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Mapping Ecosyndemic Risk and Social Vulnerability in Guatemala during the 2014-16 El Niño: An Exploratory GIS Analysis †

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Abstract: El Niño is a climatic cycle originating in the tropical Pacific Ocean that impacts countries in Latin America. It is often associated with water-based infectious diseases, many of which are also poverty-related. In this study we explore ecosyndemic risk and social vulnerability in Guatemala during the 2014-16 El Niño. An ecosyndemic is a cluster of diseases, associated with environmental changes, set within a wider context of socioeconomic inequities. Using GIS, this study examined six infectious diseases and ecosyndemic risk in Guatemala from 2014 to 2016 and factors of social risk at the department-level. Preliminary results and policy implications are discussed.

Keywords: El Niño; Infectious Disease, Ecosyndemic; Syndemic; Social Vulnerability; Guatemala; GIS

1. Introduction

El Niño, the warm phase of El Niño-Southern Oscillation (ENSO), is a climatic cycle originating in the tropical Pacific Ocean that impacts regional patterns of weather and climate, particularly in countries across Latin America. It is often associated with water-based infectious disease epidemics, many of which are also poverty-related, such as diarrheal diseases, malaria, and arboviruses, including dengue and chikungunya.

El Niño's impact on infectious disease transmission occurs through climatic and oceanic changes at regional and local scales, which in turn affect local weather, e.g., rainfall, air and sea temperatures, humidity, and subsequent effects on environments and ecologies of various water-related pathogens and vectors [1]. Furthermore, El Niño and climate-related environmental changes spawn hydrometeorological hazards, such as floods, droughts, and temperature extremes, which can impact built environments and infrastructures (e.g., damage and breakdowns), including water, sanitation and energy systems. El Niño related hazards can also lead to population movements and displacement. Such impacts in turn can increase a population's exposure and vulnerability to a multitude of infectious disease agents, as well as generate other adverse effects on health, such as respiratory infection epidemics [2].

In this study we explore ecosyndemic risk and social vulnerability in Guatemala during the 2014-16 El Niño. Unlike an epidemic, which is centered on one disease, an ecosyndemic is a cluster of diseases, associated with environmental changes, set within a wider context of socioeconomic inequities [3-4]. Guatemala represents an important region for El Niño impacts, but is less explored compared to northwest South America, a well-known El Niño hotspot [5]. From 2014 to 2016, there were close to 1.4 million cases of food and waterborne-related illnesses and 8.4 million cases of acute respiratory infections reported in Guatemala [6]. There are also several endemic mosquito-borne diseases including malaria, dengue, chikungunya, and Zika, as well as neglected tropical diseases, such as Chagas, Leishmaniasis, and Onchocerciasis. In many instances, El Niño can exacerbate patterns of preexisting health problems. Using GIS, this exploratory study examined the spatial overlap of six infectious diseases reported in Guatemala from 2014 to 2016 to understand ecosyndemic risk and associated social and health factors of vulnerability at the department-level. Preliminary results and policy implications are discussed.

2. Methodology

2.1. Study Area

Guatemala is comprised of 22 departments bordering Mexico, Belize, Honduras, and El Saldvador and outlets to the Pacific Ocean and the Caribbean Sea. In 2015, the estimated population was 16.1 million people.

