Mapping of Vector-Borne Disease (VBD) Hotspots in the Philippines: Constructing a Vector-Borne Disease Vulnerability Index using AHP

Dating, Mark Jay P.
MSPH Biostatistics (UPM)
Faculty Member (INSTAT-UPLB)

1. Introduction

The Department of Health (DOH) of the Philippines and supporting agencies are unyielding in our battle with vector-borne diseases. In 2018, DOH recorded decreasing morbidity rates of Malaria. Most affected areas are those with remote basic health services. Opportunely, DOH is now geared towards the elimination of the disease rather than prevention and control.

On the other hand, Philippines is recording high morbidity and mortality rates due to dengue fever. DOH (2019) declared last month a national dengue epidemic for there were 146,062 cases recorded from January to July this year. This is higher than recorded cases during the same period last year. The highly affected provinces were Western Visayas, CALABARZON and Central Visayas (IFRCRCS, 2019).

Another disease caused by mosquitoes which is under the surveillance of DOH is chikungunya. The disease has no known cure at the moment and all medications are focused on dismissing the symptoms (WHO, 2017). Most cases were found in provinces of Romblon, Aurora, Zambales, Batangas and Laguna within the first half of 2017. *Aedes* species mosquito is also the vector of Zika virus which causes a disease similar to influenza and accompanied by conjunctivitis (DOH, 2016).

According to WHO (2017), although vector-borne diseases or VDB comprise 17% of all infectious diseases, it is estimated that 96 million cases are recorded annually all over the globe leading to more than 700,000 deaths per year. Nevertheless, WHO believes that mosquito-borne diseases such as malaria are preventable when prevention and control measures are in place.

With all these recent statistics, there is a need to monitor VBD that have caused past and recent outbreaks and epidemic events. For a developing country like the Philippines, the key is to detect onset of such diseases during its early stage to halt mortality, spread and its impending effect to economy. Cure for certain diseases became less effective since microbes are evolving with the rapidly-changing world. Moreover, human migration, urbanization, trade of food, business of medicinal products, transformation of society, deforestation and alteration of the environment are evident. All these lead us to say that there is a need to thoroughly investigate the current situation of the Philippines.

The idea of this study was to consider as many important factors as possible and associate them with each other and eventually assess their effect on the spread of mosquito-borne diseases and susceptibility of different locations. In this study, different tools like statistical indices and mapping were utilized. Constructing an index as a measure of vulnerability results to a relevant and beneficial tool. Moreover, the index can also assess preparedness of our country during a mosquito-borne outbreak. Irregular and possibly massive outbreaks threaten national health security, so there is a need for a wide-ranging VBD vulnerability index.

The general objective of this study was to determine the exposure of Philippine provinces to factors that make them vulnerable to VBD using a composite disease vulnerability index. Specifically, the study aimed to:

1. determine provinces in the Philippines with high VBD vulnerability in terms of:
   a. demographic factors;
   b. economic factors;
   c. disease dynamics factors;
   d. public health and health care factors;
   e. infrastructure factors; and
   f. governance factors;

2. determine provinces in the Philippines with high VBD vulnerability using a composite index produced by analytical hierarchy process (AHP); and

3. assess validity of the constructed VBD vulnerability index.

2. Methodology

The population of the study was composed of the 79 provinces of the Philippines and Metro Manila (NCR) for a total of 80 units. The study excluded Davao Occidental in Region XI - Davao Region and Dinagat Islands in Region XIII – Caraga. Metro Manila (NCR) was counted as a separate unit.

Series of steps was conducted in the construction of index, namely, 1) collection of indicator data, 2) imputation of missing data, 3) normalization of indicator data, 4) index construction, 5) uncertainty analysis of indices and 6) statistical mapping of indices. These steps were illustrated in Figure 2 and were briefly discussed below. Datasets on identified indicators in each dimension per province were collected and organized using Microsoft Excel and Stata. All analyses were facilitated under R for construction of indices and Stata for data management and preliminary analyses.

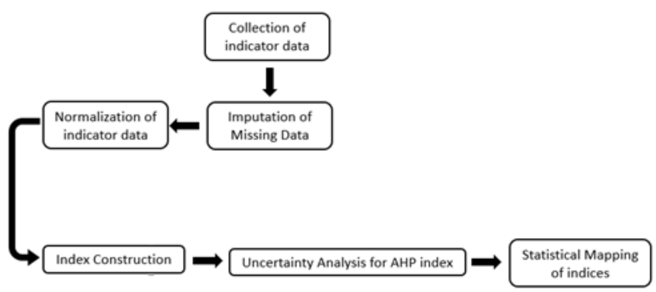

Figure 1. Flowchart of data processing and analyses steps

This study employed stochastic multiple imputation to estimate missing indicator data of provinces with missing observations. This type of imputation is best in using all available information from variables or indicators with complete observations across provinces and use these information in constructing a Bayesian model that will estimate the missing observation.

For normalization, this study employed the normalization method used by Moore et al., (2016). The min-max normalization converts the raw observations into a scale of 0 to 1. Since indicators may have opposing directions, the normalization method differed between those indicators which are preferred to be high and indicators which are preferred to be low. Ultimately, normalization resulted to a value near 1 if the measure for the indicator was not favorable or near 0 if the measure was favorable.

$$X_{normed} = \frac{X_{raw} - X_{minimum}}{X_{maximum} - X_{minimum}} \quad \text{or} \quad X_{normed} = \frac{X_{raw} - X_{maximum}}{X_{minimum} - X_{maximum}}$$

2.1 Analytic Hierarchy Process (AHP)

This study used the analytic hierarchy process or AHP developed by Thomas Saaty in the 1970s. The process starts with comparing by pair all factors involved. This comparison gives a score of 1 (equally important) to 9 (extremely important) to a factor depending on its importance. For instance, if comparison is done for all possible pairs of 4 factors, then a comparison matrix **C** for four factors can be constructed such as this.

$$\underline{C} = \begin{bmatrix} 1 & r_{12} & r_{13} & r_{14} \\ 1/r_{12} & 1 & r_{23} & r_{24} \\ 1/r_{13} & 1/r_{23} & 1 & r_{34} \\ 1/r_{14} & 1/r_{24} & 1/r_{34} & 1 \end{bmatrix}$$

The weights of each factor which will be used for construction of the index are the elements of the normalized principal eigenvector of the comparison matrix which is called priority vector by AHP.

There are measures on how to assess if the comparison matrix is consistent in the sense that rating given to a pair of factors does not appear in conflict with other pair of factors in light of transitive property of comparisons (Teknomo, 2006). This study used consistency ratio (*CR*) which can be calculated by:

$$CR = \frac{CI}{RI}$$

where CR is the consistency ratio, CI is the consistency index and RI is the random consistency index. Consistency index measures the deviation from perfect consistency through this formula:

$$CI = \frac{\lambda - p}{p - 1}$$

where λ is the principal eigenvalue and *p* is the number of factors in the comparison matrix. On the other hand, random consistency index (*RI*) is the average consistency index of randomly generated comparison matrices involving *p* factors and, therefore, measures how inconsistent a comparison can be for a set of factors. This study used the *RI*'s of Franek and Kresta (2014) who provided their own simulation of 500,000 random comparison matrices. They came up with this set of RI's.

p	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.525	0.882	1.110	1.250	1.341	1.404	1.451	1.486	1.514	1.536	1.555	1.570	1.584

A CR at most 0.10 means that there is small inconsistency and that the ratings are acceptable. Otherwise, the ratings should be revisited by transforming the ratings (Teknomo, 2006 & Franek & Kresta, 2014) using the square root function.

