Vulnerability Analysis: How the Location of Mines, Urban Areas and Elevation Impact the Distribution of Wealth in Peru

Joel Kruger, Spring, 2014, Introduction to GIS

Projection: South America Lambert Conformal Conic
Model and Density Maps Scale: 1:10,000,000
Locator Map Scale: 1: 50,000,000
Data sources:
-United States Geological Survey (USGS)
-Demographic and Health Survey (DHS)
-Tufts 'M' Drive

Introduction

Geographically, Peru is one of the most diverse countries in the world after normalizing for size. The total elevation change of Peru is 4.2 miles, a 0.3-mile larger range than the United States in 13% of the total area. As of 2014, over 30 million people live in Peru and 25.8% of the population lives under the World Health Organization's (WHO's) poverty line.

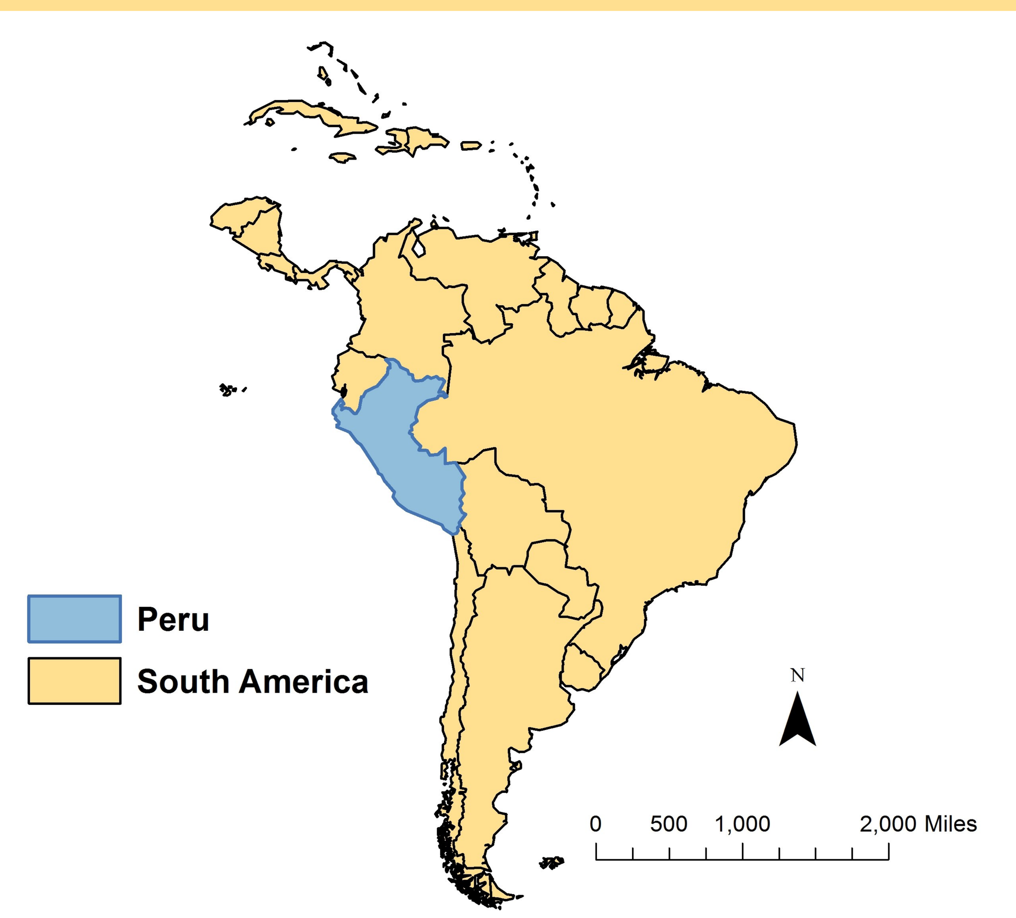
Occupationally, it is well established that living close to a mine can be physically hazardous. While mining is hazardous, the pollution produced by mines can be harmful those living near mines. In Peru, 17.4% of the labor force works in the industrial sector, the majority of which is the mining industry. It is also well established that the wealthiest Peruvians live in or near Lima, the coastal capital city. Finally, based on previous fieldwork in the Southern Andes Region, the association between wealth and elevation was clear.

