Precipitation Triggered Landslide Risk Assessment and Relative Risk Modeling Using Cached and Real-Time Data

by

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To my family, my constant strength and encouragement.

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List of Abbreviations

DNR	Department of Natural Resources
FEMA	Federal Emergency Management Agency
GIS	Geographic information system
GISci	Geographic information science
IDE	Integrated Development Environment
NDFD	National Digital Forecast Database
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
SDE	Spatial Database Engine
SSI	Spatial Sciences Institute
US	United States
USC	University of Southern California
USGS	United States Geologic Service

Abstract

Urban centers continue to densify and increase in number as the world's population grows. Landslides are a common hazard throughout the world and can cause significant loss of life and property. Landslide risk and damage to the built environment is often an outcome of urbanization, whereas in the natural environment damage due to landslides is considered part of nature taking its course. This study examines the most common landslide triggering variable, precipitation, in Western Washington State, a region prone to this geohazard. The methodology developed in this study utilizes freely available, currently cached and real-time soil, geology, land use, demographic, and weather data provided by state and federal agencies and required no field research. It is imperative in high-risk landslide zones to have easy access to accurate landslide prediction models available in an open format. Integrating real-time data into validated landslide risk and relative risk assessment models through a geographic information system (GIS) can increase the utility, accuracy, and ease of use of a given model. The model developed in this study reports potential risk to urban and rural environments as well as risk to specific demographics for a specified landslide event. Landslide triggering variables are well suited for real-time streaming due to their continuously changing behavior. By publishing and publically sharing the model as a web service thus making it available on via the internet, the methodology also encourages collegial and professional discussion. Thus, this study provides an example of data integration of traditional landslide risk assessment variables with real-time precipitation into a landslide risk and relative risk model that can be readily adapted to investigations into landslide hazards in other locations.

Chapter 1 Introduction

As populations continue to grow and densify, it is imperative that emergency response personnel, community planners, and managers are aware of the risks posed by geohazards. In the context of this thesis, risk is defined as measurable loss of property, life, or economic gain resulting from a geohazard (ICG 2014). In addition, a geohazard is typically defined as a geological state, condition, or effect, which has the potential to cause widespread damage. Geohazards include landslides, floods, earthquakes, tsunamis (hurricanes or cyclones), and other natural events. Landslides are a particularly critical geohazard and a serious risk to human settlements because slope failure can cause both widespread property damage and loss of life. In this study, a landslide is defined as a form of slope movement that includes “mud and debris flow, rockfalls, soil slips and deep-seated slides” (Varnes 1978, p 7). Geologic terms and definitions relating to landslides have been well established and in this thesis will follow those set forth by Varnes (1978) and refined by Cruden and Varnes (1996). The term vulnerability is also used when describing landslide risk in a specific geographic area where populations and built environment exist.

The purpose of the study is to develop an innovative Landslide Risk Assessment Model (LRAM) that can be understood by anyone at any level of technical proficiency in Geographic Information Systems (GIS) and landslide risk assessment and to increase the utility of a model by placing it in an accessible location. This model is implemented using commonly used GIS technology including Esri’s ArcGIS for Desktop and Server and ArcGIS.com. In addition, this research utilized non-GIS dedicated applications such as Wget. The study area chosen to carry out this effort is United States Geologic Service (USGS) Zone 10 of Washington State (Figure 1-1). This location was chosen because of the regions’ rich history of landslides including the site of the most deadly landslide in United Stated (US) history (Stone and Servic 2014). Government agencies such as the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service (NWS) and the USGS provide individual assessments of potential major natural disasters in the United States as they occur. However, there is a void in the literature concerning real-time landslide risk assessment models for predicting landslide events, though such models have been published for wildfires, tornadoes, and rainfall triggered flooding. This thesis seeks to fill that void by creating an easily communicable landslide risk assessment model and hosting it in a web service. Hosting a model within a web service has many advantages. The most significant advantage of a web service hosted hazard model is that the model is available real-time, on demand, to those who wish to use it, for example in an urgent time-sensitive situation.

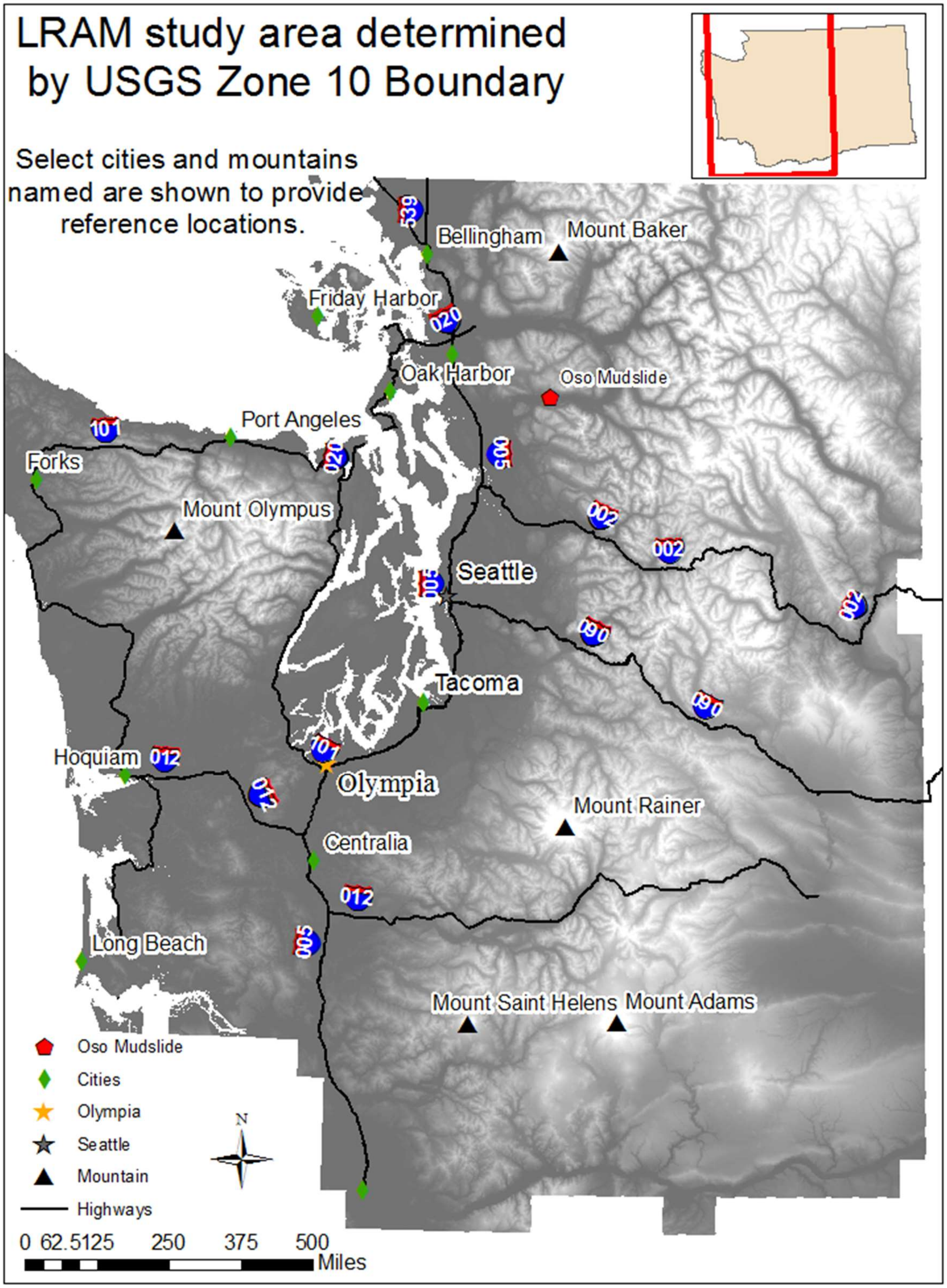


Figure 1-1 USGS Zone 10 consisting of all of Western Washington State and a small portion of Eastern Washington. Major cities, towns, and mountains are labeled to orient the viewer to local geography.

