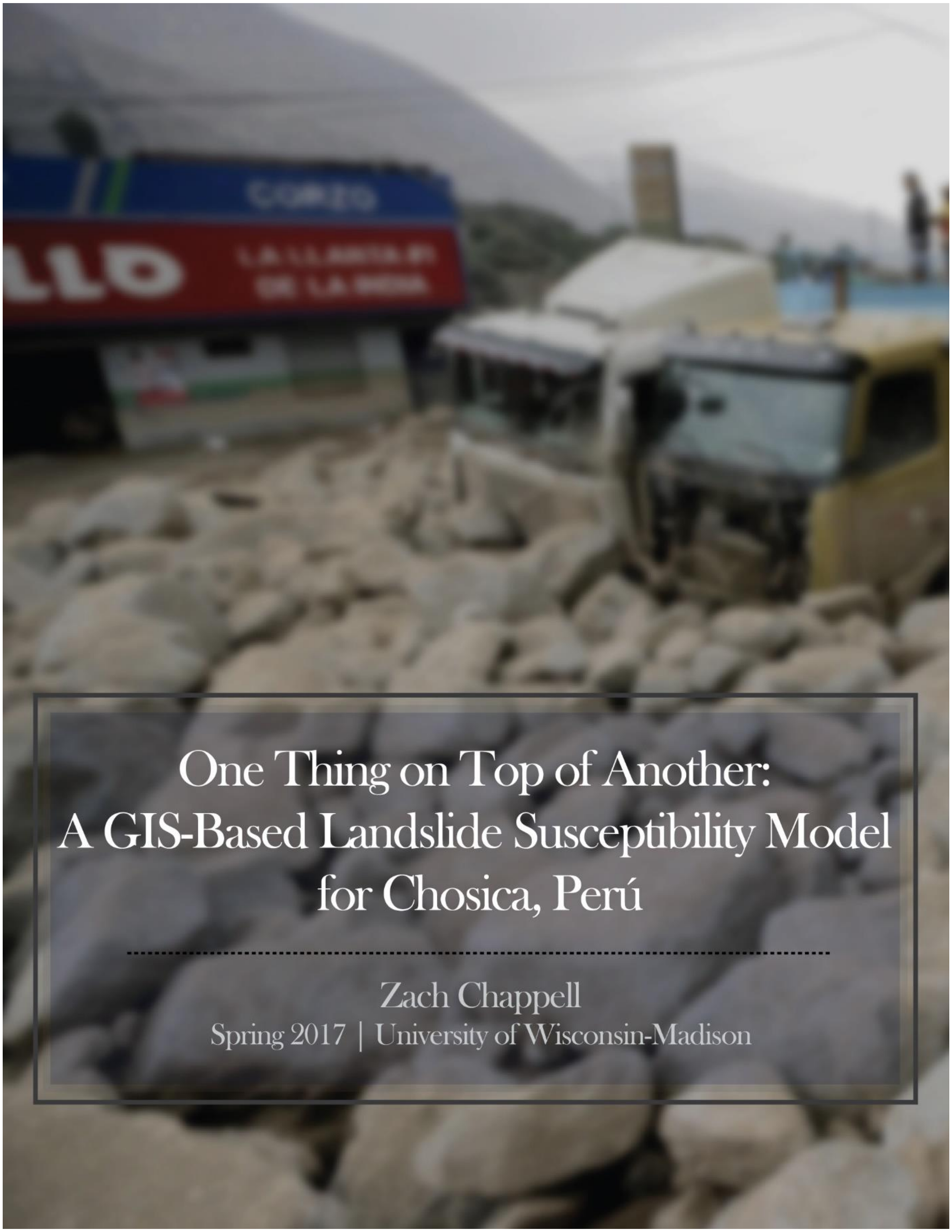

One Thing on Top of Another: A GIS-Based Landslide Susceptibility Model for Chosica, Perú

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Spring 2017 | University of Wisconsin-Madison

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Executive Summary

Since the 1950s, global urbanization has grown at a rate unprecedented in history. However, the spatial distribution of this expansion has not been uniform, with 79% of global urban population growth between 1950 and 2000 taking place in the Global South[1]. In this urban context often characterized by scarce resources and haphazard planning, a large share of city growth has taken the form of expansive slums. Of the myriad health risks inherent in slum life, one of the most prevalent is that of natural disasters, which exact an enormous human toll every year.

The present project explores the usefulness of GIS-based landslide susceptibility modelling for slum settlements within a context of imperfect information. Specifically, a landslide susceptibility model is proposed and tested for a study area where *GIS data is available*, but where *statistical expressions of the relationship between causative factors and landslide occurrence do not exist*. Assuming this situation to be representative of most slum areas in the developing world, such a model could prove highly valuable as an accessible, efficient decision support system for disaster planning where information is limited. The study area chosen for the project is the pueblo and surrounding shantytowns of Chosica, Peru, an informal settlement that has been affected throughout the 20th century by catastrophic landslide events.

Landslide susceptibility mapping refers to the division of a site into zones of varying degrees of susceptibility based on the estimated significance of causative factors of slope instability. The proposed model considers nine such factors, each represented by a GIS data layer. Employing an expert-based, semi-quantitative approach, the model first performs various geoprocessing operations on the raw raster and vector datasets to produce intermediate raster layers. These intermediate layers are then broken into subclasses and ranked based on their importance to slope instability in the project area. Finally, each of the layers is weighted relative to the others, and the layers are overlaid to yield the final cartographic output. The final landslide susceptibility map indicates four zones of landslide susceptibility, which are classified as Low, Medium, Hight, and Very High. Preliminary validation shows the model to perform well, with historical landslide events clustered in zones of High susceptibility.

[1] Though no consensus exists on their meaning, the terms “Global South” and “developing world” will be used interchangeably throughout this document to refer to those countries generally considered to suffer from the postcolonial condition. Such countries tend to have a relatively low Human Development Index rank, and have been referred to collectively as the “Third World” in the past.