The objective of this analysis is to spatially understand the association between wealth and the proximity to mines, proximity to urban areas, and elevation. The hypothesis is that there is a positive association between wealth and living a moderate distance from a mine, in an urban area, and at low elevation.

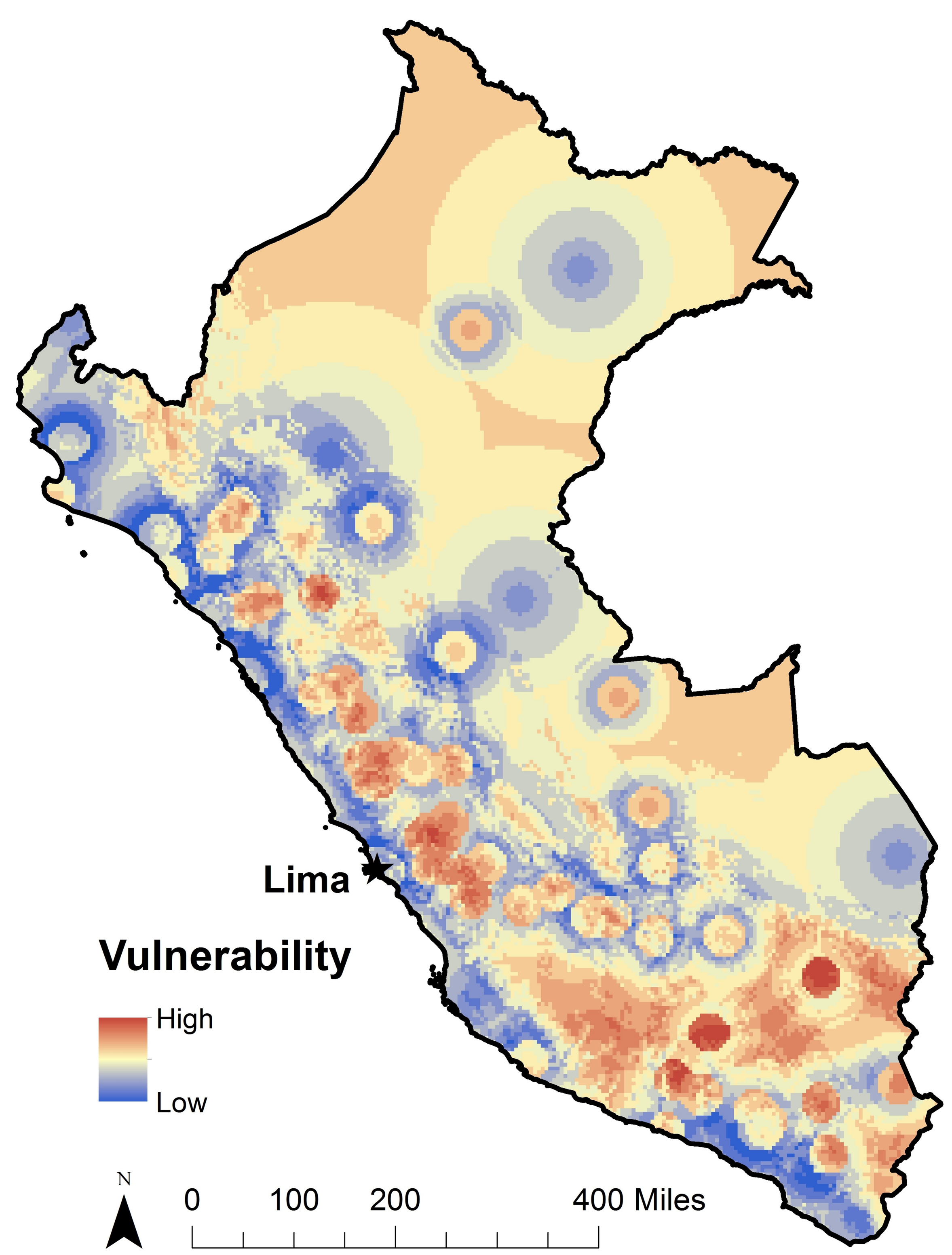
Methods

- Using IBM SPSS version 21, Demographic Health Survey (DHS) data from 2004 was cleaned and exported to excel.
- Using ESRI ArcGIS 10.1, 2004 GPS from the DHS was joined with the exported excel worksheet. Five binary shapefiles were then generated corresponding to each of the 5 levels of DHS-calculated wealth index. Kernel Densities for each of the 5 wealth index groups were then taken.
- Political boundaries (polygons), mine locations (point data), city locations (point data), and elevation data (DEM) were imported.
- Euclidean distances for mine locations and city locations were performed. Mine Euclidean distances, city Euclidean distances, and elevation data were then reclassified into 6 classes.
- Using the Raster Calculator tool, the reclassified layers were summed with equal weight. Additionally, using the Raster Calculator, the reclassified layers were re-summed with the reclassified Euclidean Distance layers weighted at 40% each and the elevation data at 20%.
- The resulting weighted model was subtracted from the weighted model using the Raster Calculator in order to visualize the difference between the two models.

