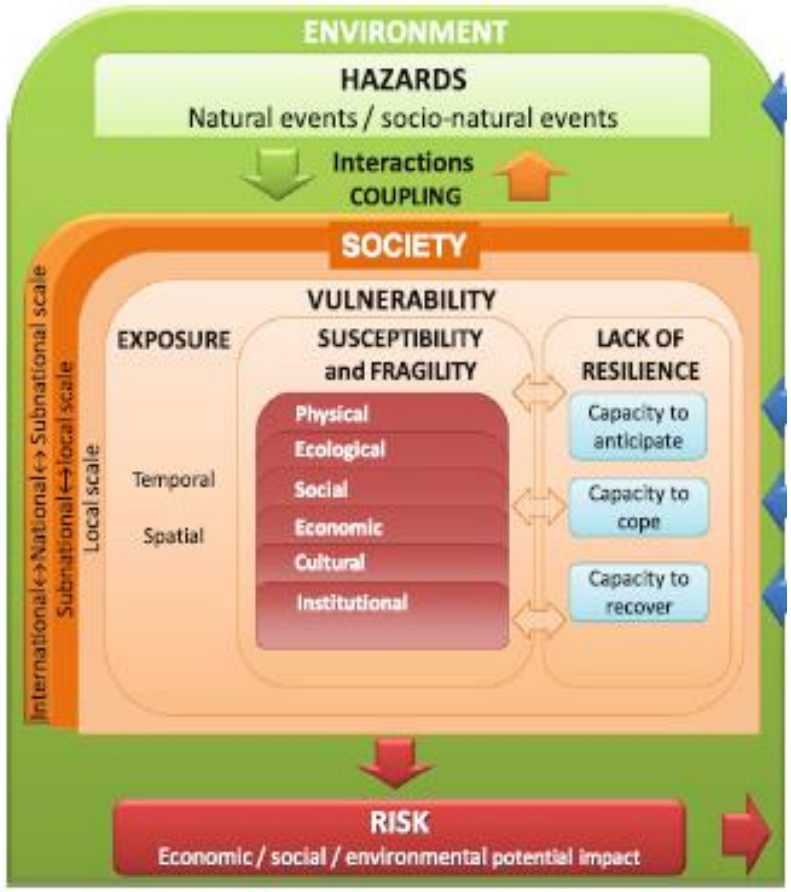

Figure 2. Vulnerability framework. Excerpted from Birkmann et al. 2013.

To help identify the possible physical, social, economic, and political aspects of the susceptibility and lack of resilience dimensions, an adaption of the ecohealth method used by Dickin et al. (2013) was applied. A diagram detailing the generalized interaction between humans, vectors, and the pathogen was created (Figure 3). The initial diagram was developed using background knowledge on malaria and then refined in an iterative manner as the literature was more deeply examined.

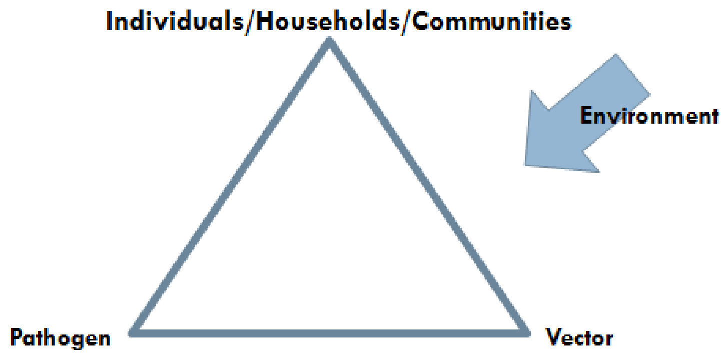

Figure 3. Ecohoealth framework. Modified from Dickin et al. 2013.

Indicator Selection

Using the diagram in Figure 3 and the overarching direction of the modified MOVE framework, indicators of the LOR and SUS dimensions were selected. A search of the literature was performed for the factors detailed in the diagram to determine which were most important for malaria and to determine what type of data could be used to define them (Bates et al. 2004, Dickin et al. 2013). After potential indicators had been selected from surveying the literature, suitable data was identified in the available household and community datasets. The end result of the indicator selection process was a set of 11individual indicators within the two dimensions of vulnerability were selected (Table 1, Table 2).

Table 1. Indicators representing the Lack of Resilience dimension of vulnerability.

Component	Selected Indicator
Access to health care	Time to minor care; Time to major care
Burden of care	Dependency ratio
Education	% Adult females w/ secondary school
Household wealth & resources	Household income bracket
Insurance	Percent uninsured
Social engagement	Index of organized groups + government involvement
Social network/Community trust	Social network score

Table 2. Indicators representing the Susceptibility dimension of vulnerability

Component	Selected Indicator
Economic activity	Economic activity score
Land cover	Community land use
Migration/Population change	Percent population change

Three indicators were selected for the susceptibility dimension, representing physical, social, and economic aspects. Population Change was identified as an indicator of susceptibility for two separate reasons. First, migration of naïve individuals into malaria endemic areas is likely to result in an increase in the number of cases as these individuals more easily acquire the disease and then are able transmit it to others (Martens and Hall 2000). Large population migration in areas of the Brazilian Amazon has resulted in increased and sustained transmission of the disease (as reported in Martens and Hall 2000). In addition, change in the population either in terms of increase or of turnover can hamper the community's ability to deal with environmental related problems that were successfully faced in the past due to a dilution or loss of that knowledge (Adger 2000, Perz et al. 2011). This indicator was created by calculating the percent change between the estimated community population in 2005 and at the time of the survey (2010 or 2011) as reported in the community surveys.