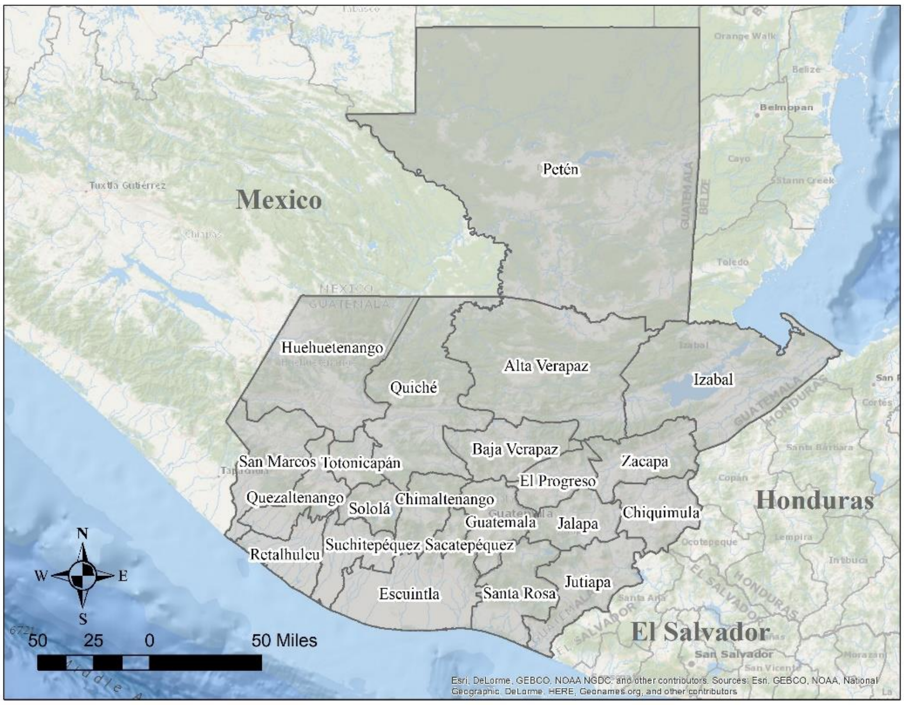

Figure 1. Map of Political Boundaries of Departments (N = 22) in Guatemala.

2.2. El Niño Index

Data from the Oceanic Niño Index comprised of a 3-month running mean (season) of sea surface temperature anomalies in the Central and Eastern Pacific Ocean were retrieved from the NOAA Climate Prediction Center (CPC) webpage (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php). This El Niño index illustrates El Niño, La Nina, and Neutral conditions.

2.3. Health Data

Infectious disease incidence data were collected from various health and epidemiological reports from the Ministry of Public Health and Social Assistance (MSPAS) in Guatemala [6]. Datasets include incidence of malaria, dengue, food and waterborne-related illnesses (ETAs), acute respiratory infections (IRAs), pneumonia, and chikungunya for 2014, 2015, and 2016. Rates per 100,000 persons were calculated using population estimates for corresponding years retrieved from Guatemala's Institute for Statistics [7]. In addition, infant mortality rate and maternal mortality ratio datasets were obtained [8]. Such health variables are important indicators of development that may reflect the condition of health infrastructure and services in countries.

2.4. Social Vulnerability Data

Variables that serve as proxies for social vulnerability were obtained from Guatemala's ENCOVI survey [9]. These data, measured as percent of population, included urban, illiteracy, no electricity, varying types of poverty (e.g., total, extreme, urban), GINI index, no water, and no sewer. With the exception of urban poverty (2011) and rural poverty (2011), variable represent conditions in 2014.

2.5. Methods

2.5.1. Calculating Disparity

Descriptive statistics, including average, maximum, minimum, and standard deviation values, were generated for all disease incidence variables. From these data, z-scores were calculated for disease variables for each year by subtracting the disease incidence average from the disease incidence value for each department and then dividing by the standard deviation for disease incidence. A disease incidence disparity was defined as a z-score equal to or greater than 0.5.

2.5.2. Disease Burden Ratio Index

A disease burden index was generated based on rate ratios calculated by dividing the incidence rate for each infectious disease of a department by the national average for that disease each year. The ratio represents the number of times higher the incidence rate is compared to the national average. All disease ratios were then summed by department to create an index for each year and all years (sum of 2014 to 2016). The all years ratio was then ranked. Rate ratios were used to compare potential disease burden across years.

2.5.3. Counts Index

A counts index of ecosyndemic risk for 2014, 2015, and 2016 was constructed using methods from Ramirez et al. [4] and Lee and Ramirez [10]. For each year, the number of disease incidence disparities was identified by department, with a possible range of 0 to 6 disparities that overlap.

2.5.4. Composite Index

A composite index of ecosyndemic risk for 2014, 2015, and 2016 was constructed using methods from Ramirez et. al. [4]. Using Principal Components Analysis (PCA), z-scores of the six infectious disease variables were analyzed and reduced to a set of non-correlated dimensions with factors scores that represent how influential a variable is in the data structure derived from the PCA output. Scores were summed and then divided by the number of dimensions to produce an index. The index value was then scaled from 0 to 1 to represent low to high ecosyndemic risk. Unlike the counts index, the composite index accounts for magnitude of each disease per department and the combination of all diseases.