Landslide hazard and risk assessment is a constantly advancing science. Landslide events impose immediate repercussions for the environment and the ways humans interact with it. Landslide prediction, quantification, and risk assessment have been strongly aided by the creation and continued use of GIS. Before GIS use became widespread, landslide hazard assessment was primarily performed through manual statistical interpretation of soil morphology, geology, ecology, built environments, and precipitation, among other factors (Carrara 1989; Cruden and Varnes 1996; Malamud and Turcotte 2004). And prior to the advent of GIS-based risk analysis of various natural hazards, landslide risk assessment was "dominated by uncertainty" (Dai, Lee, and Zhang 2001). Today many GIS hazard assessment models are typically deterministic rather than statistical (probability) models. Nevertheless, statistical models have their place in landslide risk, relative risk, and vulnerability assessments, as explained in the following discussion.

1.1 Deterministic and Statistical Models

Deterministic natural hazard assessment models determine an outcome from a fixed set of pre-determined variables with known relations. It is assumed that using a deterministic model for a given hazard analysis will always yield the same output or result, provided the same input data is utilized. For example, a deterministic earthquake hazard assessment would involve using the input parameters form an existing historical earthquake to repeat the event in the same location, to see if the model produces the same results observed following the real event. When creating a statistical landslide hazard model the researcher quantifies all variables into the model as coded variables.

Generally, a deterministic landslide hazard model is used to establish locations or zones geographically vulnerable to a landslide (De Capua et al. 2014). Each of the main input variables, such as slope and soil characteristics, remains constant within the bounds of the study area. While many types of data utilized will change over time, the changes will generally occur outside of a time frame for which a model is applied. One example is geology data, which changes over the course of hundreds and thousands of years. Landsat data is the most geographically variable data type utilized in landslide hazard models. Landsat data would need to be updated and the model re-run after any major change in the natural or built environment in a given study area. An example is the logging of forests which would affect the results of a Normalized Difference Vegetation Index (NDVI) analysis and therefore, change the land cover type in the model.

A landslide vulnerability model is a statistical model (Carrara 1989). The vulnerability is determined by the land use of the area and the populations residing in the hazard zone. Due to the nature of human populations, the inhabitants, and built environment are in flux and can only be assessed through statistical interpretations of data. There are varying levels of complexity in regards to any type of vulnerability model. Landslide models can be designed to analyze potential risk to populations or man-made infrastructure. In regards to the built environment, a landslide model can be weighted with respect to specific types of man-made structures such as schools, hospitals, tenant housing, or even to specific architectural design and construction if the information is available. Weighting a model to examine specific variables has been used in previous studies to determine the effects of a landslide on transportation infrastructure in rural locations, or in cases examining the effects of landslides in densely populated areas (Erener and Düzgün 2012). This is particularly useful for local governments when developing and issuing zoning and economic development plans.

The landslide risk assessment model (LRAM) developed for this thesis project focuses on analyzing landslide relative risk using raw population data and land use zoning to assign land use scores. In a final Web GIS deployment of the LRAM, historic and real-time predicted precipitation data was utilized in statistical analyses to further refine and predict land areas or zones most at risk in the study area. Additionally historic precipitation was used in conjunction with soil data to determine land instability potential. Lastly, predicted precipitation was then used along with the determined instability potential in the afflicted zones to determine the final landslide hazard output,, since precipitation is the primary landslide triggering variable. The development, integration, and implementation of the model are discussed in detail in Chapter 3.

1.2 Motivation

In certain geographies, landslides can occur with a relatively predictable frequency, which are generally caused by man-made alteration of the environment in the risk area (Miller and Sias 1997). These same landslides can cause greater damage than anticipated if certain environmental factors shift or change rapidly. This limits the usefulness of any landslide risk assessment model.

For example, recently a landslide in the city of Oso located in Washington State that occurred on March 22, 2014 caused catastrophic damage to residential housing and resulted in a heavy loss of life (Stone and Servic 2014). Although landslides regularly occur in this area, the land volume of this landslide was greater than anticipated and caused structural damages far beyond expectations (Miller and Sias 1998; Miller and Sias 1997)**.** While there are many questions surrounding the cause of the Oso Landslide, factors leading to the atypical severity of the damages incurred have surfaced. The most significant factor contributing to the high number of causalities is human settlement too close to the hazard zone, despite prior recommendations from earth science researchers and public surveyors against residential development in the area due to previously identified landslide risk (Miller and Sias 1998; Miller and Sias 1997). This area was further destabilized by an unusually high level of precipitation in the region which is assumed to have flooded the ground water table (Stone and Servic 2014).

It is imperative that landslide risk assessment models are communicated and disseminated to government agencies, developers, emergency management officials, and residents, to help them with the decision making process of gauging landslide risk, potential damage to structures and loss of life in the event that a landslide does occur. Current methods of communicating hazard models involve publications in government reports for agencies or businesses directly related to the environment or landscape being researched (Fell et al. 2008). Thus, a major goal of this project was to take a validated deterministic model (hazard risk assessment) and integrate real-time statistical models in a publically available Web application. The primarily goal of the latter is to increase landslide hazard awareness, in particular in the study area region. The method for disseminating these models will increase the footprint of awareness by being hosted in a Web mapping application accessible by anyone with an internet connection.

1.3 Case Study: USGS Zone 10, Western Washington State

Western Washington State was chosen as the study location for this thesis project, because this particular region experiences a high number of landslides every year due to its unique geologic, atmospheric and soil morphology and systems (see Figure 1-1) (Miller and Sias 1997). The application of real-time data is limited to NOAA weather data, since for the most precise and accurate model it is best if real-time data is updated hourly. Eastern Washington was excluded from the study area due to incomplete input data sets and other limitations in data availability. Eastern Washington holds a retired nuclear research and enrichment facility that is now the nation's largest Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) site, more commonly known as a Super-fund site (Figure 1-1). This site, in addition to being a CERCLA site, is also one of the nation's largest retired nuclear research facilities and contains a vast nuclear waste dump. As such, soil data is not available to the public.

Washington State has a natural geographic and socio-political boundary that runs through the state along the Cascade Mountain Range. The geographic dividing line is absolute as determined by the state legislature. However, the federal government, through USGS data collection, has placed the boundary location further east. The digital elevation map used for this area is USGS Zone 10 for Washington State. The Zone 10 boundaries do not match the East-West dividing line for Washington State. Due to this difference, the USGS Zone 10 area was used rather than the state's East-West dividing line.