Once all six dimension indices are constructed, these dimension indices were further aggregated into one composite vector-borne infectious disease vulnerability index using zero-corrected geometric mean. The formula is stated below where *j* identifies the six dimensions for province *i*.

$$VBDVI_i = \sqrt[6]{\prod_{j=1}^{6}\left(DI_{i,j} + 0.00001\right)} - 0.00001$$

2.2 Robustness of VBD Vulnerability Index

Composite indices, though useful in decision- and policy-making, are surrounded by uncertainties. Various sources of uncertainty need to be discussed. This study employed uncertainty analysis by investigating the changes in the composite index when an indicator is removed and when weight values are modified. To assess if the composite index is sensitive, the composite index was recalculated for each modification of a particular source. The interest was to compare the rank of the composite index across all units instead of comparing the actual index. Average difference between the original rank and the ranks after modification of a source of uncertainty can be calculated to examine the effect of modification done. This can be calculated by this formula (Nardo et al., 2005):

$$\bar{r}_{Ai} = \frac{\sum_{j=1}^{N}\left|r_{oi} - r_j\right|}{N}$$

where $\bar{r}_{Ai}$ is the average absolute difference of rank for unit *i*, r_{oi} is the original rank of unit *i*, r_j is the rank of unit *i* after modification and N is the number of modifications done.

After modification and the resulting average absolute difference is far from zero, then this means that the composite index is sensitive to that particular modification. On the other hand, if the resulting average absolute difference is near zero, then this means that the composite index is not sensitive to the modification performed.

Removing an indicator. For this uncertainty analysis, an indicator was removed one at a time and the dimension index and composite index were recalculated. The resulting rank of the index for each removal was compared to the original rank. N in this case was the total number of indicators which was 46.

Modifying weight values. In this part of uncertainty analysis, the study investigated the extent of changes in the rank if weights of dimensions were modified. Modification took place for a single dimension only, that was, modifying one dimension left the other five dimensions in their original setting. This study used four weight modification schemes: 0%, 25%, 50% and 75% weight increments. Without modification, all indices were raised to 1/6 or 0.1667 due to sixth root operation. 0% weight increment basically disregarded one whole dimension leaving the other five dimensions at their original setting. For this, fifth root was used in the geometric mean of getting VBDVI since one dimension was eliminated. On the other hand, 25% weight increment added additional 25% to the original weight of 1/6 or 0.1667 making it 1/8 or 0.125. This awarded a dimension higher contribution to VBDVI by raising its dimension index to 0.125. To preserve sixth root, the other five dimension indices were raised to 7/40 or 0.175. Notice that increasing the contribution meant raising it to a lower value since indices were from 0 to 1. The formula for 25% weight increment was:

$$VBDVI_i^{25\%} = \left(\sqrt[8]{DI_X + 0.00001} \times \sqrt[40]{\prod_{Y=1}^{5} \left(DI_Y^7 + 0.00001 \right)} \right) - 0.00001$$

where ***X*** stands for the dimension with increased weight and ***Y*** stands for dimensions with reduced weights. For 50% weight increment, weight of inflated dimension was modified from 1/6 or 0.1167 to 1/12 or 0.083 while weights of the other five dimensions were modified to 11/60 or 0.183. The formula was:

$$VBDVI_i^{50\%} = \left(\sqrt[12]{DI_X + 0.00001} \times \sqrt[60]{\prod_{Y=1}^{5} \left(DI_Y^{11} + 0.00001 \right)} \right) - 0.00001$$

For 75% weight increment, weight of inflated dimension was modified from 1/6 or 0.1167 to 1/24 or 0.042 while weights of the other five dimensions were modified to 23/120 or 0.192. The formula was:

$$VBDVI_i^{75\%} = \left(\sqrt[24]{DI_X + 0.00001} \times \sqrt[120]{\prod_{Y=1}^{5} \left(DI_Y^{23} + 0.00001 \right)} \right) - 0.00001$$

Since there were six dimensions and each had four modifications, there was a total of 24 modifications for this uncertainty analysis.

Comparing the indices generated by the methodology to current situation of vector-borne diseases. Previous analyses examined the effect of possible sources of uncertainty but a more definitive proof of how strong the indices are was resemblance to real condition. For this part, the indices as well as the statistical maps generated by constructed vector-borne disease indices were compared to morbidity and mortality rates of selected mosquito-borne diseases using *leave-one-out cross validation* (LOOCV). Ultimately, $RMSE_{test}$ and $RMSE_{training}$ were compared to each other. If the value of $RMSE_{test}$ is near $RMSE_{training}$, then the prediction is of good quality leading us to conclude that the index resembled the real condition of the provinces in terms of vector-borne infectious diseases

$$RMSE_{test} = \sqrt{\frac{\sum_{i=1}^{80} \left(\hat{V}_{i,test} - V_{i,test} \right)^2}{80}} \qquad RMSE_{training} = \frac{\sum_{i=1}^{80} RMSE_i^*}{80}$$

4. Results and Discussion

4.1 Consistency of collected responses from experts

Three experts from the field were requested to answer an online questionnaire where they compared the importance of each indicator per dimension towards assessing vulnerability of a province in vector-borne infectious diseases. Tabulated in Table 1 are the consistency ratios (CR) for each dimension. After combining their ratings, the official comparison matrices were found to be consistent as all consistency ratios were at most 0.07 which is lower than the 0.10 limit. We can therefore say that the experts performed formal judgement and subjective evaluation.

Table 1. Consistency Ratios of Comparison Matrices per dimension.

Dimension	Expert A	Expert B	Expert C	Comparison Matrix
1 Demographic	0.18	0.08	0.11	0.07
2 Economic	0.16	0.03	0.10	0.03
3 Disease Dynamics	0.08	0.02	0.09	0.03
4 PH and Healthcare	0.14	0.03	0.05	0.03
5 Infrastructure	0.23	0.05	0.05	0.03
6 Governance	0.20	0.08	0.00	0.04

4.2 Demographic Dimension

Table 2. Demographic indicators with high weights.

Demographic Indicator	Weight
Percentage of persons living in urban areas	0.1990
Population Density	0.1474
Annual population growth rate	0.1415

In demographic dimension, large weights were given to percentage of persons living in urban areas and population density which showed the relevance of the number of persons living in an area. This supported studies suggesting the effect of population density in increasing conduciveness of an environment for spread of any infectious disease (Wise et al., 1998 & Fritzell et al., 2016). On the other hand, low weights were given to literacy rate and percentage of academic degree holder opposing the findings of some studies that control programs are effective and successful if population has high literacy to health(Moore et al, 2016, Dewalt et al, 2004 & Heymann, 2006). With these weights, AHP identified NCR (index = 0.5110) as the most vulnerable province demographically. NCR was followed by Maguindanao (index = 0.4247) and Rizal (index = 0.3710). Statistical map of demographic dimension in Figure 1 shows that vulnerable provinces were clustering in Central Luzon (Region 3), CALABARZON (Region 4A), central to eastern parts of Visayas, and in most parts of Mindanao.