Economic activity has been identified as increasing the susceptibility of an individual or population to malaria as certain economic activities are more likely to lead to exposure. da Silva-Nunes et al. (2012) identified logging and mining as important economic activities for malaria exposure while Martens and Hall (2000) cited seasonal movement into agricultural areas as being important. All three activities share the commonality of deforestation which creates ideal habitat for *A. darling* (da Silva-Nunes et al. 2012). To represent this aspect of vulnerability, the Economic Risk Index was formed by scoring the communities based on the top three economic activities reported in the community survey. If a community reported mining, logging, and agriculture as being important, the community received an Economic Risk Index of 3. If none of the activities were considered important to the community, it received a score of 0.

Similar to the Economic Risk Index, the importance of land use in terms of susceptibility to malaria is related to exposure to the vector. Areas which are more highly deforested are more attractive to *A. darling* (Vittor et al. 2006). To create the Land Use indicator, an ArcGIS shapefile of registered land uses for the department of Madre de Dios was obtained. The land uses most likely to lead to deforestation were mining, agriculture, and timber extraction. Shapefiles for each community were then constructed by drawing a 2 km buffer around the locations of each household sampled in the community. These buffers were dissolved into a single community wide buffer for each community and were assumed to roughly approximate the community. The community shapefiles were then intersected with the land use shapefile. The land use types present in each community were determined and the communities were scored based on how many of the three land types likely to lead to deforestation existed within the community. A community with mining, timber extraction, and agriculture land use areas received a score of three. A community with none of those land uses received a score of 0.

Six indicators were selected to represent the Lack of Resilience dimension of vulnerability. The first is Median Income. Indicators of socioeconomic status reflect a household's access to resource which moderates their ability to recover from an adverse event (Cutter et al. 2003). Hagenlocher et al. (2013) utilized % Households Without a Phone, % Unemployed, and % Employed as SES indicators; however, personal wealth indicators (e.g. per capita income) have been used elsewhere (Cutter et al. 2003). Informants responded to a series of questions concerning income in the household survey which resulted in categorization of the household into an income bracket. Households in higher income brackets would be expected to have greater resilience than communities in lower income brackets. The median income bracket was determined for each community from the household reported income brackets. Similarly, Percent Uninsured, the percentage of community members without insurance is included due to its importance in determining how households pay for medical care (Cutter et al. 2003). The mean percent uninsured was calculated for each community using household reported insurance status.

Education is another important component of the Lack of Resilience dimension. Dickens et al. (2013) cited the importance of female education due to the need for women, the primary caretakers of many households, to read and understand health information. Mothers' education level has also been found to be protective in Zambia where children's bed net use increased with increasing education (Norton 2012). The indicator, Female Secondary Complete, is the percentage of women over 18 who have completed secondary school in each community.

Social ties can also contribute to or detract from resilience. In an exploration of vulnerability and adaptive capacity in two indigenous Amazonian communities, Hofmeijer et al. (2013) found that a strong social network was an important aspect of adaptive capacity (the converse of lack of resilience).

Cooperation was also found to be key in resilience to natural disasters in the Caribbean (Adger 2005). Four questions within the household survey were asked concerning trust and willingness to help within the community. A Social Network Index score was created for each household by summing these answers (+1 for positive answers, -1 for negative answers) and the median score was determined for each community.

Access to healthcare plays an important role in determining whether or not an individual is treated and how quickly. It therefore is an aspect of resilience. Hagenlocher et al. (2013) utilized travel time to nearest hospital as a proxy for access while Dickens et al. (2013) used percent of households more than 5km from a hospital. Hofmeijer et al. (2013) found that access to formal health care was an important aspect of vulnerability in the indigenous communities they studied. Finally, Rao et al. (2013) saw a reduction in the percentage of individuals seeking malaria treatment when the distance to treatment was greater than 5km. Two indicators, Time to Major Healthcare and Time to Minor Healthcare, were created using the community average of travel time to health care reported at the household level. Households were asked how far they traveled for care for minor and major health problems. Since no information was gathered regarding which would be utilized for malaria treatment, both were included.

The final indicator included in the Lack of Resilience component is the Dependency Ratio. This indicator was determined by dividing the total number of people less than 15 years of age and those older than 64 years of age by the number of people between 15 to 64 years of age at a community level. Information regarding the proportion of the population that must be supported by those of working age is frequently included in vulnerability indices. For example, Siagian et al. (2012) incorporated both % elderly and % under 5 years old.

Data Processing

Indicators derived from the community data set required minimal treatment as this assessment was performed at a community level (e.g. they did not need to be transformed). However, one community was identified as having no community data available and was therefore excluded from the analysis. The household data dependent indicators needed more treatment in order to be used. A measurement of central tendency of all the responses in the community was used as the raw indicator value for each community. For questions which collected ordinal data, the median was used while the mean was used for interval data. Since the household indicators required finding the central tendency of the data, the number of individuals per community was assessed. A natural break occurred between communities with less than 20 individuals and those with more than 20. Five communities with 12 or fewer subjects were dropped from the data set. The final community sample size use in analysis was therefore 40.