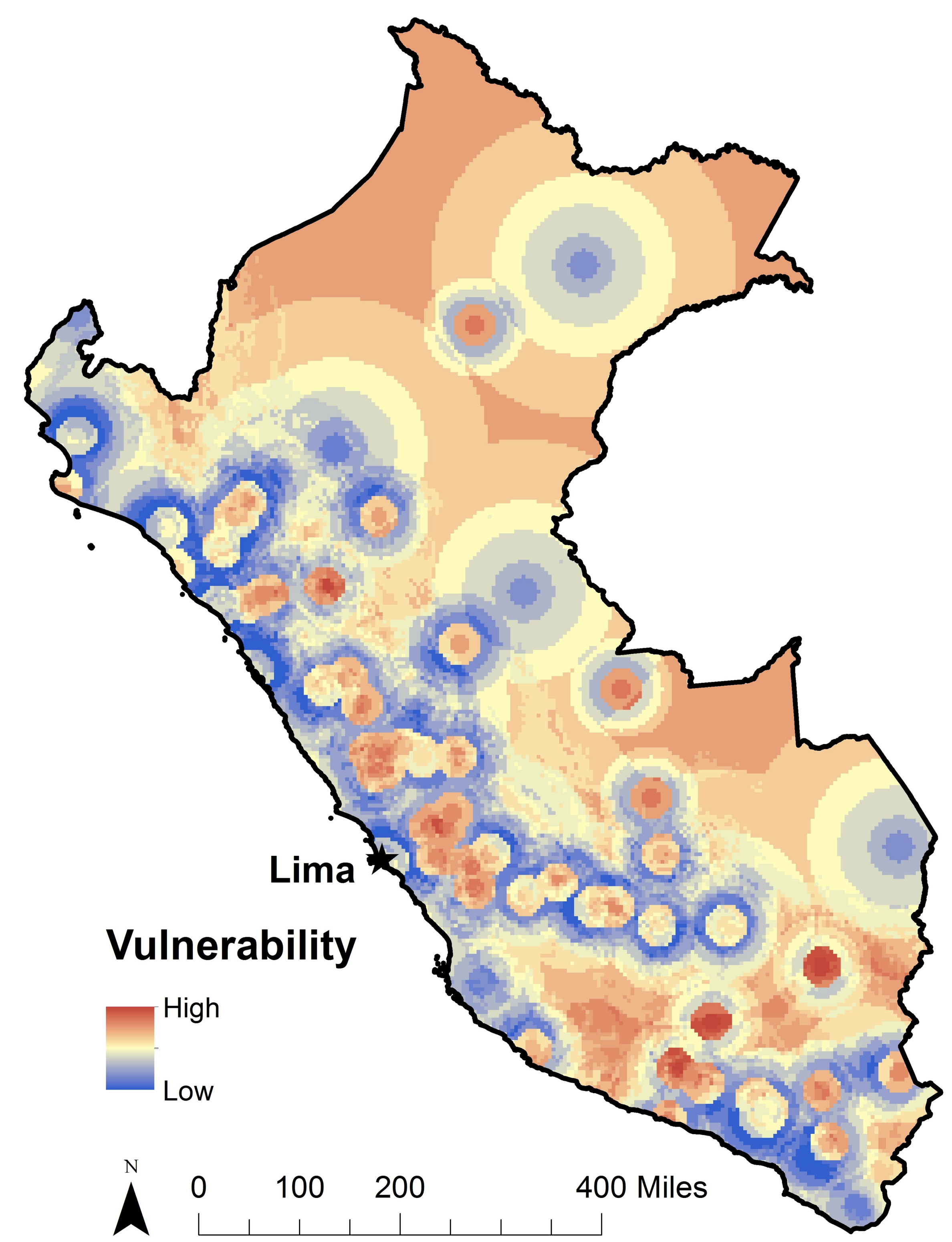
Locator Map



Unweighted Vulnerability Analysis of Peru



Weighted Vulnerability Analysis of Peru



Results

The weighted and unweighted models predict the most vulnerable places to live – the Northern Amazon region, and the Southern Central Andes region. Contrastingly, the models predict that the least vulnerable place to live is near the coast. The average vulnerability score for each of the 5 wealth index categories (Table 1).

I am 95% confident that on average for every unit increase in wealth index score, the unweighted model predicts between a 0.434 and 1.056 unit decrease in vulnerability with my best guess being a 0.745 unit decrease (linear regression, p=0.005, r^2=0.951).

I am 95% confident that on average for every unit increase in wealth index score, the weighted model predicts between a 0.105 and 0.199 unit decrease in vulnerability with my best guess being a 0.152 unit decrease (linear regression, p=0.002, r^2=0.972).

Differences between the models exist (Figure 1). Most notably, they differ in the Northern Amazon region and in the Andes Region. In the Northern Amazon region, the unweighted model had higher average scores. This could have been due to the fact that the Northern Amazon region is at a low elevation. The unweighted model de-emphasized elevation as a predictor of vulnerability so the low elevation of the Northern Amazon region would have been under-valued.

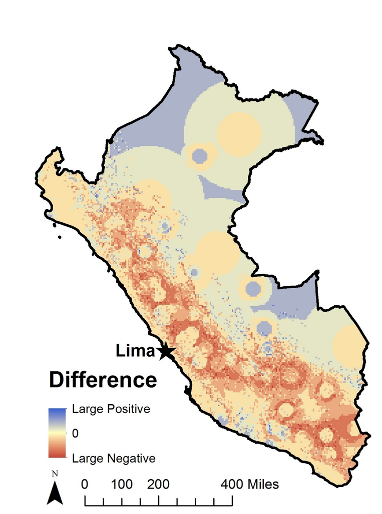
Further, the weighted model predicted average lower scores than the unweighted model in the Southern Andes region. In this region, the density of mines and cities increases and the weighted model valued those more heavily than elevation in predicting vulnerability.