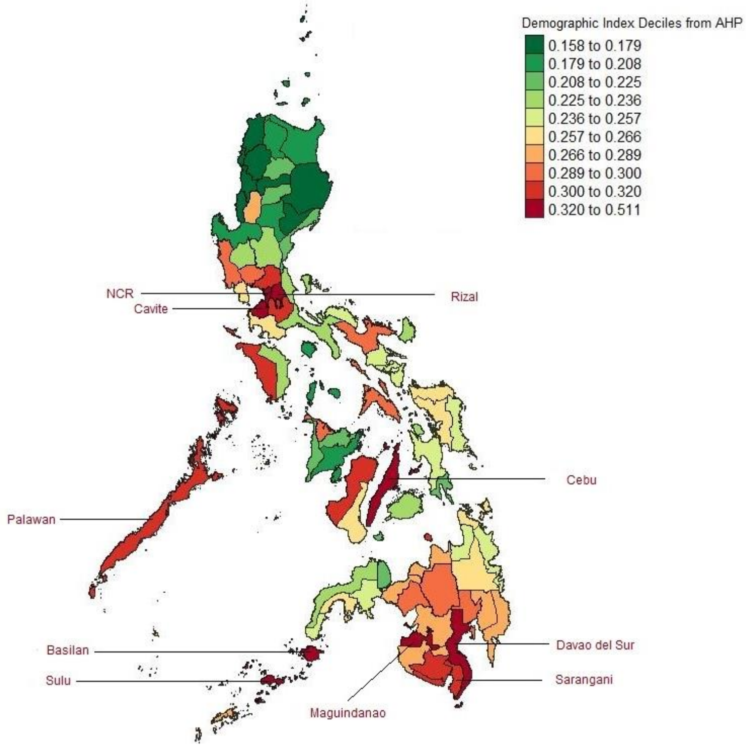

Figure 2. Most vulnerable provinces according to demographic factors using AHP.

4.3 Economic Dimension

Table 3. Economic indicators with high weights.

Economic Indicator	Weight
Poverty incidence among families	0.2771
Employment rate	0.2253
Inflation rate	0.1627

Among economic indicators, large weights were given to poverty incidence among families and employment rate which reflect the financial capacity of the population. Decreased investment to health due to poor economic status of locations translates to poor access to healthcare. In return, programs to control infection-carrying mosquitoes have slow progress causing resurgence of vector-borne diseases. Economic dimension indices identified Lanao del Sur (index = 0.9183) as the most vulnerable province economically. Lanao del Sur was followed by Siquijor (index = 0.7112) and Northern Samar (index = 0.7098). Figure 2 shows that vulnerable provinces could be seen clustering in the eastern part of the country specifically in Bicol Region (Region 5), Eastern Visayas (Region 8), and in most parts of Mindanao.

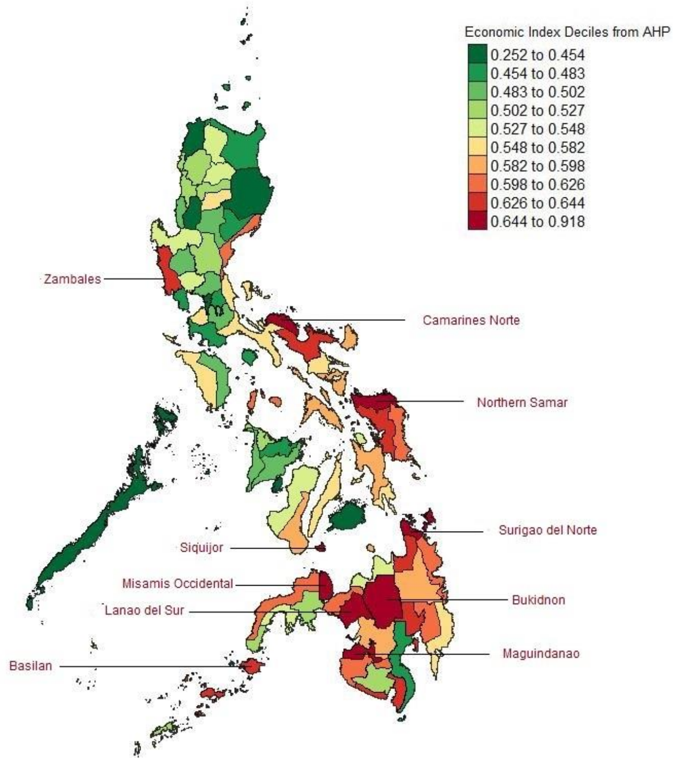

Figure 3. Most vulnerable provinces according to economic factors using AHP.

4.4 Disease Dynamics Dimension

Table 4. Disease dynamics indicators with high weights.

Disease Dynamics Indicator	Weight
Population per residential area	0.2369
Total area with agricultural crops per hectare	0.2039
Total annual rainfall	0.1876

For disease dynamics dimension, large weights were given to population per residential area and total area with agricultural crops per hectare. Results supported studies stating that land use for agricultural activities affects zoonotic infectious diseases by increasing proximity of humans to natural reservoir of hosts (Eisenberg, et al., 2007, Morse, 1995 & Alto & Bettinardi, 2013). On the other hand, low weights were given to variability of monthly mean temperature and humidity. This is in contrast with studies that have shown that seasonal and geographic differences in temperature and humidity affects the dynamics of the mosquito population as well as the pattern of disease transmission (Bai et al., 2013 & O'Meara et al, 2008). In this dimension, AHP categorized Isabela (index = 0.5731) as the most vulnerable province in terms of disease dynamics factors. The province was followed by Benguet (index = 0.5422) and Cagayan (index = 0.5074). Figure 3 shows vulnerable provinces were clustering in most part of Luzon and central part of Mindanao. Isolated vulnerable provinces appear in central part of Visayas.