Indicator Standardization

After data processing, each indicator was standardized to a 0 to 1 scale with 0 representing low vulnerability and 1 representing high vulnerability (Dickin et al. 2013, Hagenlocher et al. 2013). For indicators in which high values already reflected higher vulnerability, the Human Development Index method, a min max standardization, used in Dickin et al. (2013) was employed (Equation 1). An inverse of this method was used for indicators in which high values reflected lower vulnerability. In both methods, x is a particular observation of the indicator, x_{min} is the observation with the lowest value, and x_{max} is the observation with the highest value (Equation 2). Standardization provided a 0 to 1 value of each indicator for each community.

Equation 1: Indicator = $(x - x_{min})/(x_{max} - x_{min})$

Equation 2: Indicator = $(x - x_{max})/(x_{min} - x_{max})$

Creation of Index

Prior to creation of the index, the degree of correlation between variables was assessed to prevent "double dipping" from the data set and essentially counting an indicator of vulnerability twice (OECD 2008). Correlation overall was low, however, the Social Network Indicator and Percent without Insurance were fairly highly correlated at 0.73. Both indicators were still maintained as they do not have a conceptual link. The indicators were assigned equal weights and averaged by dimension (Lack of Resilience and Susceptibility) (Equation 3a & 3b). The dimensions were then weighted according to the percent of total indicators in the dimension (Equation 4). This was done to maintain a balanced structure between the two dimensions (OECD 2008, Hagenlocher et al. 2013). Equally weighting the indicators and then balancing the dimensions assumes that all indicators contribute to vulnerability equally. However, individual indicators and/or dimensions are frequently weighted in the development of indices (e.g. see Hagenlocher et al. 2013, Dicken et al. 2013, Parkins and MacKendrick 2007).

Equation 3a: LOR = $(I_1+I_2….+ I_8)/8$

Equation 3b: SUS = $(I_9+I_{10}+ I_{11})/3$

Equation 4: VUN = $(SUS*0.27+ LOR*0.73)/2$

Mapping/Comparison of Index

Communities were classified into 5 categories using standard deviation from the mean (Cutter et al. 2003). Those with a standard deviation greater than 1.5 are considered highly vulnerable (Cutter et al. 2003). The location and vulnerability ranking of each community was mapped using ArcGIS. A vulnerability surface for the entire 10 km buffer along the Interoceanic Highway was also created from the sampled community scores using an interpolation method. The Geostatistical Wizard was used to perform ordinary kriging. Ten models were compared using the root mean square, root mean square standardized, and the average standard error and the best model was selected. Finally, an additional map was created of malaria proportion incidence by district in 2013 (Dickin et al. 2103). The interpolated vulnerability surface and the reported malaria case map were visually compared as a qualitative assessment of the performance of the index (Dickin et al. 2013). The household survey contained a section of questions devoted to household vulnerability. These questions were used to create a second vulnerability index (designated Survey Vulnerability Index). Results of this study's vulnerability index were compared to that of the Survey Vulnerability Index in order to understand how sensitive community scores were to the method used to create the index.

Results

Vulnerability scores ranged between 0.13 and 0.31 with a mean of 0.21 (Figure 4). The most vulnerable communities (>1.5 standard deviations) were located along the southern portion of the Interoceanic Highway (Figure 5). Highly vulnerable communities (0.5 to 1.5 standard deviations) were found at the northern tip of the IOH and near to Puerto Maldonado.

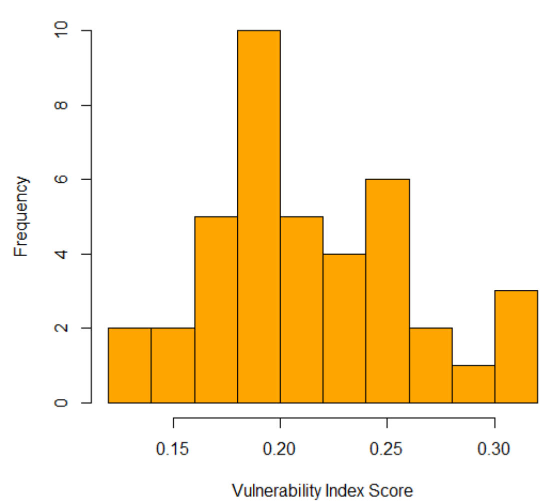

Figure 4. Distribution of community vulnerability scores (n=40).

Examination of the individual dimension scores for each community reveals an interesting trend (Figure 6). Scores were generally higher in the Susceptibility dimension than in the Lack of Resilience dimension. Peaks in the Susceptibility and Lack of Resilience scores are seen near the far left, center, and right of the graph which corresponds to High Vulnerability communities depicted in Figure 5 (Figure 6). Nueva Arequipa and Villa Santiago, the two communities with the highest vulnerability scores were selected for a detailed exploration of the indicator scores (Figure 7). The two communities scored similarly in the Susceptibility dimension indicators (Economic Risk Index, Land Use, and Population Change) (Figure 7). However, the differed greatly in certain Lack of Resilience indicators (Dependency Ratio, Time to Major Care, Community Engagement, Income, and Female Secondary Education) (Figure 7).