2.5.5. Social Vulnerability Analysis

To estimate the effect of social vulnerability variables on ecosyndemic risk, the mean differences in ecosyndemic composite indices for 2014, 2015, and 2016 were assessed between groups or levels of risk using a general linear model (one-way Analysis of Covariance, ANCOVA) in SPSS (IBM, Version 25.0). Departments in Guatemala were grouped by high, medium, and low risk using a quantile classification. A covariate of social vulnerability was added to the model in order to generate an adjusted means, controlling for confounding variables and compounding effects of social and infrastructure context (e.g., poverty and access to basic needs, such as water and electricity).

3. Results and Discussion

3.1. El Niño Context

In late 2014 as the austral summer approached, the onset of El Niño conditions were observed in the central and eastern tropical Pacific Ocean, beginning in November (OND), lasting 19 consecutive months, and ending in May (AMJ) of 2016. According to the UNOCHA [11], El Niño enhanced drought conditions in northern, eastern and western Guatemala. A state of emergency was declared in early 2015, and impacts were reported in agriculture (50% crop losses), food and water security, and people's livelihoods [11].

Table 1. ONI Index Values for 2014, 2015, and 2016 (red is El Niño, Blue is La Nina, and black is Neutral conditions in the Tropical Pacific Ocean).

Year	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
2014	-0.4	-0.4	-0.2	0.1	0.3	0.2	0.1	0	0.2	0.4	**0.6**	**0.7**
2015	**0.6**	**0.6**	**0.6**	**0.8**	**1**	**1.2**	**1.5**	**1.8**	**2.1**	**2.4**	**2.5**	**2.6**
2016	**2.5**	**2.2**	**1.7**	**1**	**0.5**	0	-0.3	**-0.6**	**-0.7**	**-0.7**	**-0.7**	**-0.6**

ONI Index values represent sea surface temperature anomalies for 3-month running means (seasons).

3.3. Disease Burden Ratio Index

In Table 2, a disease burden index based on rate ratios by individual years and all years (2014-16) along with the ranks by department is shown. Eighteen departments (80%) experienced an increase of infectious diseases compared to the national average. Of these, 8 departments (36%) experienced increasing burdens of infectious diseases for three consecutive years. In addition, there were 4 departments where the disease burden increased from 2014–2015, and 6 where the disease burden increased from 2015–2016. Overall, the departments which exhibited the greatest total disease burden based on ratio (2014–2016) were Escuintla, Santa Rosa, Zacapa, and Chiquimula, concentrated in southern and eastern Guatemala. Interestingly, although Escuintla and Zacapa had the 1st and 3rd highest disease burden indices (64.4 and 34.2), these departments' burden ratios decreased from 2014 to 2016, in contrast to increasing disease burden ratios in Santa Rosa and Chiquimula.

Table 2. Disease Burden Index with Rank Based on Ratios by Years and Total (2014–2016).

Department	2014	2015	2016	2014–2016	Rank
Alta Verapaz	**5.4**	**5.5**	**5.9**	16.8	10
Baja Verapaz	***4.8***	***7.7***	4.3	16.8	11
Chimaltenango	2.8	***2.6***	***2.7***	8.1	21
Chiquimula	**5.1**	**6.3**	**8.0**	19.4	4
El Progreso	7.9	5.9	5.5	19.3	5
El Quiché	4.3	***3.6***	***4.6***	12.6	14
Escuintla	24.5	20.3	19.7	64.4	1
Guatemala	**2.0**	**4.6**	**4.6**	11.3	16
Huehuetenango	**2.8**	**3.0**	**4.2**	10.1	18
Izabal	**4.7**	**6.6**	**6.8**	18.1	6
Jalapa	3.1	***2.7***	***3.7***	9.5	19
Jutiapa	***4.0***	***5.6***	5.0	14.6	12
Petén	***4.0***	***7.0***	6.3	17.3	9
Quezaltenango	4.0	***3.9***	***4.4***	12.3	15
Retalhuleu	6.5	6.4	4.9	17.7	8

Sacatepéquez	**4.0**	**5.3**	**8.6**	17.9	7
San Marcos	***4.4***	***4.7***	4.5	13.7	13
Santa Rosa	**9.9**	**11.3**	**13.7**	35.0	2
Sololá	**2.9**	**3.4**	**4.4**	10.7	17
Suchitepéquez	3.6	***2.8***	***3.0***	9.3	20
Totonicapán	2.6	***2.1***	***2.3***	7.1	22
Zacapa	18.6	10.6	5.0	34.2	3

Bold indicates ratio increased across all years; Bold and italicized indicate ratio increased either from 2014–2015 or 2015–2016.