Introduction

<u>The Problem of Slums: A Global Perspective</u>

At a certain moment in 2009, a shift occurred whose significance rivals that of any event in human history: someone was either born or died, or they left or arrived to a city. In this instant, the global urban population for the first time came to outnumber the rural (UN DESA, 2009).

This inversion of rural-urban balance, though only symbolic as an event, is indicative of the new trajectory of planet earth's habitation. Global urbanization occurred precipitously since the mid-20th century, catching much of the world by surprise and unfolding in an environment largely void of foresight or planning. Rocketing from a population of 746 million in 1950 to 3.9 billion in 2014, the urban realm has absorbed nearly two-thirds of global population growth since 1950, and is currently growing by over a million babies and migrants per week (United Nations, 2014; Davis, 2007). Almost unconceivable is that, one century ago, only two out of 10 people were living in urban areas, with this proportion as low as five percent in the least developed countries. By 2050, this distribution will have reversed, with seven out of every ten people living in urban areas (UN-HABITAT, 2012). At present, the global rural population has reached its maximum and will begin to decrease after 2020; thus, cities will account for virtually all future world population growth, which is expected to peak at around 10 billion in 2050 (UN-HABITAT, 2012).

However, this growth has been anything but uniform. Indeed, 79% of global urban population growth between 1950 and 2000 has taken place in the developing world, and it is estimated that 95% of humanity's final buildout will occur in urban areas of developing countries (Cohen, 2006; Davis, 2007). Troublingly, this urban explosion has not followed the classically assumed relationship between manufacturing growth and urban migration. Rather, even as cities of the Global South experienced progressive deindustrialization due to late-twentieth century neoliberalism, rural-urban migration continued to surge[2]. The resulting disparity between urban populations and employment opportunity caused immense informal economies to form within cities of the Global South. City officials, unable to extract tax revenue from their informal sectors, have struggled to accommodate growing informal workforces. Consequently, a large share of urban growth has taken the form of, and will continue to comprise, slums and squatter settlements.

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[2] The causes of this, though beyond the scope of the present project, can be attributed to the debt crisis of the 1970s, Bretton Woods-imposed structural adjustment programs (SAPs) of the 1980s, globalization and the influx of cheap manufactured goods, and other interconnected forces (UN Habitat Group, 2003).

The numbers paint a dismal picture. Per UN-HABITAT, around 33% of the developing world's urban population in 2012, or about 863 million people, lived in slums (UN-HABITAT, 2012). However, actual numbers are likely far greater than reported figures, as poor slum populations are often deliberately undercounted by officials for political reasons (Davis, 2007). In some countries, the percentages of slum-dwellers are astonishing, such as Ethiopia (99.4%), Chad (99.4%), Afghanistan (98.5%), and Nepal (92%) (McMichael, 2017). Troublingly, slum populations will only gain a larger share of the developing world's slated growth, with every third person on earth expected to live in a slum within 30 years (Vidal, 2003).

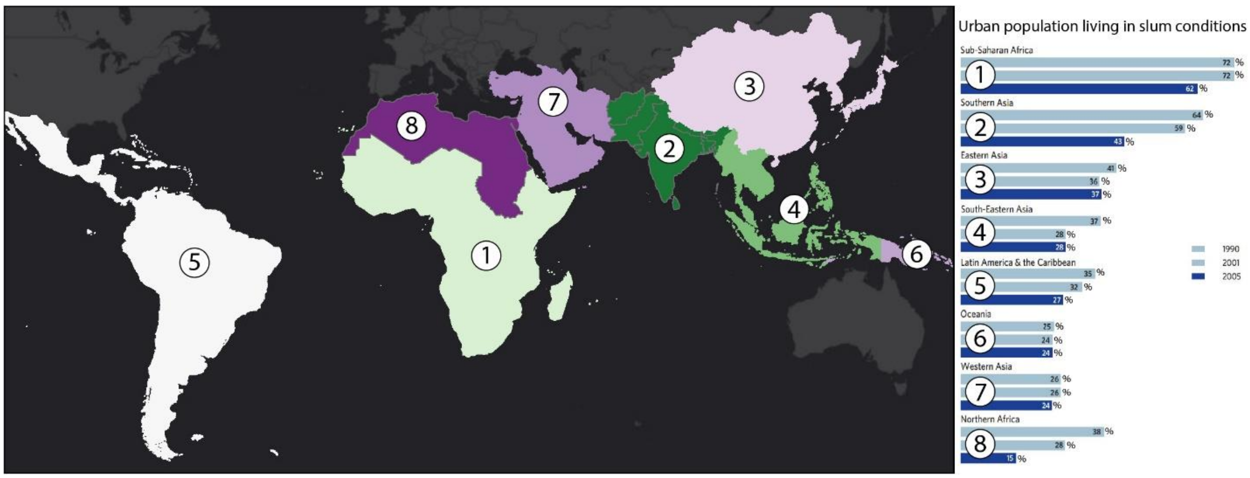

Figure 1: Shares of urban population living in slum conditions in the Global South
Source: UN Department of Economic and Social Affairs (2007)

Unnatural Disasters: The Particular Susceptibility of Slums to Natural Disasters

Slum dwellers bear a plethora of risks that, when combined and compounded, equate to alarmingly hazardous living conditions. Indeed, in addition to their "double burden of disease"[3], the urban poor suffer the noxious byproducts of toxic industries, violence and crime, and the suite of complications inherent in a lack of sewerage infrastructure. As noted by Davis (2007), "a hazardous, health-threatening location is the geographical definition of the typical squatter's settlement " (p. 121). Notwithstanding, perhaps slum dwellers' most immediate threat is that highlighted by the first criterion of UN-HABITAT's definition of "slum": the lack of "Durable housing of a permanent nature that protects against extreme climate conditions" (UN-Habitat, 2007, p. 1). Slum residents are at particularly high risk from the impacts of natural disasters because they dwell on cities' least desirable lands, sites so fraught with danger that they have been deemed valueless by the market. At present, a large share of the developing world's urban poor live as they do in Sao Paulo, where 85% of households living at "high risk" of natural disasters lie within the boundaries of the city's slums (IBRD, 2011).