Table 1. Average Vulnerability Score of the Highest Density Areas Each Wealth Index Score

	Unweighted Model			Weighted Model		
	Cell Count	**Mean***	**Standard Dev.**	**Cell Count**	**Mean***	**Standard Dev.**
Richest	103	13.69	1.84	105	4.45	0.70
Richer	81	13.40	1.77	84	4.31	0.68
Average	386	11.92	2.56	388	4.06	0.79
Poorer	495	11.55	2.37	495	3.99	0.89
Poorest	332	10.89	2.00	332	3.85	0.81

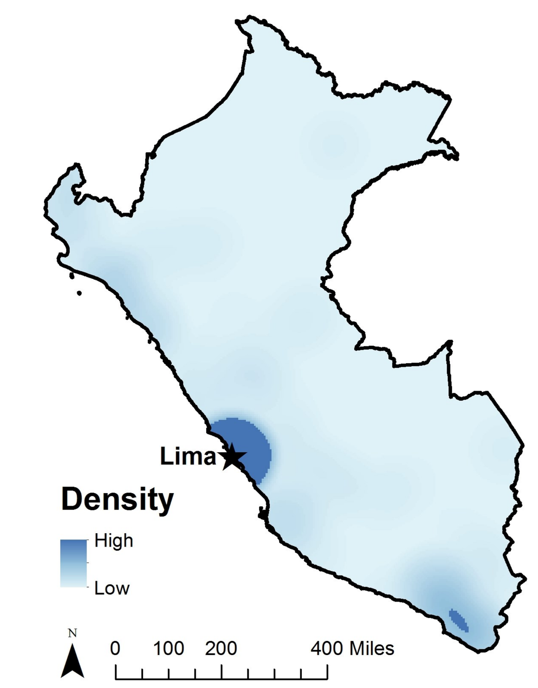
*Higher means represent less vulnerable areas.
The Unweighted model ranged from 3 to 18
The Weighted model ranged from 1.4 to 6