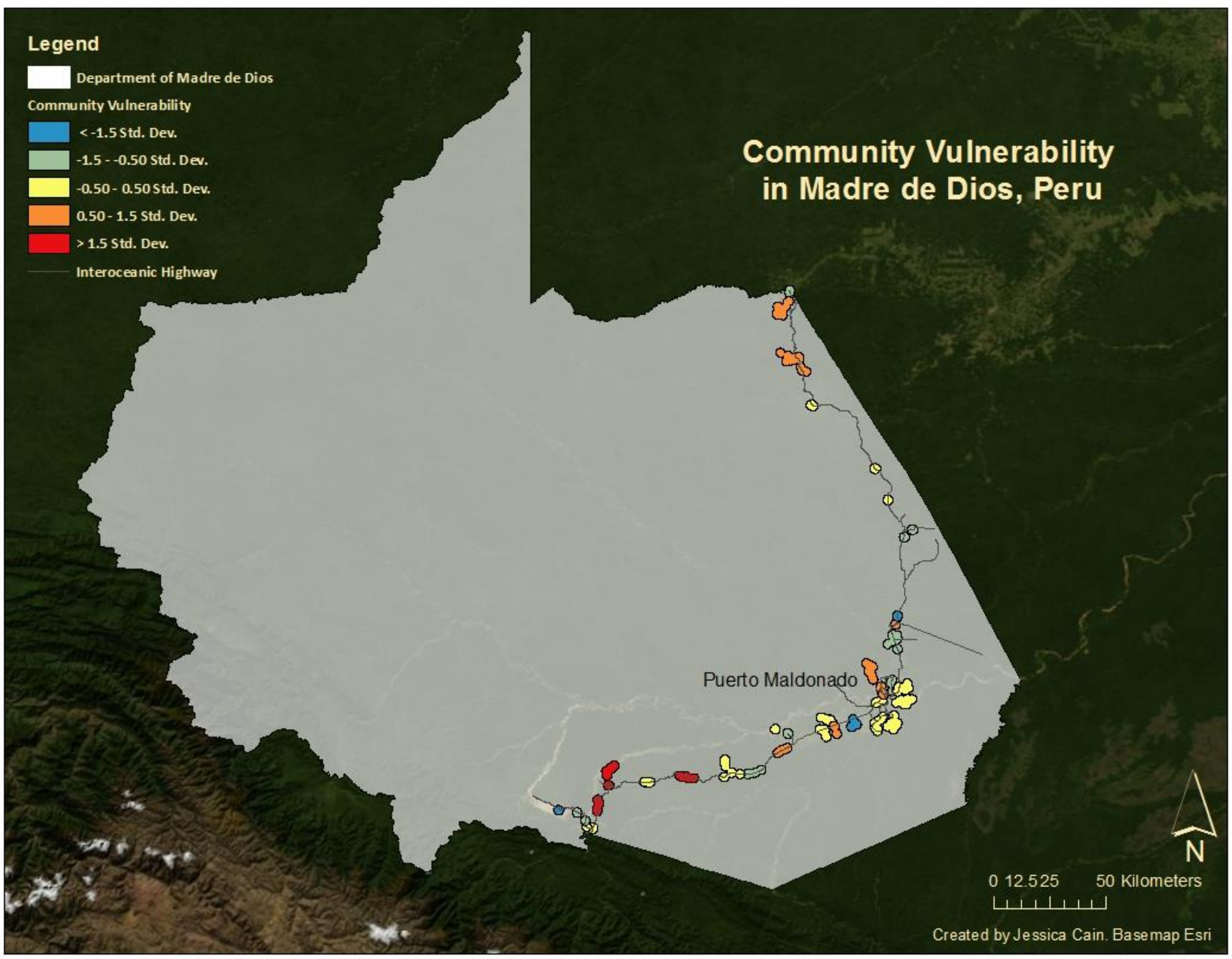

Figure 5. Spatial location and vulnerability scores of sampled communities (n=40).

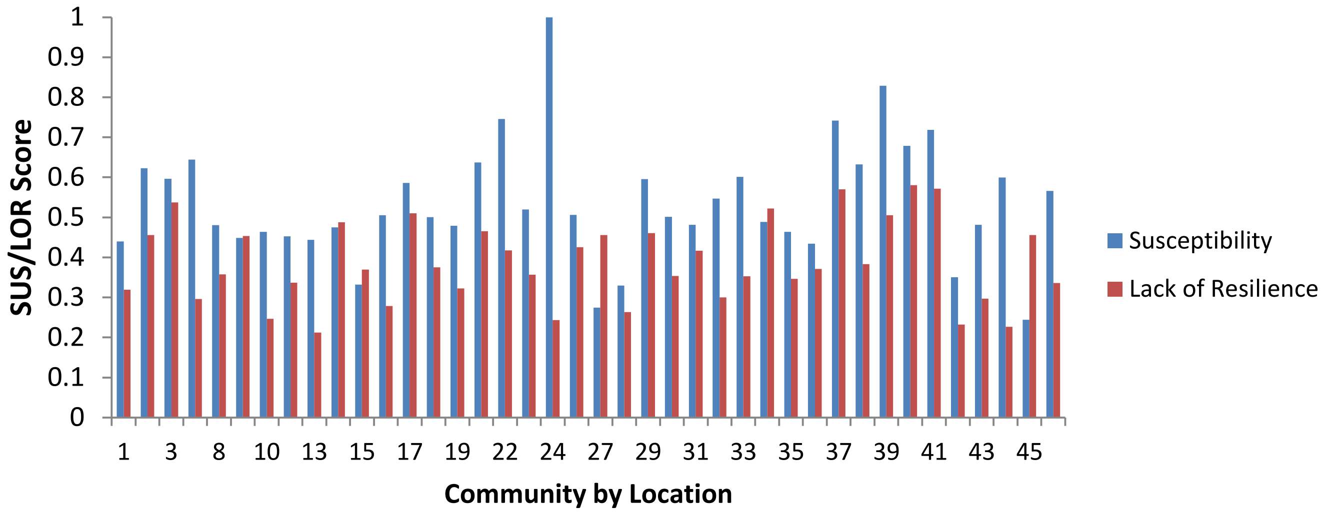

Figure 6. Susceptibility and Lack of Resilience dimension scores for each community (n=40). Communities are arranged in order of occurrence from north to south.