The data collected for the project was compiled at a state and regional level. This study was then focused on the overall smallest region for the collected data (USGS zone 10). Thus, the project environment was set to limit all analysis to this chosen region. The model was run as a single dataset to eliminate edge effects rather than running smaller geographic or political areas and stitching them together as a mosaic. The overall analysis and many of the individual steps consist of raster analysis which if mosaicked can have issues with values bleeding into other cells that do not represent a true value.

1.4 Thesis Organization

The remainder of this thesis is divided into four additional chapters. Chapter 2 provides background literature and explains concepts, such as real time data integration, in a broader context as the concepts relate to the thesis. Chapter 3 outlines the development of the LRAM and describes the methodology conducted during this thesis. Chapter 4 details the results of the LRAM after running and validation. Lastly, Chapter 5 summarizes the outcomes produced and offers concluding comments on future work needed to further the development of this work.

Chapter 2 Background

This thesis project consists of three separate but inter-woven goals regarding landslide risk assessment modeling development and deployment. These goals are examined below in the context of previous contributions by academic and government sources in the field. The first goal is the integration of a deterministic landslide risk model (Hadi 2004) with a real-time statistical precipitation slope failure risk model (Chiang and Chang 2009; Chang and Chiang 2009; Bhandary et al. 2013). In this study, these two different types of models were integrated to form the foundation of the LRAM. The second goal of this study is to publish the LRAM in a publicly available web service where it is updated hourly with the most accurate available primary source data. The third goal is to communicate the LRAM, risk zones, and inaccuracies effectively to the research community, the general public and to government entities that the LRAM output is intended to assist as a decision-making tool. Placing the LRAM model in a public location without communication has the same general outcome as printing the results and putting them in a drawer. The LRAM is published on ArcGIS.com and shared to all who want to use and find it. Additionally, after final review and validation, the model will be published on a public website that explains the dangers of landslides and what we can do to minimize risk to our communities.

2.1 Landslide Modeling

Many researchers have set forth guidelines on how to determine landslide susceptibility, and others have examined the finer aspects of modeling landslides such as considering units, scale or size of study area, directional debris flows, and elevation (Westen and Terlien 1996; Westen, Castellanos, and Kuriakose 2008; Erener and Düzgün 2012; Jagielko, Martin, and

Sjogren 2012; Fell et al. 2008). Also, the various environmental and landslide triggering conditions have been widely examined (Miller and Sias 1998; Cruden 1994; Cruden and Varnes 1996; F. Dai, Lee, and Ngai 2002; Dahal and Hasegawa 2008; Fell et al. 2008).

Although landslide vulnerability is not comprehensively examined in this study, dasymetric mapping of population is included in the methodology to provide an indication of vulnerability of people in harm's way. The term vulnerability, when applied to a geohazard, must be clearly defined. In the geohazard discussion within social science literature, vulnerability is often used to define the risk of a geohazard to a social group or society at large. Within this context, vulnerability focuses on sources that "produce explicit spatial outcomes, social and biophysical, and describe their origins and common usage within the social science hazards literature" (Cutter 1996). This vulnerability may or may not have a spatial domain. Within the more specific academic discussion of landslide prediction and analysis, vulnerability is used to describe several attributes beyond populations, societies, and social groups. These attributes include buildings, transportation networks, lifelines, essential facilities, population data (total population), agriculture data, economic data, and ecologic data. These combined attributes create the geographic area's vulnerability to a landslide event (Westen, Castellanos, and Kuriakose 2008). This paper's goal is not to assess comprehensive vulnerability from either definition but to determine the relative risk of a region.

Preparatory or environmental factors have been defined as, "variables that make the slope susceptible to failure without actually initiating it" (F. Dai, Lee, and Ngai 2002, 67). These factors include the slope gradient and aspect, the soil type and the bedrock geology, the overall elevation and the elevation change, vegetation presence or absence, and how the ground surface has weathered up to the point of analysis. These factors are what make up the geography of a given study area and allow stability to be quantified such that that researchers can estimate how they can be altered by testing different values in the triggering variables.

Landslide triggering variables are defined as “the triggering variables which shift the slope from a marginally stable to an unstable state and there by initiating failure in an area of given susceptibility” (F. Dai, Lee, and Ngai 2002, 67). Triggering factors can include earthquakes of varying intensity, heavy rainfall, changes to the built (anthropogenic) environment, and rapid rise in ground water levels. These factors are important because at least one, if not more, will result in the slope destabilization and thereby trigger a landslide.

The landslide models currently published in the literature are not without errors (Miller and Sias 1997). Noted errors include location-based assumptions when comparing similar locations, bad data, and errors in analysis. A common error that is difficult to avoid is interpolating precipitation data from one recorded point to a region. At this time, there is no way to avoid precipitation interpolation from point sets into isohyets. Nevertheless, existing models are integral to saving lives and preventing property damage from an eventual landslide. As previously stated, the LRAM developed as part of this thesis attempts to integrate real-time data into an already validated deterministic landslide risk model. This method for calling a landslide risk model on demand utilizing dynamic input data, intended to provide the most up to date risk assessment and forecasted risk as possible. While many factors in landslide analysis do not change quickly, weather and ground water can and are major triggering factors, in addition to other major geologic events such as debris flows and earthquakes (Miller and Sias 1998).

The model chosen for this analysis incorporates only environmental factors (Hadi 2004) while omitting triggering variables. The purpose of omitting triggering variables other than rainfall is to develop a baseline model where triggering variables can be applied to the region as needed to test for different landslide locations. One location within a region may be vulnerable to precipitation triggered landslides but not earthquakes, while the opposite may be true for a different region. As such, the LRAM has a peer reviewed rainfall analytical model integrated within it which attempts to correlate landslide risk with rainfall events to assess a safety factor, which has been considered a standard method for assessing landslide risk (Lepore et al. 2013). Rainfall-triggered landslide modeling is well researched and reviewed (Bhandary et al. 2013; Dahal and Hasegawa 2008; Chiang and Chang 2009; Aleotti 2004).

The original landslide assessment model utilizes a method known as infinite slope modeling to estimate risk. This modeling method accounts for the hydrological framework of a watershed or areas of slope failure, the environmental variables incorporated into the model. Arnone (2011) and Arnone et al. (2013) provide a detailed description of the infinite slope model equations and rainfall triggered modeling. Lepore et al. (2013) add to the discussion by furthering the model to include soil which is neither dry nor wholly saturated. The main advantage of the infinite slope model is that it applies to nearly any location where basic soil data and precipitation data is known (Lepore et al. 2013).

2.2 Real-Time Data Integration

Precipitation data is a requisite model variable that is updated hourly to ensure the accuracy of the LRAM. Real-time precipitation data is sourced through NOAA's National Weather Service (NWS) National Digital Forecast Database (NDFD) for the study area (NDFD 2015).To facilitate the download of real-time precipitation data and its conversion to a usable data format batch scripts were written in a text editor and saved at .bat. These scripts are run on the production server, which also hosts the LRAM public facing Web map application. These scripts are included in Appendix C. A task scheduler calls the batch scripts to run at designated times to download new precipitation data, replace the old data and run NOAA's DEGRIB application[1] to turn the precipitation data into a shapefile. This process is discussed further in Chapter 3. Thus, to best incorporate the temporal and volume fluctuation of precipitation data, the data is integrated into the LRAM in a real time format where predicted precipitation levels are computed for a 72 hour forecast period, updated hourly, with the LRAM running hourly to update the calculations utilizing the most recent precipitation data.