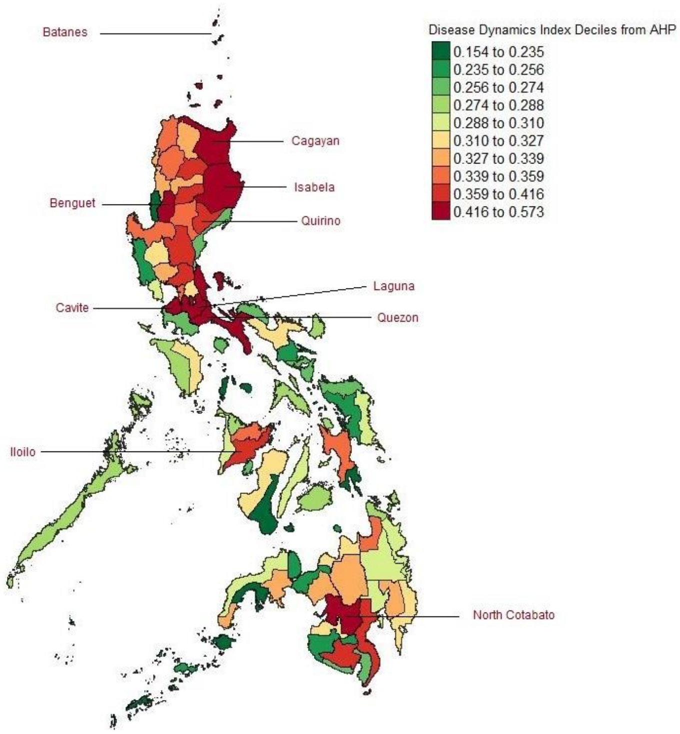

Figure 4. Most vulnerable provinces according to disease dynamics factors using AHP.

4.5 Public Health and Healthcare Dimension

Table 5. Public health and healthcare indicators with high weights.

Public health and healthcare Indicator	Weight
Number of private hospitals per population	0.1283
Number of public hospitals per population	0.1245
Number of medical doctors per population	0.1206

In terms of public health and healthcare indicators, large weights were given to number of private and number of public hospitals per population. This coincided with the findings in the study of O'Meara et al in 2008 where proximity of primary care services was considered as an important factor to malaria treatment and prevention (Levy & Meltzer, 2008). On the other hand, percentage of local citizens without PhiHealth registration in AHP received the lowest weight. The study of Levy and Meltzer in 2008 agrees to this as they mentioned that although health insurance helped improve health measures, there was no strong evidence in its association to health in general (Allen, 2015). With these weights, Lanao del Sur (index = 0.8765) was identified by AHP as the most vulnerable province under this dimension followed by Basilan (index = 0.8756) and Sulu (index = 0.8543). Figure 4 shows vulnerable provinces were clustering in the southern part of Luzon and central part of Visayas. Parts of Mindanao also had substantial share in the pool of vulnerable provinces.

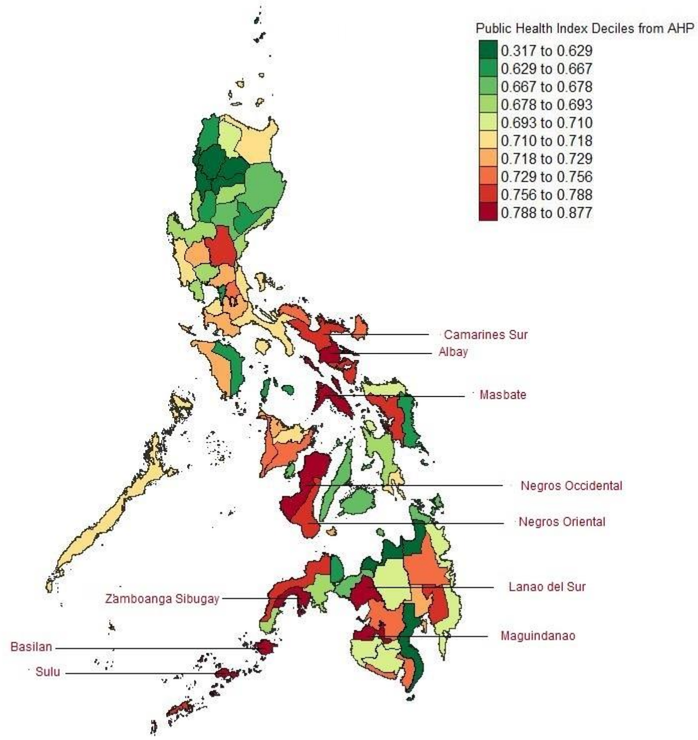

Figure 5. Most vulnerable provinces according to public health and healthcare factors using AHP.

4.6 Infrastructure Dimension

Table 6. Infrastructure indicators with high weights.

Infrastructure Indicator	Weight
Percentage of national road length	0.1499
Percentage of non-energized barangays	0.1322
Percentage of national bridges length	0.1270

Under infrastructure dimension, AHP gave large weights to percentage of national road length and percentage of non-energized barangays. These results showed that community infrastructures play a vital role. Roads allow easier and faster delivery of health products and services [24]. However, good transport system tolerates rapid movement of people which is also a factor for diseases to spread [12]. With the infrastructure dimension index, AHP identified Sarangani (index = 0.8124) as the most vulnerable followed by Compostela Valley (index = 0.8107) and Apayao (index = 0.7743). Figure 5 shows vulnerable provinces were clustering in the central part of Luzon to some provinces of CALABARZON (Region 4A) and MIMAROPA (Region 4B). Cluster of vulnerable provinces was also apparent in SOCCSKSARGEN (Region 12) and Davao Region (Region 11).

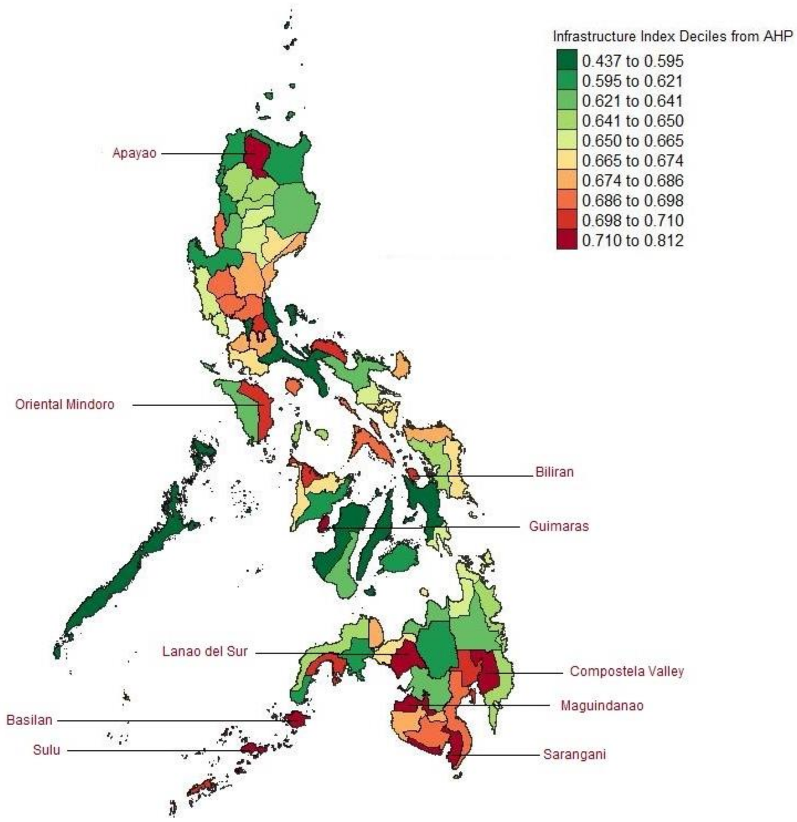

Figure 6. Most vulnerable provinces according to infrastructure factors using AHP.

4.7 Governance Dimension

Table 7. Governance indicators with high weights.