3.1.2. Ecosyndemic Risk by Counts Index

Figure 2 shows the number of infectious diseases with above average values (1 standard deviation) compared to the state present in Guatemala, 2014 to 2016. Generally, from 2014 to 2016, the spatial overlap of diseases was most concentrated in the south and east (at least 5 diseases), although it appears that the number of diseases decreased to a maximum of 4 in 2016. Zacapa for example increased from 4 to 5 diseases (2014-15), and then decreased significantly to zero diseases above the state average in 2016. There is also an increase observed in the northern department of Petén.

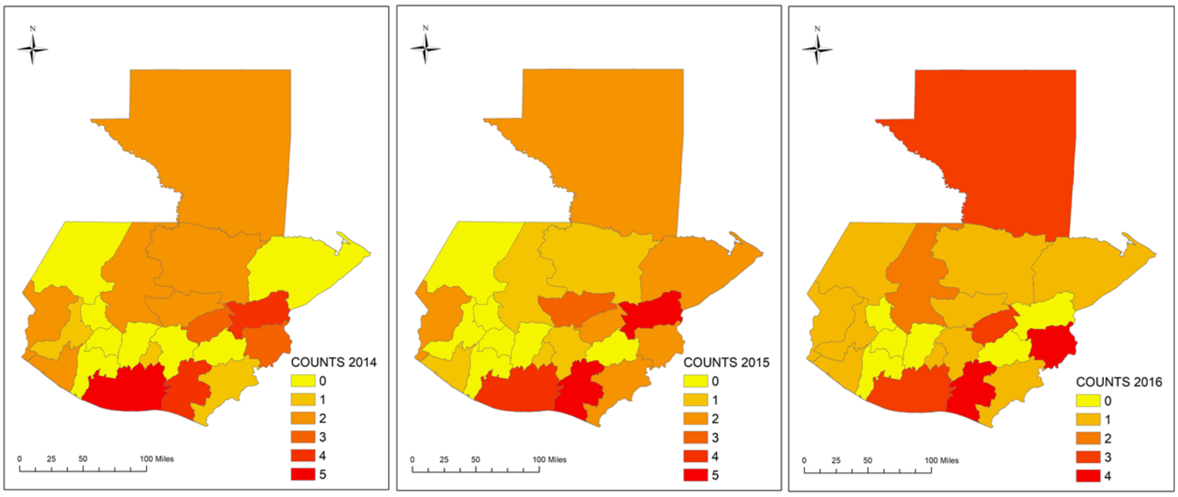

Figure 2. Map of counts index that represents ecosyndemic risk based on the number of infectious disease disparities by department.

3.1.3. Ecosyndemic Risk by Composite Index

Figure 3 shows ecosyndemic risk based on a composite index by department which takes into account magnitude of disease. Like the counts index and the disease burden index, ecosyndemic risk appears to be concentrated in the southern and eastern regions of Guatemala, particularly in 2015. However, significant shifts are observed between years. From 2014 to 2015, shifts in increased risk are observed in 5 departments (23%), mainly in the central and north, including Guatemala, Sacatepéquez, Baja Verapaz, and Petén. From 2015 to 2016, shifts in increased risk are observed in 8 departments (36%), including 2 areas where risk continued to increase since 2014 (e.g., Sacatepéquez and Petén) and 2 areas in the west (e.g., Huehuetenango and San Marcos).