2.3 Communication of Hazard Models

Geohazards are a relatively common phenomenon in the United States (FEMA 2015b). The Federal Emergency Management Association (FEMA) actively works to protect communities and prepare them for possible disasters. The USGS and FEMA both have a large amount of information available related to landslide susceptibility at the state or county level. Landslide susceptibility is defined by examining historic landslides, slope, soil morphology, normalized difference vegetation index (NDVI), and anthropogenic development. However, neither organization provides data at the city or block group level. The available data available is complex and can be difficult for a non-geologist to locate and interpret. Also, region-wide models provided through government agencies are typically static and do not include dynamic triggering variables, such as rainfall (Westen, Castellanos, and Kuriakose 2008).

FEMA utilizes GIS to quantify and predict land areas that are susceptible to geohazards and their potential cost in terms of loss (i.e. economic, property, population, built environment) (FEMA 2015a). HAZUS was created by FEMA to streamline this process and put hazard analysis tools into the hands of the public, research communities, and emergency planners. Currently, HAZUS supports modeling for flooding, hurricanes, coastal surge, and earthquakes by

[1] http://www.nws.noaa.gov/mdl/NDFD_GRIB2Decoder/

calculating hazard exposure, intensity, and loss. While HAZUS is an efficient service for modeling those events it does not include models for other hazards and disasters such as wildfires, tornadoes, and landslides. HAZUS, while free to use, does require an ArcView license for ESRI's ArcGIS and the Spatial Analyst extension for running applicable analyses. This substantially increases the cost of using HAZUS and requires a user such as a community planner to be familiar with the science behind the hazard analyses and many damage estimation tools built into this system, as well as to this proprietary software ecosystem of products. Lastly, HAZUS does not provide real-time modeling for any of the disaster analysis tools it currently supports.

The following chapter provides a detailed account of the development of the LRAM Model. This methodology is built upon the work of Hadi (2004) and Lepore and Arnone (2013; 2011), as described above.

Chapter 3 Methodology

As described in the previous two chapters, the main goal of this research was to integrate a landslide and a precipitation model together to achieve a real time, relative risk landslide analysis model customized for Western Washington State (Hadi 2004; Lepore et al. 2013; Arnone et al. 2011). The models selected were correlated with particular regions where each is most appropriate for landslide risk analysis and prediction. The LRAM was then validated using data for other locations that have already undergone landslide risk analysis in addition to field validation. The final application was made available via a public-facing Web map that allows for general consumption of the model and generation of downloadable results.

This chapter presents the methods used for integration of the two models, the method used to score the requisite data sets in the creation of the final model, and the similarities and differences between the LRAM model and the original models it is built upon. Focus was also placed on the communication of risk assessment models to the public and the service this can provide. The chosen method for communication of risk assessment models is through a Web GIS service.

3.1 Model Overview

The LRAM was created by integrating two types of landslide analysis models (Figure 3-1). The first model is an information value (Info Val) model commonly seen in the field. The specific model was inspired by Hadi (2004) and further refined by Che et al. (2012). The Info Val method was chosen because it requires less expert knowledge in the field, the data required is easily available in the United States, the model is flexible, and the computation requires minimal computer resources (Che et al. 2012). The model primarily relies on identifying environmental factors known to be variables in the event of a landslide through analyzing data sets on soil geology, morphology, land cover, and slope (see Table 3.1). These factors are scored and weighted before risk areas can be identified. Scoring of known variables is a process where variables, which have been verified in literature as environmental factors that contribute to landslides, are weighted by severity. Severity is the potential impact of the environmental variable to result or participate in causing a landslide.

The template models used in this analysis are all relative risk models rather than absolute risk models. A relative risk model categorizes risk as low, medium, and high or similar categories. The relative risk model was chosen as the input data sets are not all numerical nor categorical and thus do not lend themselves an absolute analysis. There is a single absolute analysis in this study in regards to the triggering variable, described in detail in section 3.4.

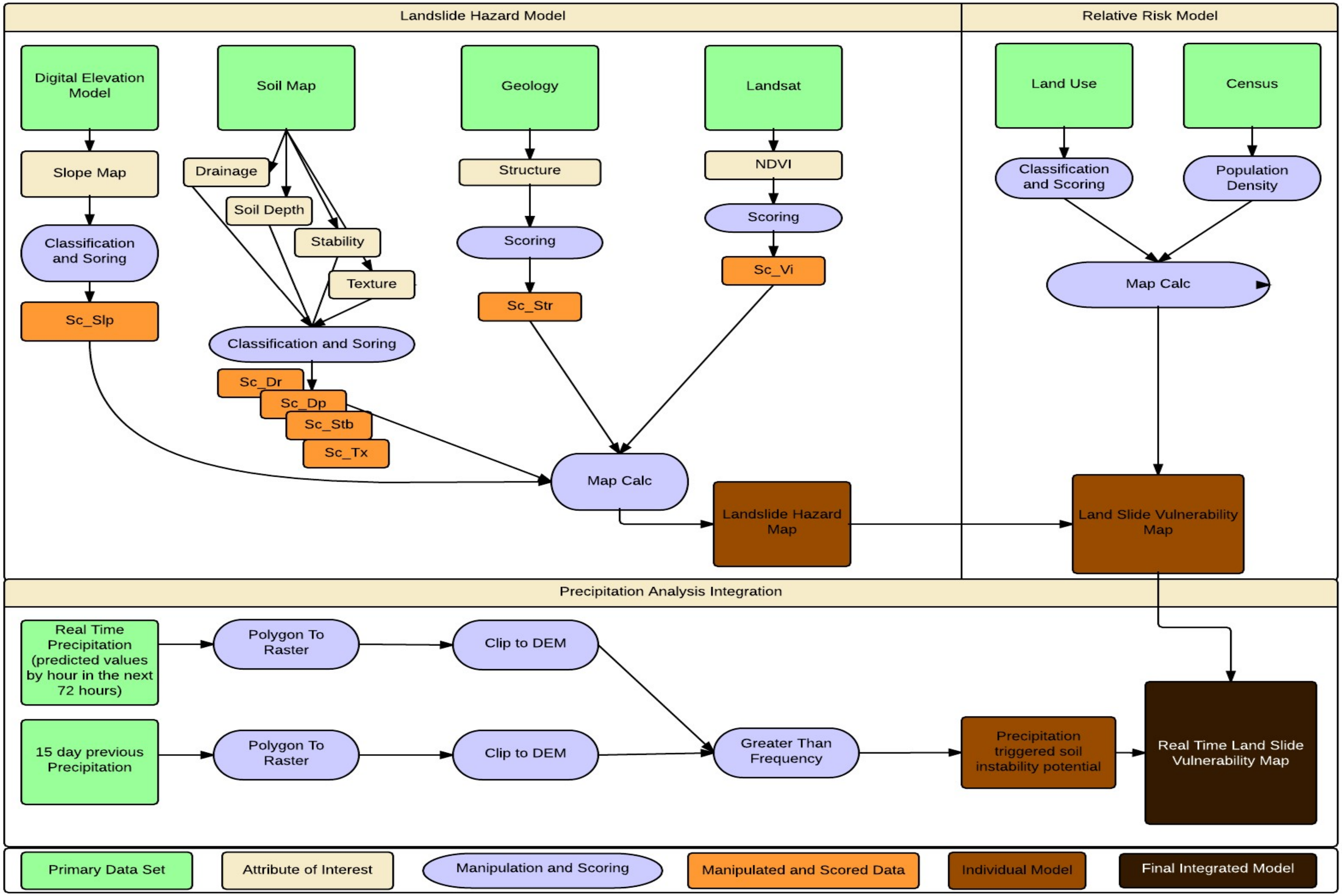


Figure 3-1 Flowchart overview of the LRAM.