Governance Indicator	Weight
Good Governance index (GGI)	0.2828
Competitiveness Index (CI)	0.2122
Evacuation centers to population ratio	0.1957

Lastly, competitiveness index and good governance index appeared to be relevant under governance dimension. These indicators are all direct measurements of good governance which supports the hypothesis that good governance affects effectiveness of response to health threats [24, 42]. AHP identified Maguindanao (index = 0.8771) as the most vulnerable in this dimension followed by Masbate (index = 0.8683) and Basilan (index = 0.8601). Vulnerable provinces were clustering in most parts of Visayas as can be seen in Figure 6. Another visible cluster can be seen in the central part of Luzon to some provinces of CALABARZON (Region 4A) and MIMAROPA (Region 4B), Zamboanga Peninsula (Region 9), Northern Mindanao (Region 10), and Caraga Region. The least vulnerable province was Batanes (index = 0.4415). followed by Mountain Province (index = 0.5246).

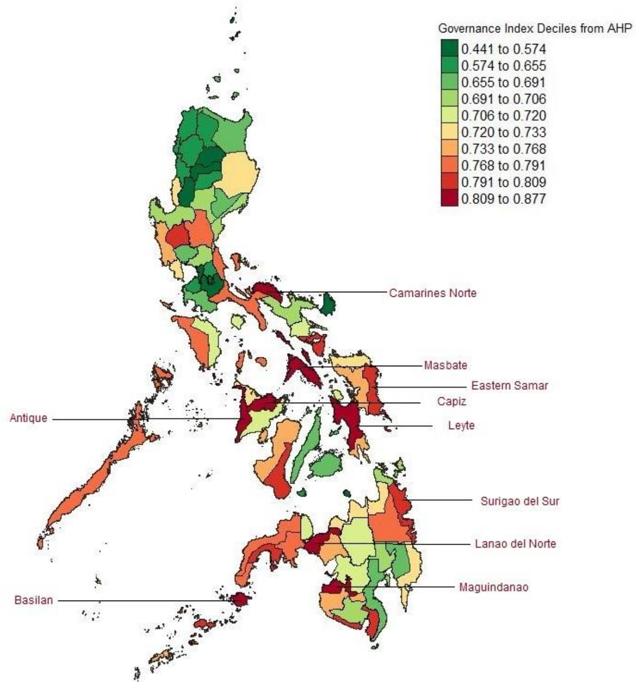

Figure 7. Most vulnerable provinces according to governance factors using AHP.

4.8 Composite Vector-Borne Disease Vulnerability Index (VBDVI)

Shown in Figure 8 are the deciles of VBDVI using AHP. Visible clusters of vulnerable provinces were prominent in Central Luzon (Region 3), CALABARZON (Region 4A), and Bicol Region (Region 5). This cluster extended up to Eastern Visayas (Region 8) and in most parts of Mindanao. Isolated provinces in higher deciles included Occidental Mindoro, Aklan, and Negros Occidental. Prominent cluster of least vulnerable provinces can be found in the northern part of Luzon. The 5 most vulnerable and 5 least vulnerable provinces are labeled in the map.

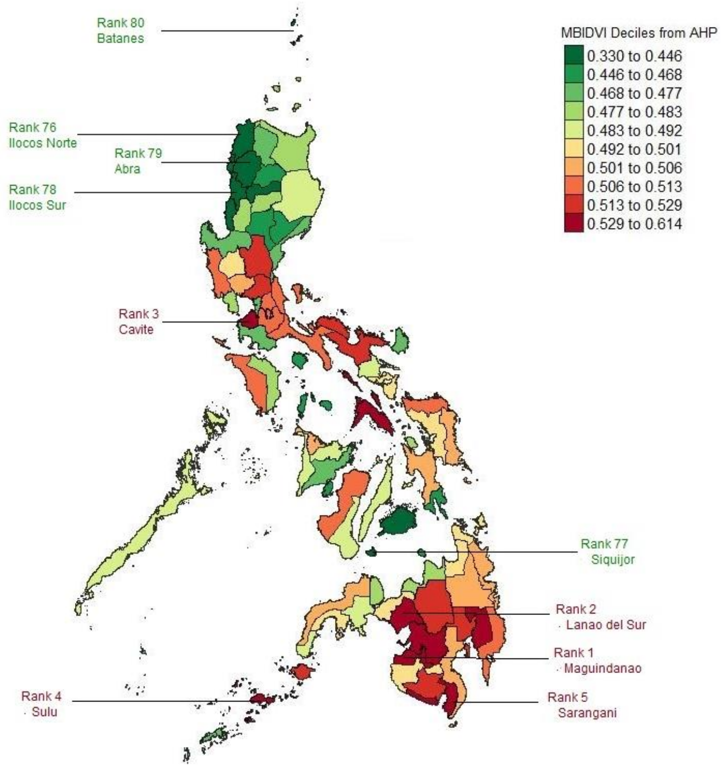

Figure 8. Vulnerability of provinces according to VBDVI using AHP.

Listed in Table 8 are the 15 most vulnerable provinces and 15 least vulnerable provinces. Maguindanao, which was categorized as one of the most vulnerable provinces in five out of six dimensions had an VBDVI of 0.6142 making it the most vulnerable province against vector-borne infectious diseases. Following Maguindanao were Lanao del Sur (VBDVI = 0.5953), Cavite (VBDVI = 0.5562), Sulu (VBDVI = 0.5458), and Sarangani (VBDVI = 0.5447).

On the other hand, Batanes is the least vulnerable province. Its VBDVI is 0.3304. Though Batanes was noted as one of the most vulnerable provinces under disease dynamics dimension, the province was the least vulnerable province under economic, PH and healthcare and governance dimensions.

Table 8. Fifteen (15) most and least vulnerable provinces using VBDVI from AHP.

MOST VULNERABLE				LEAST VULNERABLE		
Rank	Province	Index		Rank	Province	Index
1	Maguindanao	0.6142		66	Kalinga	0.4634
2	Lanao del Sur	0.5953		67	Nueva Vizcaya	0.4626
3	Cavite	0.5562		68	Quirino	0.4624
4	Sulu	0.5458		69	Romblon	0.4619
5	Sarangani	0.5447		70	Marinduque	0.4573
6	North Cotabato	0.5428		71	Southern Leyte	0.4506
7	Masbate	0.5385		72	Guimaras	0.4464
8	Compostela Valley	0.5352		73	Bohol	0.4388
9	Basilan	0.5281		74	La Union	0.4300
10	Bukidnon	0.5232		75	Mountain Province	0.4266

MOST VULNERABLE				LEAST VULNERABLE		
Rank	**Province**	**Index**		**Rank**	**Province**	**Index**
11	Bulacan	0.5220		76	Ilocos Norte	0.4247
12	Davao del Norte	0.5219		77	Siquijor	0.4238
13	Camarines Sur	0.5206		78	Ilocos Sur	0.4237
14	South Cotabato	0.5195		79	Abra	0.4191
15	Camarines Norte	0.5187		80	Batanes	0.3304

4.9 Robustness of composite VBDVI against influence of an indicator

On the average, a given province may change its rank up to approximately two positions when an indicator was removed from the calculation (2.43 ± 1.31). There were events where ranking of provinces did not change even when an indicator was removed but there were also provinces that moved up to 6 positions, on the average.