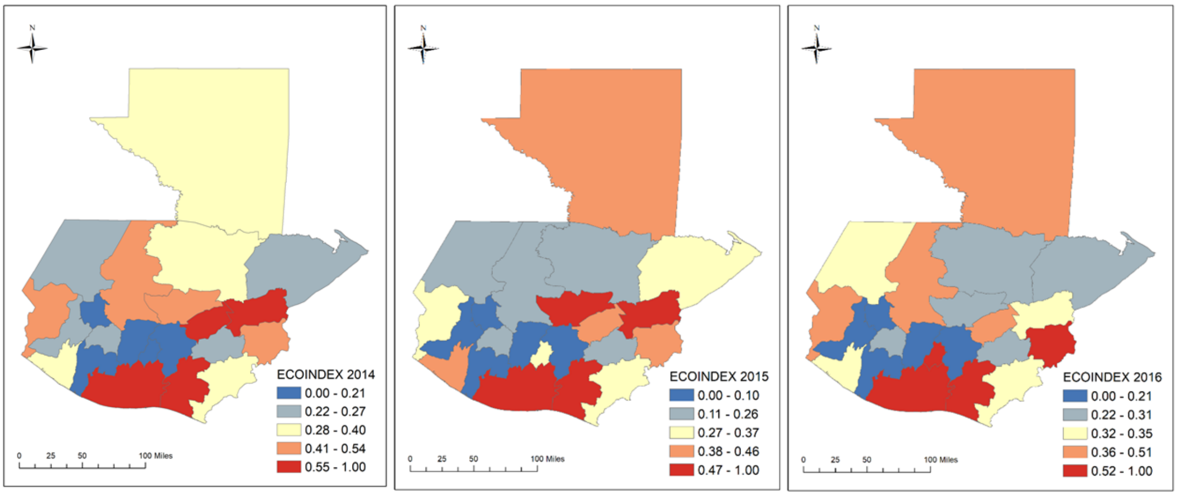

Figure 3. Map of ecosyndemic risk based on a composite index by department, where 0 represents low risk and 1 represents high risk.

3.2. Ecosyndemic risk and Social Vulnerability

Table 3 shows group means of high, medium, and low ecosyndemic risk and mean differences of ecosyndemic risk (based on the composite index) comparing between groups of risk (high & medium, high & low, and medium & low risk), controlling for social vulnerability. The results suggest there are significant mean differences between groups of risk at the 0.05 or 0.01 levels, particularly in 2015. Group means (M_h, M_m, and M_l). Mean differences were adjusted for social vulnerability variables as covariates and among these, TPOV (%) and NOELEC (%) were statistically significant and positive, suggesting that ecosyndemic risk (based on the composite index) increased with poverty and/or lack of a basic need such as electricity. In terms of geography, departments with high(er) means of ecosyndemic risk (data not shown) are located near the Pacific coast in the west but also inland in the southeast (e.g. Chiquimula and Zacapa).

Table 3. Comparing group means by level of risk (high, medium, and low) and mean differences between groups of risk (high-medium, high-low, and medium-low), controlling for social vulnerability.

	2014	2015	2016
Group Means, *adjusted (std .error)* for *selected* social vulnerability parameters (TPOV [%] and NOELEC [%])			
High (N_h=7)	0.67 (0.13)	0.80 (0.14)	0.66 (0.12)
Medium (N_m=8)	-0.11 (0.13)	-0.07 (0.13)	-0.10 (0.11)
Low (N_l=7)	-0.55 (0.14)	-0.72 (0.15)	-0.541 (0.12)
Estimated mean difference			
High-Medium (M_h - M_m)	0.77**	0.87**	0.75**
High-Low (M_h-M_l)	1.21**	1.56**	1.19**
Medium-Low (M_m-M_l)	0.44*	0.65**	0.45*

Covariates appearing in the model are evaluated at the following values: TPOV = 62.30, NOELEC = 20.67. * The mean difference is significant at the 0.05 level. ** The mean difference is significant at the 0.01 level.

4. Conclusions

Using GIS, this study explored six infectious disease variables and ecosyndemic patterns of risk in Guatemala during 2014, 2015, and 2016, years associated with 19-month El Niño conditions.

Differences between groups of risk (high, medium, and low) were also assessed, controlling for social vulnerability. In sum, preliminary results showed that 36% of departments experienced an increase in disease burden subsequently from 2014 to 2015 and 2015 to 2016. A greater number of departments observed increased disease burden in 2015-16 (27%), compared to 2014-15 (18%). Ecosyndemic risk was most concentrated in the southern and eastern areas of Guatemala, and also shifted from year to year in the central and northern areas, as well as west. The greatest mean differences between groups of risk were observed in 2015, and total poverty and no electricity were significantly related, suggesting ecosyndemic risk increased with increase percent of these variables.

This study had several limitations, which can be addressed in future analyses. They include more localized data in order to better understand patterns of ecosyndemic risk within departments for public health planning; more comprehensive analysis of social vulnerability (e.g., spatial regression); and measuring the effects of temperature and rainfall patterns on ecosyndemic risk to discern changes across time and space. A better understanding of multiple infectious disease burden associated with ecosyndemic risk and social factors of risk can assist the Ministry of Public Health to improve and coordinate interventions during current and future climate events.

Author Contributions: I.J.R. and J.L. designed the study. I.J.R. collected the data. I.J.R. and J.L. performed analyses. All authors contributed in writing and reviewing the paper. All authors read and approved the final manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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