[3] "The urban poor are the interface between underdevelopment and industrialization, and their disease patterns reflect the problems of both. From the first they carry a heavy burden of infectious disease and malnutrition, while from the second they carry the typical spectrum of chronic and social diseases" (Davis, 2007, p. 147).

The most obvious risk factor for slum dwellers is, of course, location: slums often establish themselves on the banks of rivers, on steep slopes, in drainage basins, or in some other physical orientation of know vulnerability to natural disasters. The examples abound: Sao Paulo's famous *favelas* are located either on steep, highly-eroded hillsides or easily erodible riverbeds, and as expected, display a catastrophic proneness to slope failure and landslides. Here, over 16 percent of residents are under imminent to medium-term "life risk and/or loss of their property" (Davis, 2007, p. 122). The case of Caracas is more alarming still, with slums housing almost two-thirds of the urban population resting on unstable hillsides and within deep gorges surrounding the Caracas Valley. But it is more than bad location which accounts for the acute vulnerability of slum dwellers to natural disasters; indeed, even a city's wealthiest residents can be affected by earthquakes and landslides. Rather, coupled with the increased likelihood that slums lie in the path of natural disasters are the factors inherent in urban poverty which exacerbate the effects of such events.

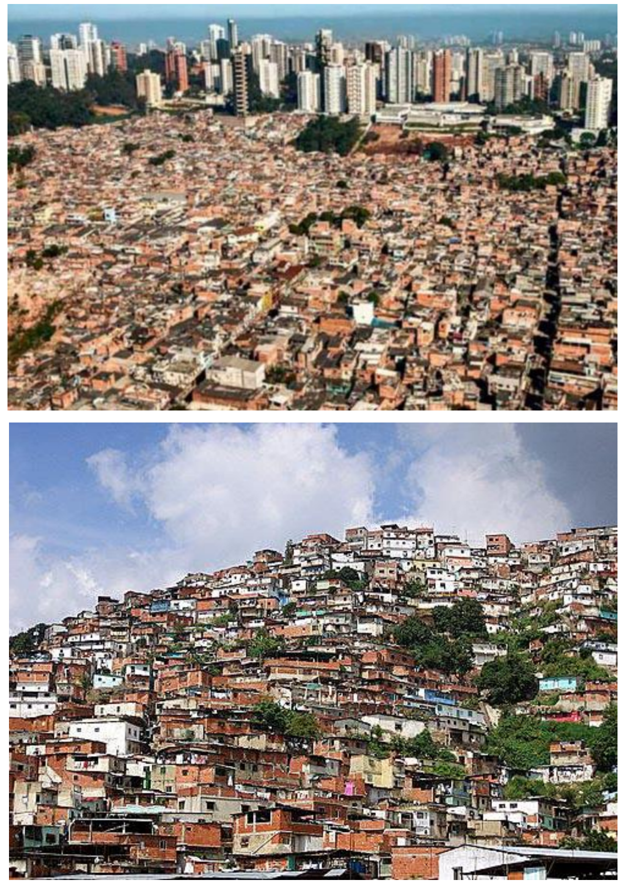

Figure 2: On top, the vast Favela Paraisópolis of São Paulo, Brazil. On the bottom, the slums of Caracas, Venezuela.
Source: Bullivant (2008); http://secretworldwiki.com (2015)

Conditions typical of slum life, such as overcrowded living conditions, unsafe housing, and a lack of infrastructure and services can quickly turn a natural hazard into a disaster. In this context, what are benign natural events to upper-class urban residents become problematic for slum dwellers, and indeed, it is often the more frequent low or moderate-intensity events that have the most significant impact on the urban poor (Davis, 2007). As an example, a heavy rain could quickly become a disastrous event for a slum settlement: poor location and lack of drainage systems lead to flooding and accumulation of water and debris, inadequate access to the site complicates the arrival of rescue services, and stagnant water combined with damage to waste management systems adds the element of waterborne illness. Such situations become increasingly severe in the presence of more extreme disaster events.

Slum life inherently increases the risks of natural disasters. Unfortunately, slums have proliferated throughout the Global South, with poorer nation-states lacking the resources, and often political will, to protect their urban poor. This project explores a method by which a settlement’s most susceptible zones may be identified, thus increasing the effectiveness of resource allocation by targeting the most vulnerable residents. Ideally, this would strengthen the case for incremental investments towards disaster mitigation, and increase the pressure on governments for action.

Project Focus

Peru: A Catch-22

The project study area is located in Peru, a country with very high vulnerability to natural disasters. It is necessary to distinguish between the terms “hazard” and “vulnerability” in the context of natural disaster events. As explained by Urby (2014), the former refers to “the inherent danger associated with a potential problem, such as an earthquake or avalanche” (p. 4). The latter, on the other hand, describes “the characteristics of a person or group and their situation that influences their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard” (Wisner, 2003, p. 11).

Peru has “always been a very hazard-prone region of the world,” with interacting climatological and geological conditions that frequently cause earthquakes, volcanic eruptions, hurricanes, floods, and landslides (Urby, 2014, p. 4). However, the vulnerability of Peru’s population to natural disasters cannot be understood without recognizing the role of poverty. Yes, the country’s high rate of poverty (in 2002, more than half of the country’s population was designated as poor in absolute terms, and 15 percent as extremely poor) and dense urban slums housing 68 percent of urban residents equate to a populace alarmingly ill-equipped to respond to extreme weather events (Davis, 2007). Sadly, the Peruvian state has steadily diminished funding for the glaciologists and geologists necessary for research and prevention, leaving its urban poor lacking not only the means to respond to, but also the tools to predict, the next natural disaster (Urby, 2014). Bluntly, the majority of Peru’s urbanites find themselves in the crosshairs of nature’s ire with little more than luck to protect them.