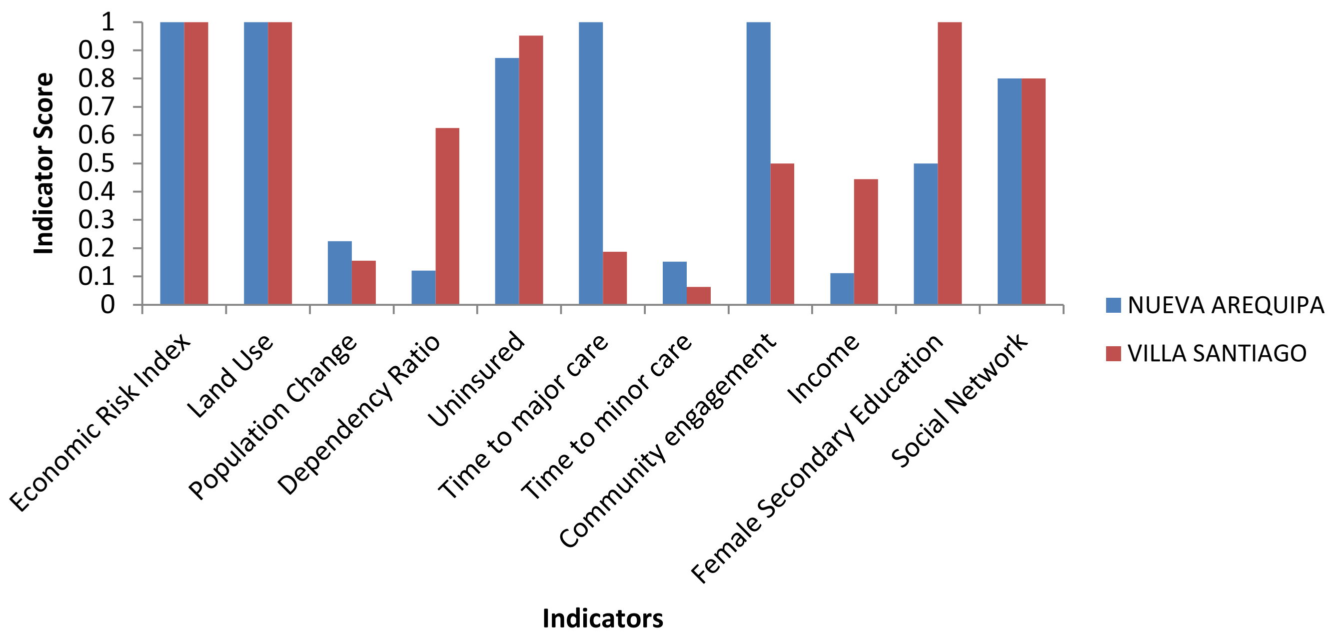

Figure 7. Individual indicator scores for the two most vulnerable communities.

The interpolated vulnerability surface is depicted in Figure 8. Communities located in the blue colored areas are predicted to have lower vulnerability scores relative to others in the department while those in red colored areas are expected to have higher scores (Figure 8). The area of highest predicted vulnerability is located along the southern stretch of the IOH (Figure 8). Other relatively high prediction locations are located at the northern end of the IOH and in the center, near the department's capital of

Puerto Maldonado (Figure 8). Malaria cases reported by district in 2011 are depicted in Figure 9. Using reported malaria cases as a proxy for vulnerability, comparison of Figures 8 and 9 suggest that the index performed well in the southern region of the department, but not the northern region.