3.2 Data Overview

The LRAM model utilizes easily accessible datasets (Figure 3-1). In the United States, datasets can typically be located through federal, state, and municipal agencies. All data sets are raster images or polygon shapefiles imported into a file geodatabase. Real time data is provided in a binary format that is converted into a shapefile as described later in this chapter. Before being uploaded to the server, all datasets were imported into a Spatial Database Engine (SDE). Raster analyses were performed according to the lowest resolution raster included in a given analysis. For example, in step 1, Raster A and Raster B have the same resolution of 0.5 x 0.5 feet and therefore the output raster had a resolution of .5 x .5 feet. However, when raster B was analyzed against Raster C with a resolution of 10 x 10 feet, the lower resolution was selected for resampling of Raster B, so both raster were analyzed at a 10 x 10-foot resolution. This ensured that the best possible accuracy of data was maintained throughout each analysis. The raster resolution was used to normalize scoring by multiplying the score of smaller resolutions to that of the largest to ensure equal weighting of the variables in the final analysis.

Name	Type	Source	Description	Raster Scale in feet	Raster Depth
National Elevation Dataset (NED)	Raster	USGS compiled into Zone 10 by University of Washington	NED is used for slope analysis and raster calculation. Scoring is performed on slope intensity ranging from flat to steep.	10, 10	16 Bit
Soil	Polygon	Washington State DNR	Feature to raster tool was used on fields- Soil Texture, Soil Depth, Soil Drainage, Soil Stability, Soil Percolation Rate, Soil Displacement, and Moisture Capacity. Rasters were reclassified and scored based on each field's unique contribution to landslides.	5100, 5100	8 Bit
Block Population	Polygon	2010 Census Summary File and Block level shape files joined outside of model	Polygon to Raster and reclassified by population density.	0.5, 0.5	16 Bit
Land Use / Parcel Map	Polygon	Washington State WAGDA geoportal	Parcel map with land use of open areas.	n/a	n/a
Land Cover Data	Raster	Landsat Imagery	Data is utilized to create a vegetation index and then scored based cover density of area	30,30	8 bit
Geology	Raster	Washington State DNR	Bedrock Structure. Contains information regarding rate of weathering, exposed bedrocks, and the shape and slope of the bedrocks structure	4988, 4988	8 bit
Precipitation Data	Binary Data	NOAA through hosted live feed	Real time precipitation forecasts for the next 72 hours and 15 day previous total precipitation	n/a	n/a

Table 3-1 Raw Data sources used to populate the Landslide Risk Analysis Model

3.3 Hazard Map Data Types and Calculations

Classification and scoring for the GIS-based landslide assessment analysis developed in this study are intended to produce a hazard map, based on procedures describe in Hadi (2004). All data types and scoring were adapted from Hadi (2004), Chang and Chiang (2009), Hadji et al. (2013) and were consolidated by the author. The calculation of the hazard map is:

$$Hazard = (Sc\_Slp + Sc\_Dr + Sc\_Dp + Sc\_Stb + Sc\_Tx + Sc\_Str + Sc\_Vi) \quad [1]$$

Where

Hazard : Hazard map

Sc_Slp : Scored slope map

Sc_Dr : Scored soil drainage

Sc_Dp : Scored soil depth

Sc_Stb : Scored soil stability

Sc_Tx : Scored soil texture

Sc_Str : Scored geologic structure

Sc_Vi : Vegetation index

The output of this computation was raster with an 8-bit pixel depth, where each pixel on the map was assigned a Hazard value according to the equation above. In the output Hazard map, the minimum value is 7 and the maximum is 35. Values closer to 7 have lower risks of landslides while values closer to 35 are high risk. The following sections document spatial analysis and scoring for each variable in Equation 1 above. Hazard scores are given on a scale from 1 to 5 where 1 is the lowest hazard, and 5 is highest. Table 3-2 includes the hazard risk (class) as associated with scoring (score) which applies to all other variables.

3.3.1. Digital Elevation Model

The digital elevation model (DEM) used in this study was created by the United States Geologic Survey (USGS 2015b). The DEM is based on the National Elevation Dataset (USGS 2015a). The dataset used in this model is a 10-meter DEM containing all of Zone 10. This file was obtained in a raster format with a cell size of 10 x 10 and a 16-bit pixel depth.

A slope analysis was performed using ESRI's Slope tool in the Surface toolbox within the Spatial Analyst Extension, with the DEM as input. This tool analyzes the slope of the DEM by examining the z-values present. The variable "z" corresponds directly to elevation in most rasters. The slope tool generated a new attribute field (slope) and inserted the slope value based on the surrounding cells.

Table 3-2 Description and scoring for the final slope map (Adapted from Hadi 2004)

Criteria		Class	Score
Description	Steepness (°)		
Flat	0 - ≤ 8°	Lowest Hazard	1
Flat to Moderate	8 - ≤ 15°	Low Hazard	2
Moderate	15 - ≤ 25°	Moderate Hazard	3
Steep	25 - ≤ 45°	High Hazard	4
Very Steep	> 45°	Highest Hazard	5

3.3.2. Soil Map

The soil map was obtained from the Washington State Department of Natural Resources is a polygon shapefile format (DNR 2015). Four attributes are required for the hazard analysis. These include soil texture, soil depth, soil drainage, and soil stability. These four feature classes were converted to a 5100 x 5100 feet raster with an 8-bit pixel depth.

3.3.2.1. Soil Texture

Soil texture was standardized into nine classes. Standardization of soil data consisted of aggregating broad terms into single terms to bring the number of soil classes in line to match the scoring from Hadi (2004). For example, in the original soil layer, "sandy loam" and "loamy sand" were present. Each of these soil types is different regarding soil morphology. In the LRAM, these similar soil types were standardized to "loamy sand." Standardization of terminology was performed across the entire soil texture attribute field before analysis. After standardization, the model assigns a score based on soil texture class (Table 3-3). These scores were originally obtained from Ilaco (1981) and Hadi (2004). The scoring of soil texture is in direct correlation to the laboratory analysis or provided soil texture and does not need calculations to arrive at a final score. A raster re-classify tool is used to score the soil textures.

Table 3-3 Description and scoring for soil texture (adapted from Ilaco 1981 and Hadi 2004).