The Case of Chosica: A History of Landslides

The study area chosen for this project is Chosica, Peru (Figure 3). Though referring to a rather small and inconspicuous town at the base of the Central Andes, the name "Chosica" has become recognizable to most Peruvians. This notoriety is due to the wide coverage that the town has received in the news media, where it's landslides are commonly cited as one of the country's starkest examples of the effects of climate change. And though the absence of thorough records makes it hard to establish trends regarding damages caused by natural disasters in Chosica, it is clear that the frequency and severity of such events has not declined throughout the 20th century, and in all likelihood has increased. Indeed, significant landslide events are recorded to have affected the town every couple of years since the turn of the century, with the most severe perhaps being those of 1926, 1987, and 2015. The 1987 event, recognized as one of the greatest disasters to affect Lima in the 20th century, affected some twenty squatter settlements, causing more than 100 deaths, destroying 1,052 living units, and leaving more than 30,000 people without water (Pérez, 2009). Clearly, the ground occupied by the town of Chosica should not be populated by humans; the fact that it is speaks to the state of disaster planning in Peru.

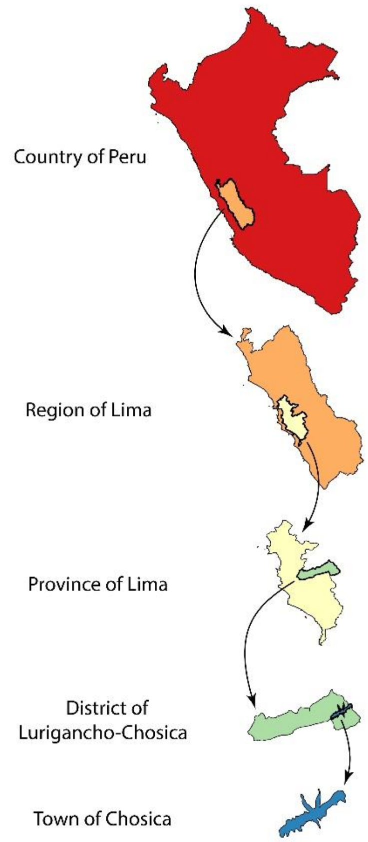

Figure 3: The town of Chosica, Peru lies between the Andean Mountains and the Pacific Ocean

Chosica (Figure 4) is perhaps the disaster planners "perfect storm", presenting the concurrence of an alarming number of risk factors. The town is nestled within a long and narrow gorge which emerges from the Central Andes and joins with the city of Lima's eastern border, bisecting almost perfectly the mountainous district of Lurigancho-Chosica. Blanketing the deepest points of the gorge's basin and climbing the shallower slopes of its walls, Chosica from above resembles a viscous liquid which has spilled into a confined space and gradually filled every available crevice. Here, the concentrated mass of shanty dwellings, bounded by steep walls of sand and rock, occupies exactly the drainage basin carved into the earth over millennia by the River Rímac. Much of this location's treacherousness can be attributed to the nature of the ravines which form the gorge's walls. Here, the steep incline, coupled with a near-complete absence of vegetation, results in strong flows of water and debris in the presence of torrential rain. The ravines of the valley walls have become highly unstable from erosion, and are known to easily release sand, clay, rocks, and even boulders of up to 10 meters in diameter (Pérez, 2009).

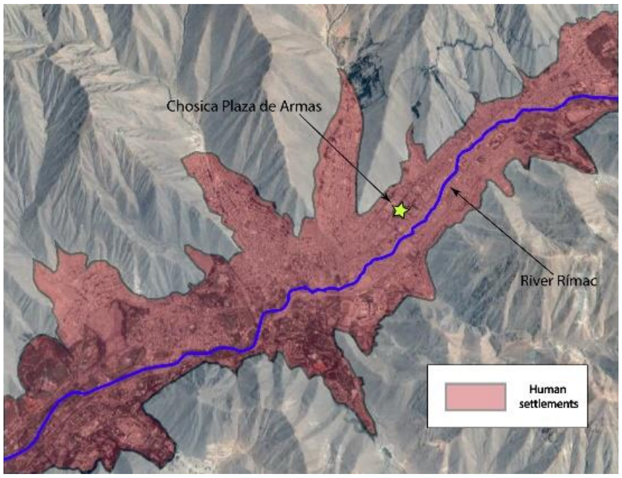

Figure 4: The town of Chosica, located in the basin of a deep gorge, is bisected by the River Rímac

The risks are understood. What remains uncertain is why a town would appear in a known floodplain. The answer to this lies at the nexus of negligence and bad luck. Squatter settlements began to occupy the divaricate gorges of Lurigancho-Chosica district in the 1950s, and by the mid-1970s, had grown to an expansive urban mass. Although flooding events were common throughout this period, they did not become severe until the catastrophic landslides of 1987. As explained by Pérez (2009), what resulted was a general perception of low risk under which settlements were left to expand and fill the gorge basins, natural drainage channels feeding into the River Rímac. Responses of the Peruvian state to recent disasters have ranged from absent to insufficient, with most relief and recovery activities being managed by nonprofits and NGOs. Most troubling is that sites of past landslides are found to be repopulated shortly after the events (América Noticias, 2016). The behavior is puzzling: presumably aware of the danger, why would someone return to a location recently ravaged by landslides? It appears that, absent state regulation, desperation trumps rationality in the ambit of housing choices. The situation is captured succinctly by Young (2009):

> *"Even if people perceive, recognize, and acknowledge the presence of risks from these natural hazards, they are often constrained in the way that they can or will respond. Vulnerability in Peru to natural hazards is amplified by poverty and by a disconnection between what science can predict and what people will do." (p. 1)*

A Landslide Susceptibility Model for Chosica, Peru

Conceptual Framework

Given its history of landslides, the town of Chosica would benefit from a decision-support tool that can aid in the designation of zones of particular susceptibility to such events. The approach most adequately suited to this task is that of the GIS-based landslide susceptibility model. Landslide susceptibility refers to "a division of the land into zones of varying degree of stability based on an estimated significance of causative factors in inducing the instability" (Foumelis, 2004, p. 904). A GIS-based susceptibility model produces cartographic output indicating areas with the potential of experiencing landslides in the future based on a consideration of the causative factors which have produced landslides in the past (Chalkias, 2014). Though such analysis has been conducted by various methods over time, GIS has emerged and has been accepted as the most effective means of susceptibility modeling because of its capacity to integrate and synthesize large amounts of spatial data in a short period.