Figure 9 shows the number of times out of 46 that a province retained its spot in the list of most vulnerable (Ranks 1 – 15) and least vulnerable (Ranks 66 - 80). Clearly, counts decreased dramatically going to the middle ranks suggesting that provinces which should be prioritized were classified as such by VBDVI even during removal of indicators.

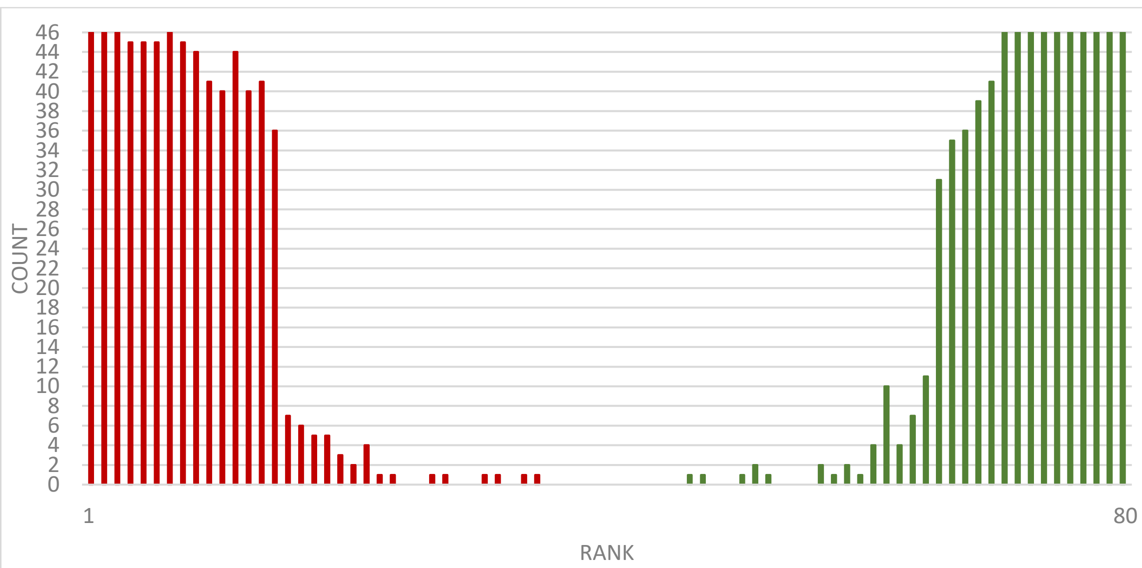

Figure 9. Provinces according to AHP rank with number of times the province was correctly classified after removal of an indicator.

4.10 Robustness of composite VBDVI against modification of dimension weights

On the average, a given province may change its rank up to approximately 4 (± 2.60) positions when dimension weights were modified. All changes were approximately at most 10 positions, on the average. Disease dynamics dimension created varying rankings when its weight was changed. Eliminating demographic dimension in AHP resulted to an average of 10.28 change in ranking.

Figure 10 shows provinces arranged according to rank with counts signifying the number of times out of 24 that the province was categorized correctly. Evidently, most vulnerable and least vulnerable provinces were classified as such by VBDVI even during modification of dimension weights. AHP methodology detected the most and the least vulnerable provinces. There were no provinces that were categorized reversely (going from most to least or vice versa) but there were provinces that had big jumps in their ranking. For instance, Cavite at rank 3 went down to rank 21 when disease dynamics dimension was eliminated (0% weight).

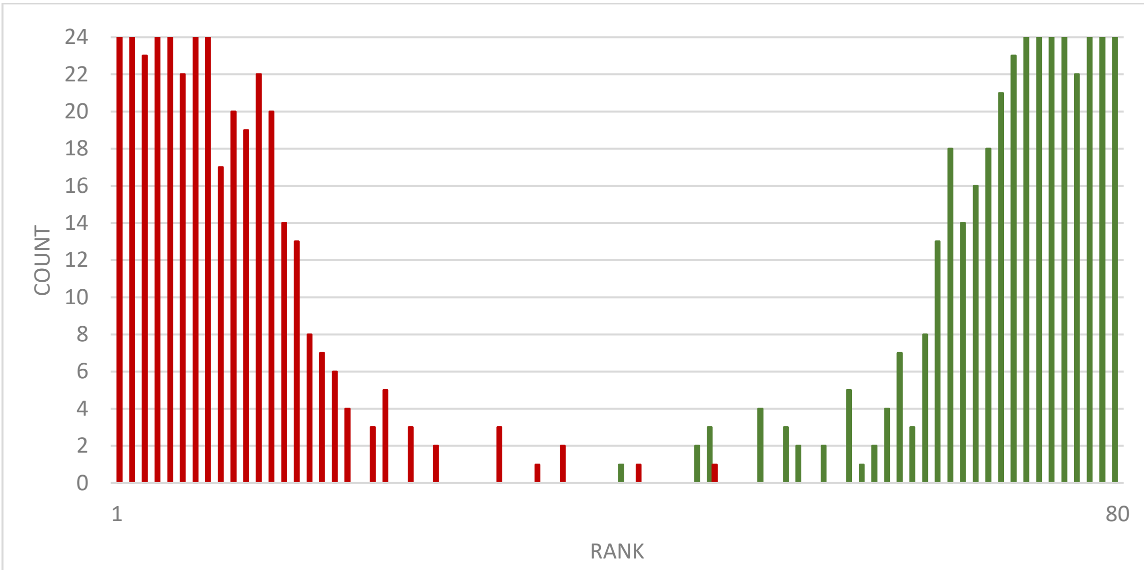

Figure 10. Provinces according to AHP rank with number of times the province was correctly classified after modification of dimension weights.

4.11 Robustness of composite VBDVI by comparing it to current situation of VBDs

Table 9. Root Mean Square Errors (RMSE) of training and test data sets using LOOCV.

Mosquito Disease	RMSE $_{TRAINING}$	RMSE $_{TEST}$	% Error
Malaria	0.1105845	0.1126754	1.89%
Dengue HF	0.2203943	0.2258323	2.47%
Filariasis	0.1286342	0.1305853	1.52%
Chikungunya	0.1391988	0.1435773	3.15%

LOOCV showed that RMSE of test data set was acceptably low since values were very close to the RMSE of training data set. In fact, the highest percent error was only 3.15% with an average of 2.26%. With low percent errors, results suggested that the prediction of the actual vector-borne infectious disease rate was satisfactorily achieved by VBDVI. Since prediction was of good quality, we can therefore say that VBDVI had been sensitive enough to resemble the real condition of the provinces in terms of vector-borne infectious diseases.