Figure 1. Differences Between the Vulnerability Models

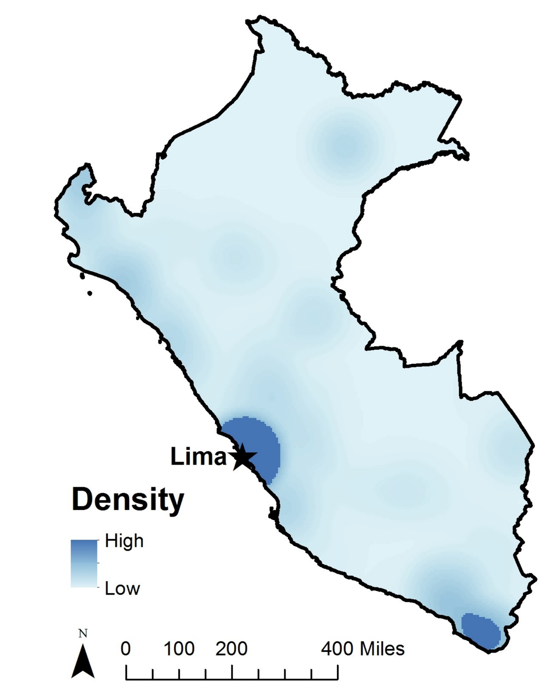


Density of Peruvians by Wealth Index Score

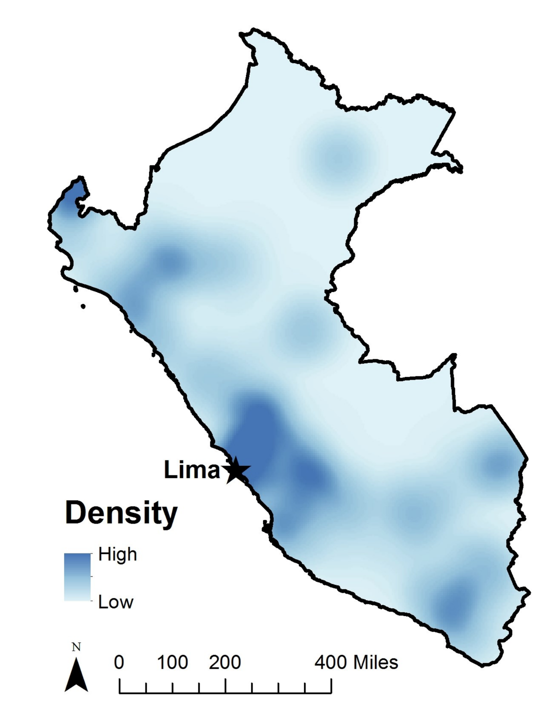
Richest Peruvians



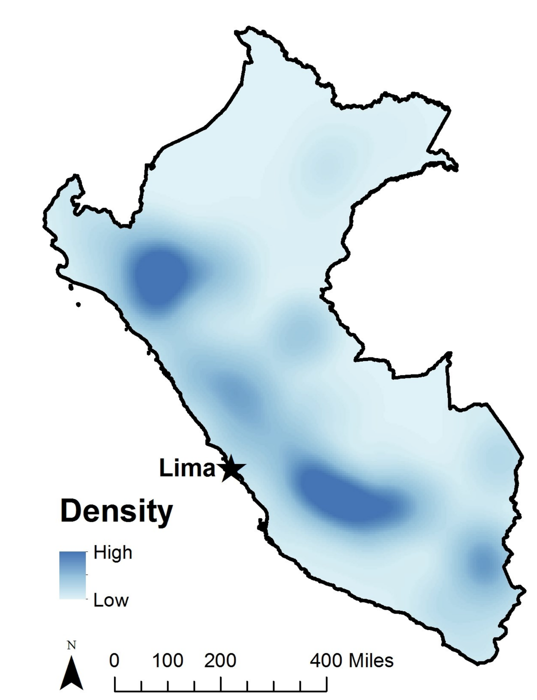
Richer Peruvians



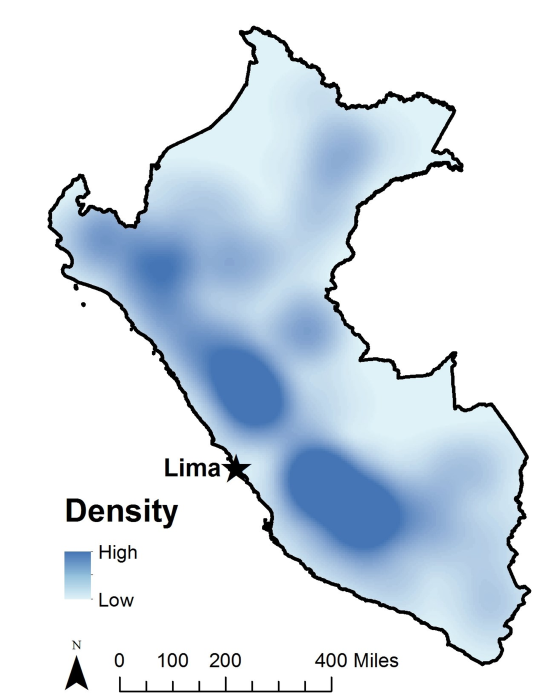
Average Peruvians



Poorer Peruvians



Poorest Peruvians



Conclusions

Major Findings and Suggestions

1. The most suggestive finding of the vulnerability models is that, on average, it is safer to live near the Coast in Peru.
2. One potential problem with this wealth distribution analysis stems from the interpretable DHS data. Although there were 41,000 initial cases, there were only 1,405 GPS coordinates. Thus, only 3.4% of the possible points could be used.
3. Further, The role of elevation on wealth in Peru is not yet fully understood. Thus, an analytical leap of faith was taken in order to employ elevation as a methodologically viable measure of wealth.

Future Research

These models predict the economic vulnerability of living near a mine, outside of urban areas, and at a high elevation. The association between wealth and health is well established in the literature. However, in Peru, models that associate vulnerable health areas with mines, urban areas, and elevation would allow for geographically tailored interventions to be created and implemented.