As explained by Chalkias (2014), landslide susceptibility modeling can be generally separated into two categories: qualitative and quantitative. The most important difference between these methods is the degree of objectivity with which causative factors are valuated. Quantitative methods base themselves largely on statistical expressions of the relationship between factors and landslide events, whereas qualitative methods depend on the knowledge and experience of experts to valuate and weight these factors. Often, qualitative landslide susceptibility models incorporate the idea of ranking and weighing parameters, thus resulting in semi-quantitative approaches (Chalkias, 2014).

It is important to emphasize that the use of qualitative methods should not been understood as a less accurate option than that of quantitative methods; rather, the most appropriate method must be selected according to the nature of available data. For example, a quantitative approach may be most fitting where sound statistical analysis has been conducted on the relationship between causative factors and landslide events within the study area; such data will most likely be available for known sites of susceptibility in wealthier countries, such as Oso, Washington in the United States, where meticulous historical records and extensive research provide a wealth of data with which to work. However, such statistical data may be absent or, if haphazardly collected, misleading, for sites where resources are insufficient for this degree of study. As asserted by Chalkias (2014), "the quality of a landslide risk assessment is related to the extent the hazards are recognized, understood, and explained, *which is not necessarily related to the extent to which they are quantified*" (p. 525). Accordingly, for many sites, the rank value and weight of model parameters can be most accurately determined with the guidance of experts having a good understanding of the behaviors of causative factors.

Chosica, like most developing-world slum settlements, is a site for which statistical data is absent or incomplete. However, the ubiquity of such technologies as satellite imaging and electronic precipitation loggers make it reasonable to assume that considerable GIS data can be acquired for most human settlements, and this is indeed the case for Chosica. Thus, this project has employed an expert-based, semi-quantitative GIS-based method.

Methods

The landslide susceptibility model for Chosica, Peru considers nine causative factors for slope instability. The model was constructed using ArcGIS ModelBuilder, which enables automation of the geoprocessing workflow (Figure 5).

Briefly, each of the causative factors, represented by GIS datasets of either continuous or discrete data, is separated into subclasses. For continuous data, subclasses (six) are designated using the equal area categorization method proposed by Chalkias (2014); for discrete data, pre-existing classes at the nominal scale are preserved. After, each subclass is assigned a relative ranking from 1 to 6, indicating its significance as a causative factor for landslides. Finally, each factor (dataset) is assigned a weight, and a weighted overlay is conducted. The final cartographic output of the model consists of 14,852 mapping units of 8,100 m^2, each representing its relative susceptibility to landslide events. A detailed description of the model processes can be found in Appendix A. Schemes used for subclass ranking, as well as assignation of weights, are detailed in Appendix B.