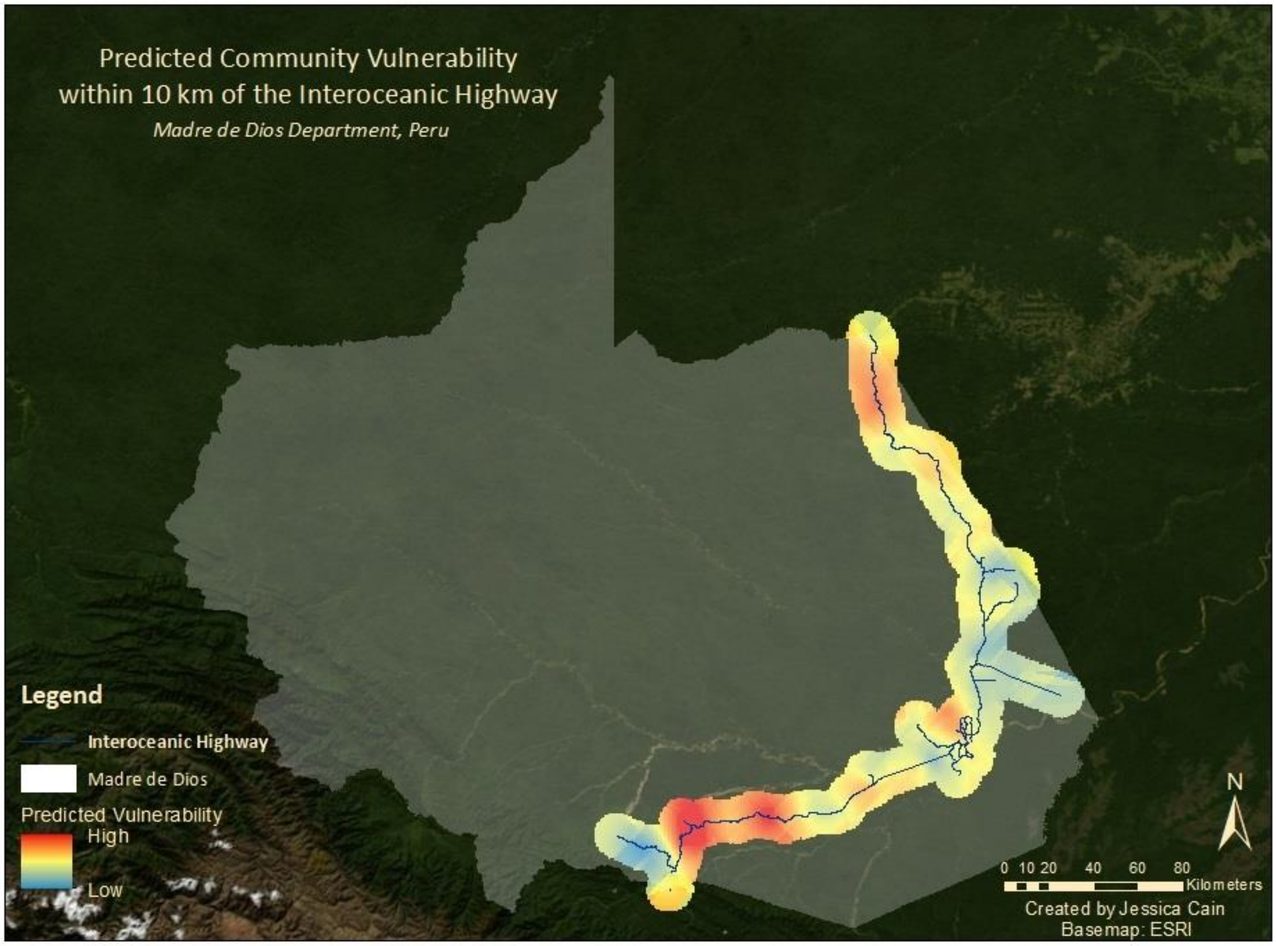

Figure 8. Vulnerability surface interpolated for the 10 km buffer surrounding the Interoceanic Highway.

Comparison of the vulnerability scores of the current study's index and the Survey Vulnerability Index showed that the indices varied greatly (Figure 10). The Survey Vulnerability Index scores had a much larger range and were generally higher than the current study's index scores (Figure 10). The same spatial pattern (areas of high vulnerability at the ends of the IOH and in the center) was not seen in the Survey Vulnerability Index scores (Figure 10). Instead, communities in the northern portion of the IOH generally have higher scores (Figure 10).