Soil Texture	Score
Loam	1
Loamy Clay	2
Loamy Silt	2
Loamy Sand	3
Heavy Clay	4
Silt	4
Heavy Sand	5
Sand	5
Sandy Clay	5

3.3.2.2. Soil Depth

Soil depth is included as a value in inches. Similar to soil texture, soil depth is scored according to values provided in *Soils Profile Descriptions* by Worosuprojo and Jamulya (1991).

Table 3-4 Description and scoring for soil depth, a field located on the soil map (adapted from Hadi 2004).

Class	Soil Depth (In)	Score
Very Shallow	0-12	1
Shallow	13-24	2
Moderate	25-35	3
Deep	36-59	4
Very deep	>60	5

3.3.2.3. Soil Drainage

Soil Drainage is scored using the same profiles as soil depth and given in Soils Profile Descriptions (Worosuprojo and Jamulya 1991). Two additional fields were added which were not present in the soil profile but were present in the soil map. These fields, "excess drained" and "some excess drained," refer to soil types, which hold large amounts of water and have high drainage rates enabling them to move water quickly, which might cause instability. These soils were scored as moderate risk based on their similarity to variable drained and moderately well drained.

Table 3-5 Description and scoring for soil drainage, a field located on the soil map.

Class	Score
Well drained	1
Moderately well drained	2
Excess Drained	2
Variable drained	3
Some Excess Drained	3
Poor drained	4
Very poor drained	5

3.3.2.4. Soil Stability

This study utilized a pre-determined soil stability and erosion potential analysis, also included on the soil map. The original model and study also utilized a laboratory analysis of field-collected soil samples to determine texture, shear inclination, cohesion, shear pressure, shear resistance, and safety factors. These factors were used to rate the erosion potential of the area, from stable to high instability. The soil map provided by Washington State Department of Natural Resources (DNR) classified the soils from low to high instability potential. The scoring of the study is translated to local soil analysis in the following table.

Table 3-6 Description and scoring for soil stability, a field located in the soil map.

Hadi et al. - Classes	Wa State- Class	Score
Stable	Low	1
Unstable	Moderate	3
High Instability	High	5

3.3.3. Bedrock Geology

A 24k geology was obtained from the Washington State DNR (DNR 2015). A point shapefile with bedrock observations for inclination, attitude, strike, azimuth, dip angle, bedrock geology, and analysis of landslide risk. This shapefile was converted to a raster using a natural neighbor interpolation method resulting in a 4,988 by 4,988 foot (default raster resolution based on inputs) and 8-bit pixel depth for the purpose of this analysis. Scoring was based on models determined by the inclination and shape of the rock structure validated in previous studies (Misdiyanto 1992). The model accounts for both slope of the landform and for bedrock slope or steepness. Slope measurements include vegetation and soil while the geology raster includes the slope or steepness of the bedrock only.

Table 3-7 Description and scoring for bedrock geology (Adapted from Hadi 2004)

Criteria		Score
Description	Steepness (°)	
Horizontal, Flat	0 - 3°	1
Vertical, sloping on flat-undulating landform	>3 - 8°	2
Non structural on steep slope	>20°	3
Sloping on undulating landform	>8-14°	3
Sloping on undulating landform	>8-20°	4
Sloping on heavy rock on undulating landform	>20°	5

3.3.4. Landsat

Landsat data was used to create a Normalized Difference Vegetation Index (NDVI) using a mapcalc function within a new field (NDVI) (Hadi 2004). This calculation required two satellite bands that were previously georeferenced. One band must show visible red reflectance while the second must show near infrared reflectance. The following expression was used to calculate this variable, where a = visible or red reflectance (Landsat band 3) and b = near infrared reflectance (Landsat band 4):

$$NDVI = (b - a) \,/\, (a + b) \qquad [2]$$

The output of this computation was raster with an 8-bit pixel depth, where each pixel on the map was assigned an *NDVI* value ranging between -1 and 1. Areas with dense coverage will have a higher score due to the high near-infrared reflectance. Conversely, areas with minimal coverage will have a higher visible reflectance and a lower NDVI values (Hadi 2004). Areas are given a score based on their NDVI, provided in Table 3-8.

Table 3-8 Description and scoring for Normalized Difference Vegetation Index (Adapted from Hadi 2004)

Cover Density	NDVI	Score
Dense Coverage	> 0.4	1
Fairly Dense Coverage	0.24 - 0.4	2
Moderate Coverage	0.08 - 0.24	3
Sparse Coverage	0.08 - (-0.08)	4
Bare land and Water	(- 0.08) – (-0.24)	5

The final reclassified scoring of NDVI was then run through the Majority Filter tool in Esri's Spatial Analyst extension to remove as many errors as possible.

3.4 Relative Risk Map Data Types and Calculations

Classification and scoring for the relative risk map were also based on Hadi (2004). All data types and scoring were pulled from different published journals and had been consolidated and validated in the aforementioned work. The relative risk map is the hazard map normalized by population and land use. The final calculation for the relative risk map is given in equation 3.

$$Vulnerability = (Hazard * LU) \text{ / Population} \qquad [3]$$

3.4.1. Land Use

Land use was determined by running a majority filter generalization tool on a statewide land use map. This tool identified and scored areas based on the majority use as shown in Table 3-9.

Table 3-9 Description and scoring for land use data

Land Use	Scored
Water Bodies	1
Agriculture	2
Industrial	3
Commercial	4
Mixed use	5
Residential	5

3.4.2. Census

Dasymetric mapping was used to determine population density in the study area. Hadi (2004) used a choropleth density map in the original analysis. However, dasymetric mapping provides a more accurate population density analysis by using ancillary data to standardize data (Eicher and Brewer 2001). Dasymetric mapping is required for the relative risk map as a core component of determining which geographic area is most vulnerable to a landslide as previously explained in Chapter 2. In this study, dasymetric mapping consisted of utilizing census data from the 2010 Census and the National Land Cover Database. This data set was provided complete through the Washington State Geospatial Data Archive (WAGDA 2015). A detailed explanation of the creation of the dasymetric mapping is outside the focus of this thesis and is provided in Zandbergen (2011) and Mennis (2015).

3.5 Statistical Rainfall Modeling and Integration

This study modeled a single complex landslide triggering variable, rainfall. Above average rates of precipitation over time can cause soil instability in two ways. The first is by causing the ground water table to flood, causing pressure exerted on the soil to have a greater ability to shear the soil (Iverson 2000). Groundwater flooding can be the result of short periods of large rainfalls or a long-term increase in rainfall causing rivers, lakes, and aquifers to hold above average levels of water. Ground water flooding may occur over long periods, and the effect may not be noticeable immediately. The second effect of above average rates of rainfall is landslides induced by storm flooding. Storm flooding generally coincides with large amounts of rapid rainfall over short time periods. Flooding occurs when the soil becomes saturated with excess water, and the water cannot move quickly enough (percolation) out of the soil. Ground water flooding is a generally slower than storm flooding and usually causes less loss of life but greater loss of property (Miller and Sias 1998).