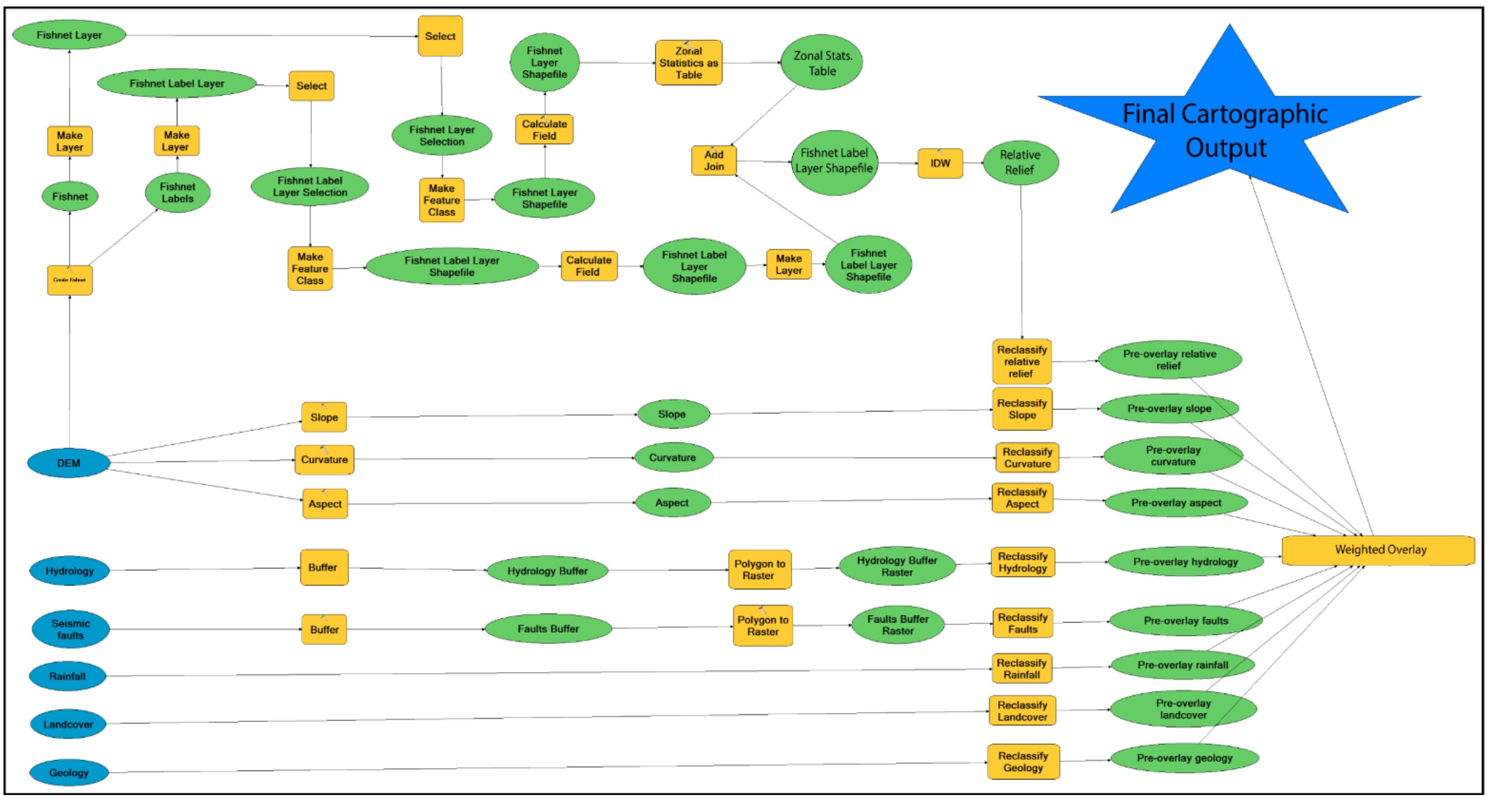

Figure 5: The landslide susceptibility model, built in ArcGIS, automates the geoprocessing workflow

Data

The database used to conduct the present landslide susceptibility analysis is composed of nine geospatial layers representing causative factors for slope instability. Though there are no standard guidelines for selecting such parameters, the nature of a study area, precedent studies, and data availability are often used to determine the factors to be considered (Chalkias, 2014). For this project, factor choice was based on commonalities between four precedent studies, as well as the availability of data for Chosica, Peru (Figure 6).

Precedent Study	**Causative Factors Considered**								
	Geology	**Land cover**	**Slope**	**Relative Relief**	**Rainfall**	**Geology**	**Hydrology**	**Aspect**	**Curvature**
Foumelis (2004)	X	X	X	X	X	X	X	X	X
Chalkias (2014)	X	X	X		X	X		X	
Sarkar (1995)	X	X	X	X			X		
Ministerio del Ambiente (2015)	X	X	X	X	X				

Figure 6: Factor selection was based in part on commonalities between precedent studies

As discussed in the previous section, factors (layers) representing continuous data were each divided into six subclasses. For factors (layers) representing discrete data, pre-existing classes at the nominal scale were preserved. Each subclass was assigned a rank value, and each factor (layer) was assigned a weight (Table 1).

Table 1: Subclasses, ranks, and weights for causative factors[4]

Causative factors (Layers)	Subclass	Subclass Rank	Weight
Slope (°)	0 - 5.8 5.8 - 12.5 12.5 - 18.6 18.6 - 24.3 24.3 - 30.1 30.1 - 43.4	1 2 3 4 5 6	.15
Aspect	N NE E SE S SW W NW	3 3 1 1 1 2 1 2	.10
Curvature (1/100 Z)	-1.21 - -0.40 -0.40 - -0.14 -0.14 - 0.07 0.07 - 0.30 0.30 - 0.54 0.54 - 1.46	6 5 4 3 2 1	.11
Relative relief (m)	0 - 53.5 53.5 - 92.1 92.1 - 123.4 123.4 - 151.6 151.6 - 196.2 196.2 – 379.0	1 2 3 4 5 6	.15
Geology	Volcanic rocks Volcano-sedimentary rocks Superficial deposits Intrusive rocks	1 2 3 3	.09
Land cover	Woodland Wooded Grassland Closed Shrubland Open Shrubland Grassland Cropland Bare Ground	1 2 2 2 3 4 6	.10
Seismic faults	Distance ≤ 200 meters Distance > 200 meters	2 1	.09
Hydrology	Distance ≤ 50 meters Distance > 50 meters	2 1	.09
Rainfall (mm/km/month)	0.83 - 2.50 2.50 - 4.58 4.58 - 6.58 6.58 - 8.75 8.75 - 11.5 11.50 - 15.17	1 2 3 4 5 6	.12

[4] Schemes used for subclass ranking and weight assignation are detailed in Appendix B

Results

The final cartographic output of the landslide susceptibility model for the town of Chosica, Peru is shown in Figure 7. The output indicates that landslide susceptibility in the town is clustered into four distinct zones, which can be classified as Low Susceptibility, Moderate Susceptibility, High Susceptibility, and Very High Susceptibility.