Shown in Figure 11 is the statistical map of VBDVI together with the map showing the normalized actual rates for malaria, dengue hemorrhagic fever, filariasis and chikungunya. For malaria, VBDVI captured the situation in northern parts of Luzon. However, most parts of Mindanao were categorized as vulnerable when in fact most provinces there had low malaria rates. In the case of dengue hemorrhagic fever (DHF), indices seemed to be closer to the actual scenario. VBDVI captured most vulnerable provinces in Mindanao. However, VBDVI seemed to have resulted to high indices even when the actual DHF rates was zero, which was almost the same scenario as that of the malaria rates. Non-zero filariasis rates were isolated in only nine provinces and this is clearly depicted in the map shown in Figure 11. VBDVI worked in capturing non-vulnerability of provinces in the northern part of Luzon. Outputs appeared to be better in the case of chikungunya rates. VBDVI captured the situation in central to southern parts of Luzon and in most parts of Visayas.

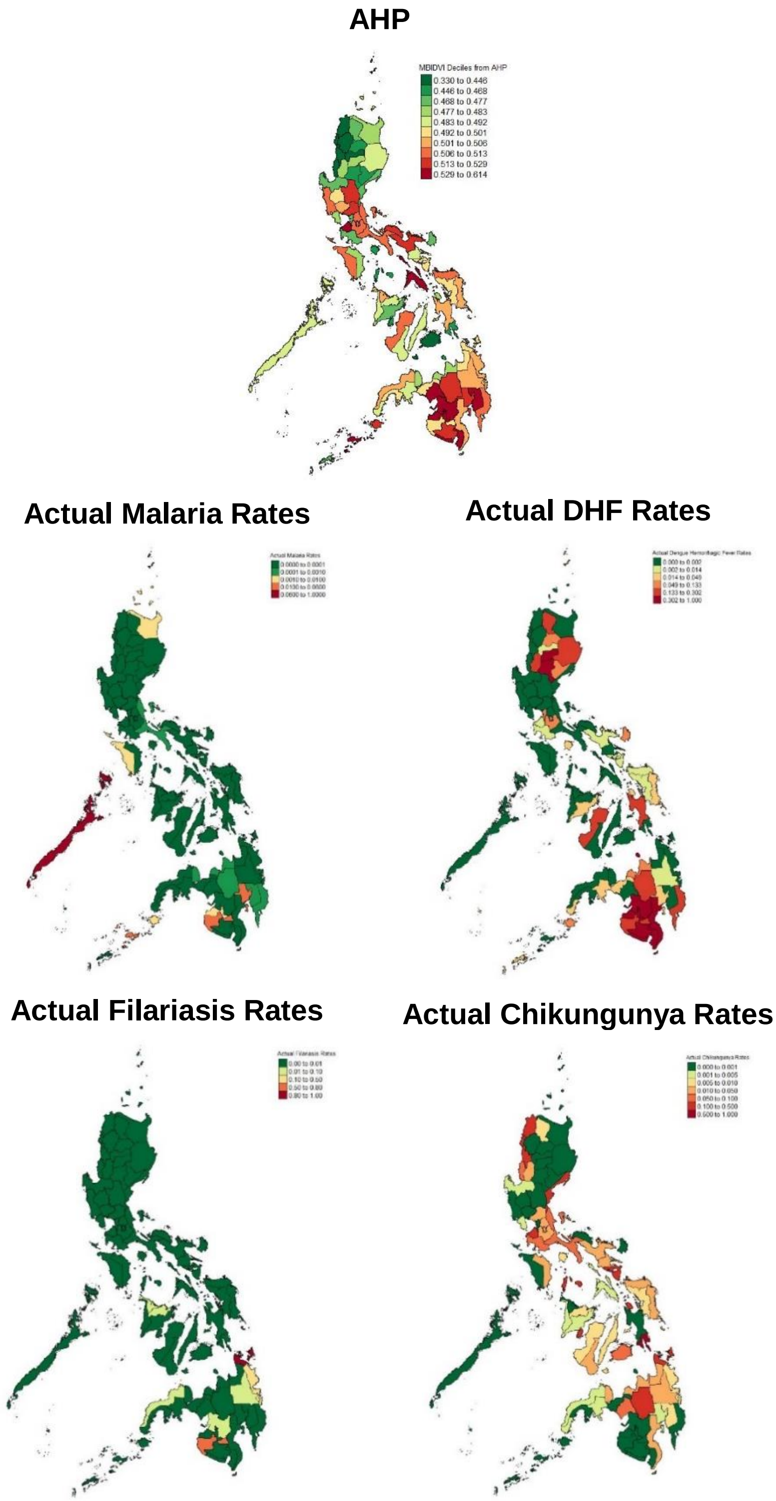

Figure 11. Comparison of VBDVI to normalized actual VBD rates.

5. Conclusion and Recommendation

Aggregating the dimension indices, VBDVI using AHP pointed out Maguindanao as the most vulnerable province with an index of 0.6142. It was followed by Lanao del Sur, Cavite, Sulu and Sarangani. Least vulnerable provinces, in the contrary, were Batanes followed by Abra, Ilocos Sur, Siquijor and Ilocos Norte. To validate the results, a series of uncertainty analyses was performed. Results somehow challenged the validity of VBDVI due to instances of big jumps in the ranking. Nonetheless, results showed that VBDVI appeared useful in classifying most vulnerable provinces.

Results of the study have shown that administrative boundaries of provinces do not serve as barriers for vector-borne diseases to spread. Actual rates and constructed indices showed clustering of vulnerable provinces implying that such diseases cannot be enclosed in certain provinces. A notable trend that can be deduced from the results was the fact that most vulnerable provinces were in Mindanao making the geographical area a potential hotspot of vector-borne diseases. Involved bodies can target governance, PH and healthcare and infrastructure for these dimensions were the weaknesses of this hotspot. On the other hand, most of the least vulnerable provinces were from Luzon which generally got lower economic dimension indices. This implied that strong and developed economy can keep a province safer from vector-borne diseases.

Though VBDVI was not constructed to directly predict outbreaks, it can give us comprehensive idea in identifying locations that needs practical and apt support. Actions might include targeting those indicators with high impact to vulnerability mentioned in the discussion. These include those pertaining to plans to solve overcrowding, projects to promote financial stability of families, health projects for those working in agricultural lands, construction of neighboring healthcare facilities, investment to communication technologies for easy dissemination of health information, and effective relay of information across government units. Moreover, other indicators with direct relation to vector-borne diseases can be added to improve VBDVI. This may include percentage of school children in the population, distribution of virus serotypes, feature-specific characteristics of houses in the community, sewage infrastructure status, number of children and women per household, presence of irrigation channels, dams and ponds in the community, presence of illegal settlers, and construction of unplanned urbanization.