Statistical modeling of rainfall triggered events was directly based on Alan Chleborad (2003). This paper was sponsored by the USGS in an attempt to precisely estimate the amount of precipitation necessary to cause a landslide in the greater Seattle Area. The study utilized a landslide database of 187landslides in the Seattle area since 1897 and the historical precipitation records for NOAA in an attempt to determine the threshold of rain needed to trigger a landslide. Chleborad (2003) determined that 89% of all landslides in Seattle, and 68% in the Seattle area, occurred if the 72 hour cumulative precipitation was greater than the 15 day prior antecedent precipitation (2003). The paper noted that seven of the 12 landslides that occurred when the threshold was not met occurred in areas of high levels of anthropogenic activity. Examples given for why these landslides occurred include poor drainage during construction, blocked culverts, and water lines leaking into the groundwater table (Chleborad 2003).

3.5.1. Precipitation Integration Methods

Real-time precipitation data in binary format was collected from NOAA using a server side query and download function (NDFD 2015). The interpolation and creation of NOAA precipitation forecast and historical precipitation are outside the focus of this thesis and is provided in Fielder (2003), Brown (2014), and National Weather Service (2016) .Wget (GNU

2015) is an ideal software package for this implementation. Wget is a free and open source software package with the ability to retrieve files from HTTP, HTTPS, or FTP architecture. Wget works on most operating systems including Windows, Linux, and Apple. Wget has both a command line interface and a visual interface in a Windows operating system environment. This software can be set up to allow Wget to resume failed or aborted downloads, to run recursively, and utilize wildcards and timestamps to determine which file to download. The only significant limitation of Wget is a 2-gigabyte file size limit when using a 32 bit operating system. For this project, Wget was downloaded to the server and commands were created in a text file and run through Window's Task Scheduler[2]. Specifically, the script for the download process was written in a text editor and saved as a batch (.bat) file. This commented script is located in Appendix C.

Wget also allows the user to set up many parameters for the download and environment both in command line and in its visual interface. This solution was chosen as it relied on a visual interface while still allowing the script to be run from command line without direct input from a user. This command line program was run hourly to acquire the weather forecast data and daily for the recorded precipitation data. The program queried the NOAA servers for the Pacific Northwest region's real-time precipitation forecast for 36 hours ahead, and for the previous day's recorded precipitation day data. The data downloader needed to be run for 15 days, with the data being cached on the local server before the model had enough information to analyze potential rainfall triggered events. Using the same command line method, the 72-hour data was deleted 5 minutes before the new dataset was downloaded. In addition, the 15-day actual recorded precipitation data had the 16th or oldest record deleted 5 minutes before the new dataset was

[2] http://windows.microsoft.com/en-US/windows/schedule-task#1TC=windows-7

downloaded. This method of deletion kept the server environment organized and efficient while maintaining the necessary datasets.

NOAA's DEGRIB (National Digital Forecast Database (NDFD) GRIB2 decoder) was also run during the same process to convert the original binary data into a shapefile for analysis (NWS 2015). This process was also scheduled in Windows Task Scheduler and run as a batch file. A wildcard needs to be used in the naming convention of the script to accurately convert the binary file into an Esri shapefile. The converted shapefile was placed into the primary data folder for the model on the server hosting the LRAM. Once in a shapefile LRAM clipped the data to the USGS Zone 10 outline. As aforementioned, the downloader must run for 15 days before the converted shapefiles can be compiled by the model into a single aggregate of the antecedent 15 day precipitation totals. Then the data was interpolated across the study area to create a raster using inverse-distance weighting (Fiedler 2003; Chiang and Chang 2009).

3.5.2. Real-Time Precipitation

There are two different methods to incorporate the precipitation data into the LRAM. For the first, a weighted score could be applied to the predicted precipitation levels in conjunction with the antecedent 15-day precipitation levels. This method would leverage a large vulnerable area and identify them in ranges in the Info-Val method, according to Che et al. (2012). The most significant problem with this method of incorporation relies on the Chleborad (2003) method of identifying precipitation-triggered landslides, which does not take into account critical fault thresholds of the soil and slope in conjunction with the total water load. Due to this weakness, the highest score of increased risk is capped at 80% without having clear delimitations above or below the point where 72-hour precipitation is greater than the antecedent 15 day precipitation levels. The classification of this method is shown in Table 3-10.

Table 3-10 Weighted precipitation scoring for 72 hour predicted compared to antecedent 15 day precipitation levels.

72 hour predicted precipitation as a percentage of antecedent 15-day precipitation.	**Scored**
Less than 50%	0
Greater than 50% and less than 75%	1
Greater than 75% and less than 100%	2
Greater than 100%	5

The second route to incorporate precipitation data is to use a definitive method of classifying precipitation-triggered landslide hazard. This is the route chosen in the LRAM. The ArcGIS tool, Greater Than Frequency, was run within the model to determine if any cells in the 72 hour predicted precipitation forecast were greater than the antecedent 15-day precipitation. This method produced an output of identified zones that had an 80% increased chance of a landslide due to precipitation. Identified areas were then multiplied by 1.8 against the previous relative risk score to give an 80% increased chance of a slide event. This formula is given below.

$$Hazard\ Risk\ (section\ 3.3) + Relative\ Risk (section\ 3.4) * Precipitation\ Trigger\ Assessment\ (section\ 3.5) = Final\ Relative\ Risk \quad [4]$$

3.6 Web Map Application Environment

The ability to quickly and accurately communicate the model to the public is one of the most significant factors in determining the success of model creation. If a relative landslide risk analysis is performed but not made available for public consumption, there is no difference than if the model was never run. As such, the web map application needed to be hosted with several important requirements in mind. It is desirable for the model to be hosted on the internet on a server that provides public access, be readily available to any person with or without access to a GIS, and the model must be communicated in a way that was easily understandable to anyone viewing despite personal levels of technical (computer as well as scientific) proficiency. Furthermore, the model needed to be hosted in an environment that was easily updated, reliable and allowed expansion as the datasets required. In addition, a low-cost environment was crucial.

Thus, an Amazon EC2 (Elastic Compute Cloud) instance was chosen to host the web model. The EC2 instance was built with ArcGIS Server 10.3, using ArcMap for Desktop integrated with Microsoft SQL spatial databases. Additional programs required to run the web model included Wget, NOAA's DEGRIB, PyScripter[3], Fiddler[4], and Microsoft's Task Scheduler. Wget, DEGRIB, and Task Scheduler are explained in detail in section 3.5. PyScripter is an integrated development environment (IDE) specific to the Python coding language. The program is utilized to write, amend, and check python code, such as the final model. The final model was not run in the IDE but was exported as a python script, checked for bugs, and then run by Task Scheduler executing a run command (see Appendix C) at a set interval of 4 hours. Fiddler, while not required, is an application used to test that a server and client are communicating. While no problems arose in the Web environment between the server environment and the client requests, testing of the map the application using Fiddler ensured that communication was flowing both ways without error.

Next, the final raster layers were published as a feature service. The features are hosted in a spatial database engine (SDE). The database is versioned, and the model writes to a single ancestor of the default database as it updates. The branch is then reconciled and posted with the default table as it is updated. A detailed explanation of versioning in an SDE environment is given by Derek Law (2016). The LRAM updates every 4 hours with up to date precipitation data

[3] At the time of writing PyScripter's website appears to be offline. A link for download can be found at http://sourceforge.net/projects/pyscripter/
[4] http://www.telerik.com/fiddler

provided by NOAA and delivered through Wget (GNU 2015; NDFD 2015) as described in section 3.5.