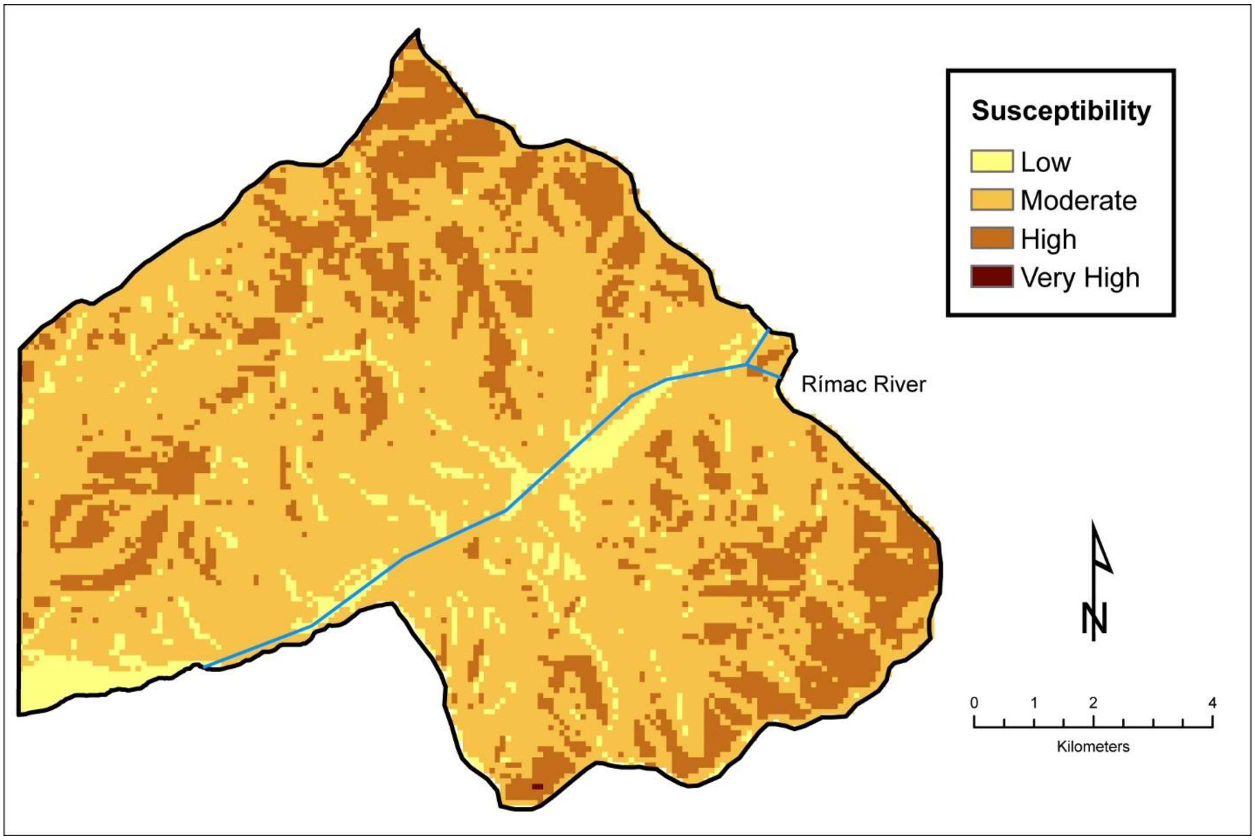

Figure 7: The final cartographic output indicates zones of low, moderate, high, and very high landslide susceptibility

A preliminary examination suggests the results to be logical and compelling. Low Susceptibility zones represent 6.7% of the map area, and are generally located at the gorges' deepest basins and highest peaks, areas exhibiting the least extreme topographic characteristics of slope, curvature, and relative relief. Moderate Susceptibility zones comprise the largest share of the map area at 71.5%, a figure consistent with Chosica's infamy as a precarious region. High Susceptibility zones represent 21.7% of the map area, and are generally located at points of extreme topographic characteristics, such as steeply sloping gorge walls with high positive curvature. Finally, Very High Susceptibility represents less than one tenth of a percent of the map area.

Though the absence of complete and accurate historical records of landslide events in Chosica makes a comprehensive validation of the landslide susceptibility model difficult, a primary validation can be conducted by comparing model results with those events for which documentation is available. The results of such a validation are shown in Figure 8, which indicates the location of 20 landslide events occurring from 1909 to 2015 (Villacorta, 2015). As we can see, historical landslides are clustered within and around zones of High Susceptibility, particularly within the Quirio and Pedregal Gorges. These results would suggest the model to be a useful tool for preliminary analysis of landslide susceptibility.

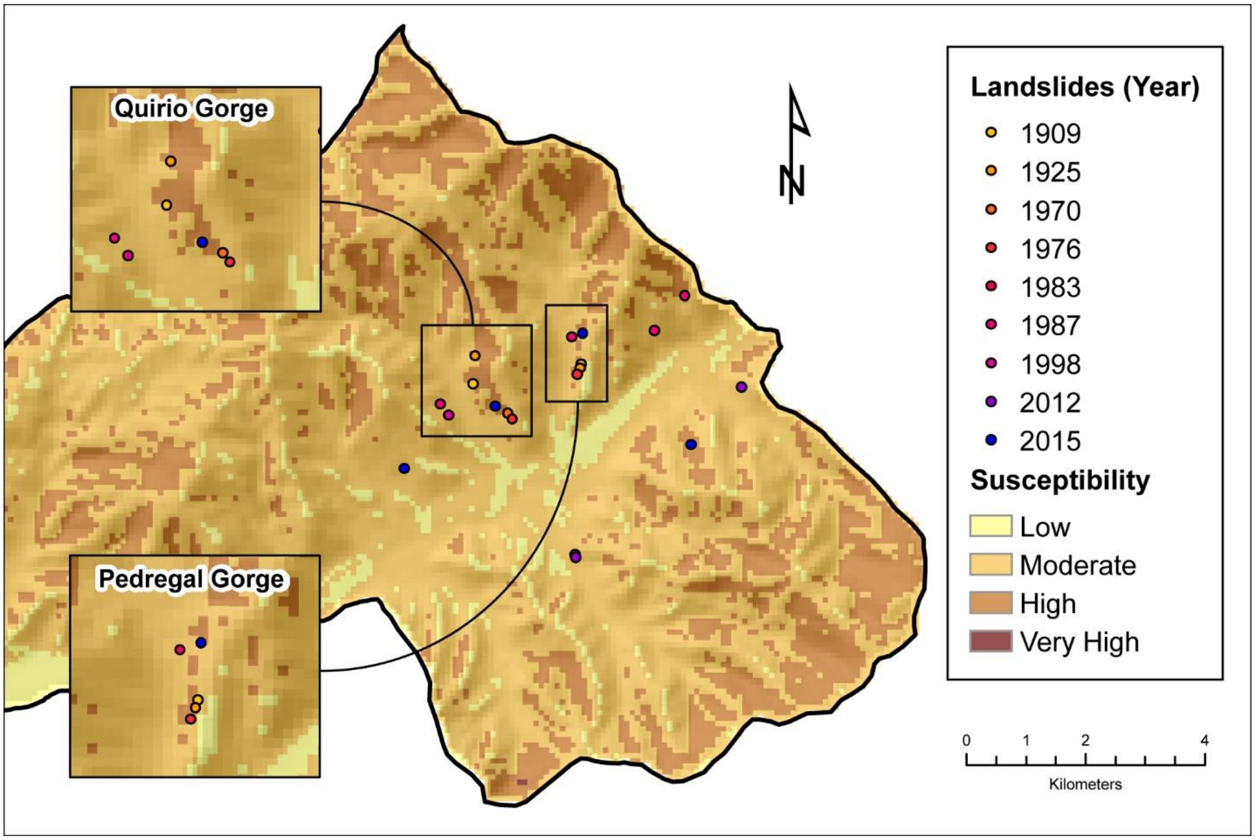

Figure 8: Historical landslide events are clustered in the Quirio and Pedregal Gorges

Discussion

The central objective of this project is to explore the usefulness of GIS-based landslide susceptibility modelling within a context of imperfect information. Specifically, the project employs an expert-based, semi-quantitative method, which assumes the *availability* of GIS data, but the *lack* of statistical data for causative factors of landslides; this situation can be assumed to represent most slum settlements in the developing world. The results of the analysis show this approach to have been effective for identifying zones of landslide susceptibility in Chosica, Peru, despite its subjectivity in ranking and weighing of causative factors. Clearly, the success of this model in a single project does not affirm its validity; however, it does make the case for further study.