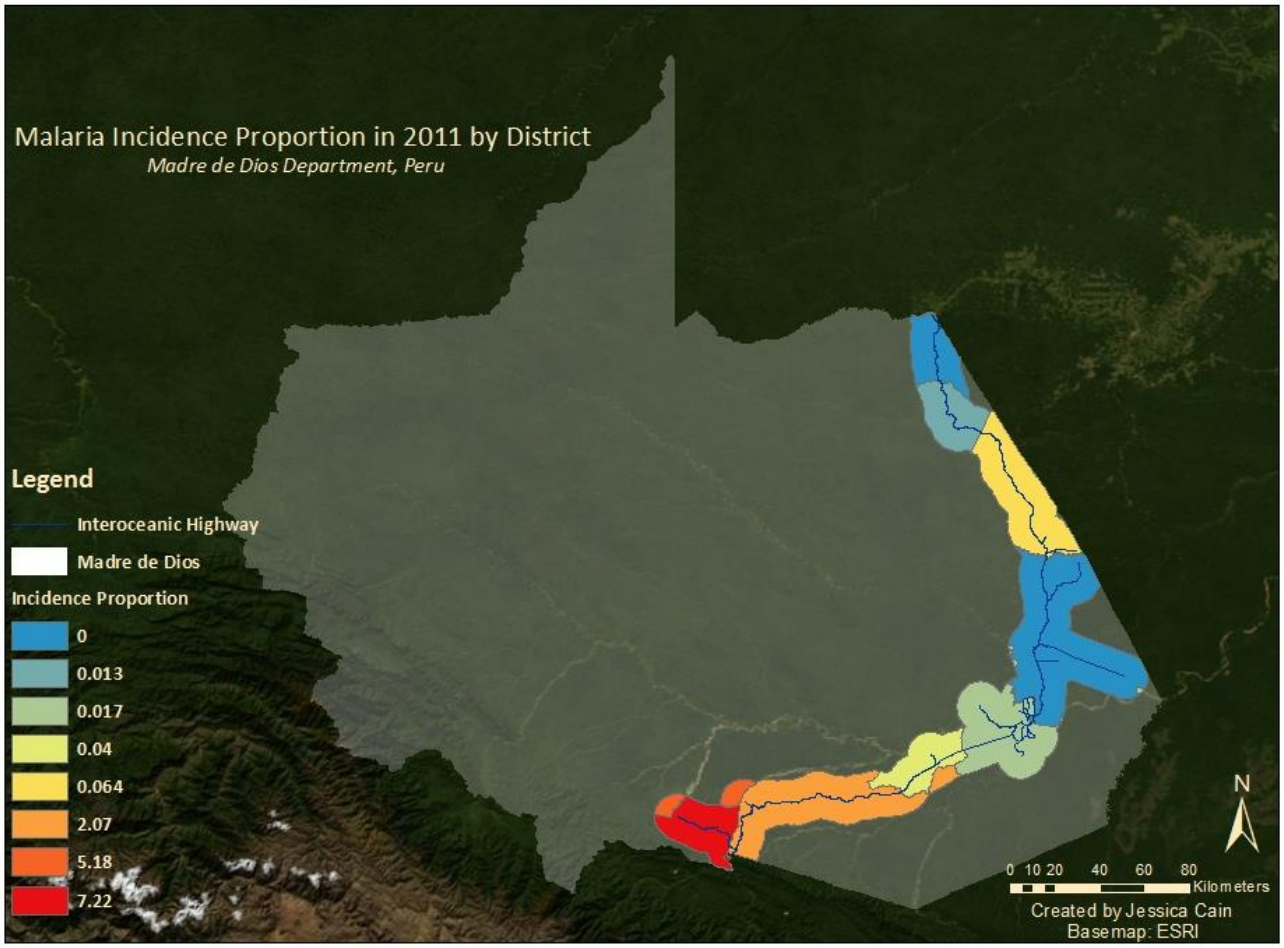

Figure 9. Malaria incidence proportion by district in 2011.

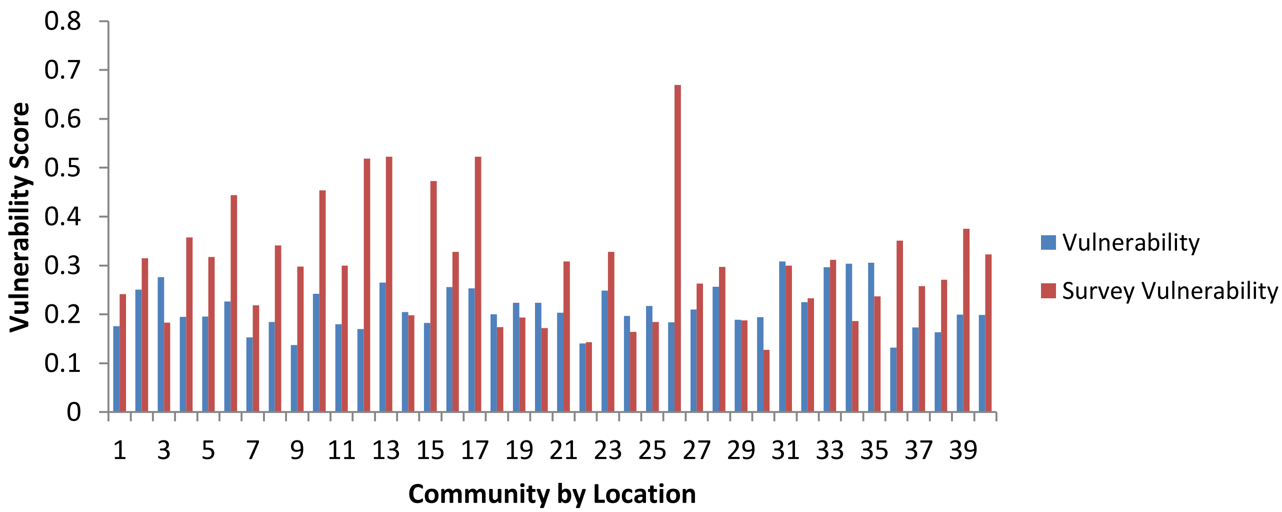

Figure 20. Comparison of vulnerability scores derived from the current study's index (Vulnerability) and the Survey Vulnerability Index.

Discussion

Using a modified vulnerability framework influenced by the political-ecology approach to vulnerability, an index of vulnerability was created for forty sampled communities in Madre de Dios, Peru. Application of the index identified which communities were the most vulnerable (> 1.5 standard deviations from the mean) of those sampled. In addition, the results of the analysis were extended to un-sampled areas within a 10 km buffer of the Interoceanic Highway using Kriging, an interpolation method. An area in the southern region of the buffer emerged as having the highest predicted vulnerability.

Development and application of vulnerability indices like that in the current study hold promise for use in the control and eradication of disease. Diseases such as malaria which do not have vaccinations available for prevention particularly need an integrated approach to eradication (Dickin et al. 2013). An aspect of this integrated approach is to understand why certain areas or portions of the population are vulnerable to a disease and the negative impacts which extend beyond the illness itself (Dickin et al. 2013, Hagenlocher et al. 2013). One of the issues complicating the eradication of malaria is the maintenance of the pathogen in populations of people defined by small geographic areas and unique demographic characteristics (Cotter et al. 2013). The vulnerability index created and applied in this analysis may identify such hotspots in Madre de Dios as indicators incorporate such issues as potential for exposure, proximity to treatment, and protective household attributes which would influence the ability of the community to harbor the pathogen. In particular, Cotter et al. (2013) discussed how changing livelihoods are resulting in populations of adult men who harbor the pathogens as well as the importance of population movement. Both of these are explicitly taken into account in the index developed for this analysis.