6. References

1. Department of Health, *Malaria Control Program*, (2018)
2. Department of Health, *DOH Declares National Dengue Epidemic*, (2019)
3. International Federation of Red Cross and Red Crescent Societies, IFRC Information Bulletin, *Philippines: Dengue Outbreak*, (2019)
4. World Health Organization, WHO Fact Sheets, *Chikungunya*, (2017)
5. Department of Health, Disease Surveillance, *Chikungunya Disease Surveillance Report,* (2018)
6. World Health Organization, WHO Fact Sheets, *Zika virus*, (2018)
7. J. Davies, EMBO reports, *Microbes have the last word*, **8(7)**, 616-621. (2007)
8. B. D. Gushulak , D. W. MacPherson, Clinical Infectious Diseases, *Globalization of infectious diseases: the impact of migration*, **38(12)**, 1742-1748. (2004)
9. M. Tong, A. Hansen, S. Hanson-Easey, S. Cameron, J. Xiang, Q. Liu, Y. Sun, P. Weinstein, G. S. Han, C. Williams, P. Bi, IJERPH, *Infectious diseases, urbanization and climate change: challenges in future China*, **12(9)**, 11025-11036. (2015)
10. L. Martinez, IJID, *Global infectious disease surveillance*, **4(4)**, 222-228, (2000)
11. P. Martens, L. Hall, EID, *Malaria on the move: human population movement and malaria transmission*, **6(2)**, 103, (2000)

12. M. Palaniyandi, P. H. Anand, T. Pavendar, Int J Mosq Res, *Environmental risk factors in relation to occurrence of vector borne disease epidemics: Remote sensing and GIS for rapid assessment, picturesque, and monitoring towards sustainable health*, **4(3)**, 9-20. (2017)
13. S. M. Lemon, P. F. Sparling, M. A. Hamburg, D. A. Relman, E. R. Choffnes, A. Mack, Workshop summary. In Vector-borne diseases: understanding the environmental, human health, and ecological connections. *Vector-borne diseases: understanding the environmental, human health and ecological connections*, (2008)
14. L. Pray, S. Lemon, A. Mahmoud, S. Knobler, (2006). Workshop Summary, *The Impact of Globalization on Infectious Disease Emergence and Control: Exploring the Consequences and Opportunities*, (2006)
15. D. J. Gubler, Trends Microbiol, *Epidemic dengue/dengue hemorrhagic fever as a public health, social and economic problem in the 21st century*, **10(2)**, 100-103. (2002)
16. M. A. Johansson, N. Arana-Vizcarrondo, B. J. Biggerstaff, N. Gallagher, N. Marano, J. E. Staples, Am J Trop Med Hyg, *Assessing the risk of international spread of yellow fever virus: a mathematical analysis of an urban outbreak in Asuncion, 2008*, **86(2)**, 349-358. (2012)
17. J. Stoler, J. R. Weeks, A. Getis, A. G. Hill, Am J Trop Med Hyg, *Distance threshold for the effect of urban agriculture on elevated self-reported malaria prevalence in Accra, Ghana*, **80(4)**, 547-554. (2009)
18. P. M. De Silva, J. M. Marshall, J. Trop. Med., *Factors contributing to urban malaria transmission in sub-Saharan Africa: a systematic review*, (2012)
19. C. Saugeon, T. Baldet, M. Akogbeto, M. C. Henry, MED TROP (MARS), *Will climate and demography have a major impact on malaria in sub-Saharan Africa in the next 20 years?*, **69(2)**, 203-207, (2009)
20. D. J. Gubler, EID, *Resurgent vector-borne diseases as a global health problem*, **4(3)**, 442. (1998)
21. A. A. Ikemba, MACEPA, *How governments can help in the fight against vector-borne disease,* (2014)
22. M. S. Gold, P. M. Bentler, Struct Equ Modeling, *Treatments of missing data: A Monte Carlo comparison of RBHDI, iterative stochastic regression imputation, and expectation-maximization*, **7(3)**, 319-355. (2000)
23. M. Moore, B. Getfeld, A. Okunogbe, P. Christopher, Rand Corporation, *Identifying future disease hotspots: infectious disease vulnerability index,* (2016)
24. T. L. Saaty, IJSSci, *Decision making with the analytic hierarchy process*, **1(1)**, 83-98. (2008)
25. R. H. Ansah, S. Sorooshian, S. Bin Mustafa, GJPAM, *Analytic hierarchy process decision making algorithm*, **11(4)**. (2015)
26. K. Teknomo, Revoledu. com, Analytic hierarchy process (AHP) tutorial, 1-20, (2006)
27. J. Franek, A. Kresta, Procedia Econ., *Judgment scales and consistency measure in AHP*, **12**, 164-173. (2014)
28. M. Nardo, M. Saisana, A. Saltelli, S. Tarantola, OECD Statistics Working Paper, *A. Hoffman and E. Giovanni (OECD) (2005) Handbook on Constructing Composite Indicators: Methodology and Userguide,* (2005)
29. H. Hu, K. Nigmatulina, P. Eckhoff, MATH BIOSCI, *The scaling of contact rates with population density for the infectious disease models*, **244(2)**, 125-134. (2016)
30. R. Wise, T. Hart, O. Cars, M. Streulens, R. Helmuth, P. Huovinen, M. Sprenger, BMJ, *Antimicrobial resistance: Is a major threat to public health*, **317(7159)**, 609–610. (1998)
31. C. Fritzell, J. Raude, A. Adde, I. Dusfour, P. Quenel, C. Flamand, PLoS Negl Trop Dis, *Knowledge, Attitude and Practices of Vector-Borne Disease Prevention during the Emergence of a New Arbovirus: Implications for the Control of Chikungunya Virus in French Guiana*, **10(11)**, e0005081. (2016)
32. D. A. Dewalt, N. D. Berkman, S. Sheridan, K. N. Lohr, M. P. Pignone, J GEN INTERN MED, *Literacy and health outcomes: a systematic review of the literature*, **19(12)**, 1228–1239. (2004)
33. D. L. Heymann, PASSV, *Effects of social, environmental and economic factors on current and future patterns of infectious diseases*, **106**, 290-303, (2006)
34. P. Martens, A. J. McMichael, Cambridge University Press, *Environmental change, climate and health: issues and research methods*, (2009)
35. J. N. S. Eisenberg, M. A. Desai, K. Levy, S. J. Bates, S. Liang, K. Naumoff, J. C. Scott, Environ. Health Perspect., *Environmental Determinants of Infectious Disease: A Framework for Tracking Causal Links and Guiding Public Health Research*, **115(8)**, 1216–1223, (2007)
36. S. S. Morse, EID, *Factors in the Emergence of Infectious Diseases*, **1(1)**, 7-15, (1995)
37. B. W. Alto, D. Bettinardi, Am J Trop Med Hyg, *Temperature and dengue virus infection in mosquitoes: independent effects on the immature and adult stages*, **88(3)**, 497–505, (2013)

38. L. Bai, L. C. Morton, Q. Liu, Globalization Health, *Climate change and mosquito-borne diseases in China: a review*, **9(1)**, 10, (2013)
39. W. P. O'Meara, A. Noor, H. Gatakaa, B. Tsofa, F. E. McKenzie, K. Marsh, Trop Med Int Health, *The impact of primary health care on malaria morbidity--defining access by disease burden*, **14(1)**, 29–35. (2008)
40. H. Levy, D. Meltzer, Annu. Rev. Public Health, *The impact of health insurance on health*, **29**, 399-409. (2008)
41. H. A. Allen, Res Vet Sci, *Governance and One Health: Exploring the Impact of Federalism and Bureaucracy on Zoonotic Disease Detection and Reporting*, **2(2)**, 69–83. (2015)