Rather than a definitive measure of landslide susceptibility, this approach is valuable as a preliminary analysis tool where information is insufficient to employ more quantitative methods. Given its accessibility, and initial effectiveness, this type of analysis may prove the best option for planners working with slum populations in the Global South. Indeed, it implies the opportunity for first steps towards disaster planning where it otherwise may not have occurred. Ideally, for a given slum settlement, such preliminary analysis would attract further academic attention, prompt more comprehensive research, and hopefully, engender the public support and political will necessary for concrete steps towards disaster planning.

Appendix A

Processes included in the landslide susceptibility model for Chosica, Peru are detailed below. This represents an expert-based, semi-quantitative GIS-based method for landslide susceptibility analysis.

a. Construction of Geodatabase
    1. Seven core spatial datasets are collected, including:
        i. Digital elevation model (DEM)
        ii. Geology
        iii. Soil depth
        iv. Land cover
        v. Seismic faults
        vi. Hydrology
        vii. Rainfall
b. Preparation of Data
    1. Deriving raster datasets from the DEM: Four raster datasets were derived from the DEM, including slope, aspect, relative relief, and curvature.
        i. While ArcGIS tools exist for slope, aspect, and curvature, a custom tool needed to be created for relative relief.
            1. For the relative relief dataset, a 5x5 cell matrix was used, as recommended by Foumelis (2004)
    2. Geoprocessing of vector data and conversion to raster datasets:
        i. Geoprocessing is conducted on the following vector dataset:
            1. Seismic faults: A 200-meter buffer was created around polyline features
            2. Hydrology: A 50-meter buffer was created around polyline features
        ii. The following vector datasets are converted to raster. The resulting raster datasets have cell dimensions equal to that of the DEM (8,100 m^2):
            1. Seismic faults buffer
            2. Hydrology buffer
            3. Geology
    3. Resampling of core raster datasets: Two core raster dataset are resampled to match the cell dimensions of the DEM (8,100 m^2), thus resulting in all raster datasets possessing homogenously sized cells. This is necessary so that datasets can be overlaid. Resampling is conducted on the following two datasets:
        i. Land cover
        ii. Rainfall
    4. Division in subclasses: Division of each of the nine raster datasets into subclasses is necessary to enable the assignation of rank values.
        i. For continuous data, subclasses (six) were designated using equal area categorization, as proposed by Chalkias (2014). This method was employed for the following layers:
            1. Slope
            2. Curvature
            3. Relative relief
            4. Rainfall

ii. for discrete data, pre-existing classes at the nominal scale were preserved.
    1. Aspect
    2. Land cover
    3. Geology
    4. Seismic faults
    5. Hydrology

c. Ranking and Weighing
    i. Data layer subclasses were assigned a rank denoting the relative degree of susceptibility they represent. This “expert-based” method is detailed in Appendix B
    ii. Each of the data layers (causative factors) was assigned a weight, ranging from 0.0 to 1.0, according to its relative importance to slope instability in the study area. Here, weight values were adopted from Foumelis (2004)

d. Weighted overlay
    1. The nine layers are overlaid, yielding the final landslide susceptibility map

Appendix B

Ranking of factor subclasses

As explained by various authors having employed the expert-based, semi-quantitative method, ranking of factor subclasses is inevitably somewhat subjective, as it is conducted according to human discretion (indeed, it is this aspect of the expert-based, semi-quantitative method which makes it so accessible and dynamic). For example, Chalkias (2014) asked three experts to rank each subclass separately, and then averaged the rankings to arrive at the final subclass value. On the other hand, Foumelis (2004) decided to base their classification on informed assumptions using statistical analysis conducted on the relationships between individual factors and slope instability in other regions of the world. Regardless, all landslide susceptibility studies examined for this project cited similar relationships between causative factors and susceptibility. Thus, two assumptions were made in this project for the ranking of factor subclasses:

1. Intensity of continuous data is positively correlated with landslide susceptibility
    - Ex: high slope = high susceptibility; low rainfall = low susceptibility
2. Nominal subcategories of discrete data bear a similar relationship to landslide susceptibility throughout the country of Peru
    - Ex: Intrusive rocks present higher susceptibility than volcanic rocks

Accordingly, factor subclasses were ranked as follows:

- Continuous data, including **slope**, **curvature**, **relative relief**, and **rainfall**, have been given rankings 1 – 6. Here, a progressively higher ranking was given to each of the six subclasses, with 1 assigned to the least intense subclass and 6 assigned to the most intense subclass (least to most causative).
- **Aspect**, **geology,** and **land cover** were ranked according to the ranking schemes proposed by Diercksen (2008) in her study of landslides on the central west coast of Peru. Given the close proximity of this study area to that of the present project, it is assumed that these factors will possess a similar relationship to slope instability.
- The variables **distance to faults** and **distance to streams** were ranked according to the scheme used by Foumelis (2004).

Weighing of factors

Similar to subclass ranking in an expert-based, semi-quantitative model, weighing of causative factors is inevitably somewhat subjective. For this project, I have adopted the ranking scheme employed by Foumelis (2004) in their GIS-based model for landslides susceptibility in Greece.

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