Chuquiyauri et al. (2012) examined the relationship between sociodemographic factors and lifetime cases of malaria, citing their likely importance in the rise in malaria in the Amazon. Factors which they found to be positively and significantly correlated with increasing number of malaria cases included job type and habitation with an individual engaged in logging or agriculture (Chuquiyauri et al. 2012). Again, the current analysis incorporates these factors on a community level, resulting in identification of communities where such risk factors are found in high combinations. While the results of this study give an indication of which communities in Madre de Dios are most likely to be hotspots for malaria and harbor populations with high risk factors, it should be noted that the scores received are relative to the communities included in the sample due to use of the minimum and maximum standardization. Furthermore, a standard for defining what scores constitute low or high vulnerability does not exist. Though the standard deviation approach has been used prior to this study (Cutter et al. 2003), other methods could potentially be used.

Validation of vulnerability assessments are difficult to perform as there is no tangible, direct measurement of vulnerability (Dickin et al. 2013). Hagenlocher et al. (2013) did not perform a validity assessment, but instead compared the results of two methods. Dickin et al. (2013) analyzed the correlation between the results of their index and state level dengue rates as well as consulted experts in the region. Cutter et al. (2013) used presidential declarations of a state of emergency for validation of an index assessing county vulnerability to natural hazards. A similar, but qualitative, comparison of the predicted malaria vulnerability map to the malaria incidence proportions by district indicate that the created vulnerability index and resultant predicted values performed fairly well. The area of greatest predicted vulnerability coincides with the region in which the greatest incidence proportion. However, a hot spot of relatively high predicted vulnerability in the north is not reflected in the incidence proportion. There are several limitations to this form of validation. First, malaria incidence does not truly measure vulnerability to malaria. Second, the incidence proportions were calculated per district. This is a much coarser grain of data then the community level data from which the vulnerability map was created. Finally, cases are reported by the district the person was treated in, not the district in which they live permanently. This means that if a person is traveling for work or pleasure and develops malaria in another district, the person will be treated there and the case reported as occurring in that district. Therefore, indicators such as median household income bracket which do not reflect the physical location but the attributes of the people claiming the community as their permanent residence are not suited for comparison to district malaria incidence proportion. Other indicators such as the community land use and distance to medical care reflect the locality and are therefore appropriate for comparison to the incidence proportion.

Much of the value of vulnerability assessments lies in the potential usefulness for decision makers. In a vulnerability analysis of counties in the United States, Cutter et al. (2003) argue that developing indicators of the different components of vulnerability and exposure allows for selection of communities for target interventions based on scientific decision making process rather than arbitrary political selection. Hagenlocher et al. (2013) developed and applied an index for vulnerability to dengue in the city of Calli, Colombia. The results were then visualized using an interactive, online ArcGIS platform so that decision makers could examine drivers of vulnerability in neighborhoods classified as being highly vulnerable (Hagenlocher et al. 2013). While lacking the interactive component, the current analysis enables stakeholders to examine which communities received the highest vulnerability score and then examine what is driving that score. Using Nueva Arequipa and Villa Santiago as examples, it can be seen that the drivers may differ substantially between communities. Similar results were seen in both Hagenlocher et al. (2013) and Dickin et al. (2013). Similar high scores in the Susceptibility dimension indicate that both communities would benefit from an intervention in this area; perhaps prevention strategies targeted to workers engaged in the higher risk economic activities. However, differences in the Lack of Resilience dimension indicate that different interventions would be needed to build resilience in each community. Nueva Arequipa would possibly benefit from greater community engagement by the government or another organized group while Villa Santiago may benefit more from an intervention that targets female education. Parkins and MacKendrick (2007) emphasized the utility of the assessment to the community members. Identification of drivers of vulnerability at the community level provide the communities with an opportunity to mitigate the vulnerability themselves (Parkins and MacKendrick 2007).

Though the results of the current analysis are believed to be useful, it is important to understand the dependence on the construction of the index. The comparison the current study index with the Survey Vulnerability Index emphasizes this. The two indices yielded significantly different results. The difference is likely due to the inclusion of only social network and community engagement indicators in the Survey Vulnerability Index. As communities were assessed on just these two aspects of lack of resilience, the results varied widely from the current study index in which a wide range of lack of resilience indicators as well as susceptibility indicators were included. Another aspect which greatly influences an index is the weighting schemes used. In the current study, indicators within each dimension were equally weighted similar and the dimensions were weighted according to the percent of total indicators in order to maintain equal contribution from each. Cutter et al. (2003) equally weighted their indicators due to a lack of *a priori* knowledge concerning importance of each. Hagenlocher et al. (2013) utilized weighting schemes for the indicators within the two dimensions they defined but then weighted the two dimensions using the percent of total indicators method. Two separate weighting schemes for the indicators were used: expert judgment and statistical analysis (Hagenlocher et al. 2013). While the correlation between the two methods was high, some differences existed in the spatial distribution of high vulnerability scores (Hagenlocher et al. 2013). The dataset used in the formation of the current vulnerability index was not appropriate for statistically derived weights. However, an expert based judgment or modification of the data set to allow statistical analysis could be possibly used in the future.

In conclusion, the vulnerability index and predicted vulnerability map produced in this study give an indication of which communities are most vulnerable within the department of Madre de Dios, Peru. While limitations such as the relative nature of the index, the importance of the construction, and the uncertainty associated with interpolating values across a surface exist, the index is expected to be useful to stakeholders such as government officials in community leaders. It enables not only the identification of which communities appear to be most vulnerable, but also what is driving that vulnerability. This knowledge can then be used to develop targeted interventions that address communities which are more likely to be or become hotspots of malaria in the department.

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