The front-end environment of the model, where an end user will experience the final Web map, was created in ArcGIS through the Web AppBuilder for ArcGIS. This method of publishing the map was chosen due to ease of application creation and the ability to host the map in an environment that allowed the model to be viewed in any internet browser capable of consuming HTML and JavaScript. The Web AppBuilder service gives a developer a wide array of template maps to choose from and widgets to allow customization of the final Web map application. A simple map design was chosen so as not to hinder or distract an end user from utilizing the Web map content as intended (see Chapter 4). Future suggested improvements to the Web map environment are provided in detail in Chapter 5 Section 2.

Chapter 4 Results

The LRAM functions well as a proof of concept in landslide risk assessment modeling without field work being required. The outcome of this study adds to the growing body of literature about real-time landslide prediction and risk analysis, and more specifically rainfall triggered events. There are three distinct phases of results resulting form each run of the LRAM. These include the hazard map (section 3.3), the relative risk map (section 3.4), and the statistical rainfall modeling (section 3.4). The LRAM is only able to perform as a relative risk model instead of a vulnerability or statistical model due limitations in the input data available for this study.

4.1 Hazard Map

The Info-Val method proved to be highly customizable in accounting for variables specific to the study location while still relying on peer-reviewed scoring and interpretation of results as described in Chapter 3. Figure 4.1 provides the resulting landslide hazard map produced using Equation 1, as described in Chapter 3 Section 3. The landslide hazard map incorporated soil texture, soil depth, soil geomorphology, soil stability, NDVI, and slope data.

Based on the resulting hazard map, it is evident that Southwestern Washington experiences the largest area of highest risk terrain. This area is represented by deep clay-silt soils with high moisture retention. Additionally, low soil shear strength and slow soil percolation rates result in unstable wet soil throughout the year.

This same pattern is reflected in the western coastline of the state. In the highest risk areas, the terrain is flatter than it is to the east where the foothills of Mount Saint Helens and Adams dominate, and to the central northwestern peninsula where Mount Olympus resides. Whereas the Cascade and Olympic mountain ranges have relatively very low risk when compared to their foothill regions. This is a direct result of soil texture, soil percolation, soil moisture capacity, and soil drainage data for the national parks not being present in this analysis. Federal and state soil data fields differ to an extent that including federal soil data was outside the scope of this project, as it would take significant effort to reconcile any differences between the two datasets[5]. Furthermore, the increased data from the Federal soil data would include areas with low populations while the majority of the Cascade Mountain Range and the Hanford Site would still be missing.

[5] Federal soil data provided by United States Department of Agriculture is located at https://gdg.sc.egov.usda.gov/GDGOrder.aspx. Washington State soil data is provided by the Department of Natural Resources at https://wagda.lib.washington.edu/data/geography/wa_state/.

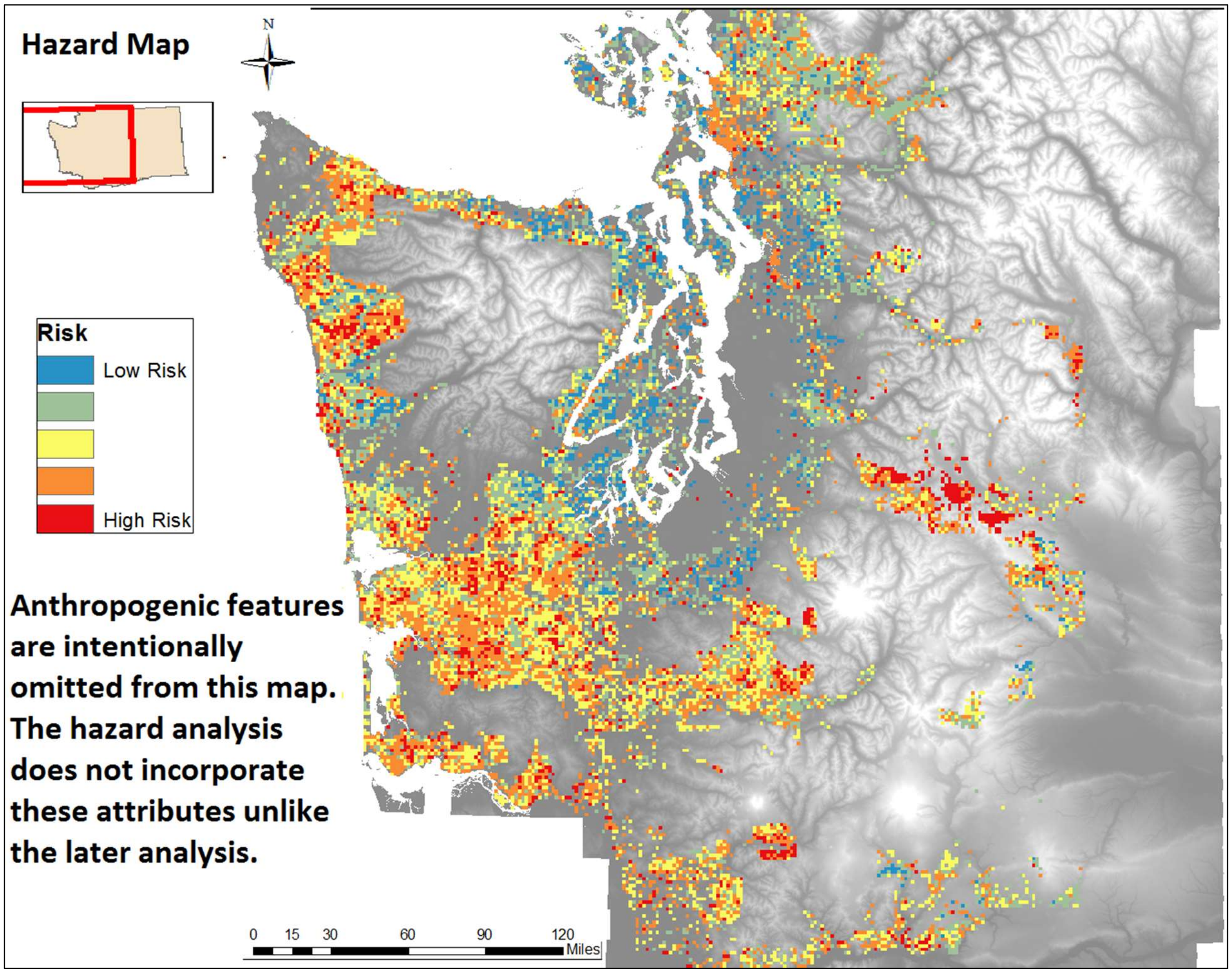


Figure 4-1 Hazard map utilizing soil texture, soil depth, soil geology, soil stability, NDVI, and slope

In the Cascade Mountain Range, two different passes have a very high risk of landslide. Both paths are outline in Figure 4.2. This risk is increased due to the natural geologic erosion and shallow soil depth on steep mountain slopes. The risk is higher along these passes due to the large amount of anthropogenic alterations to the landscape. The southern pass is known as Snoqualmie Pass and runs along Interstate 90. The northern pass is Stevens Pass runs along State Highway 2. This freeway landscape alteration is further examined in the relative risk map.

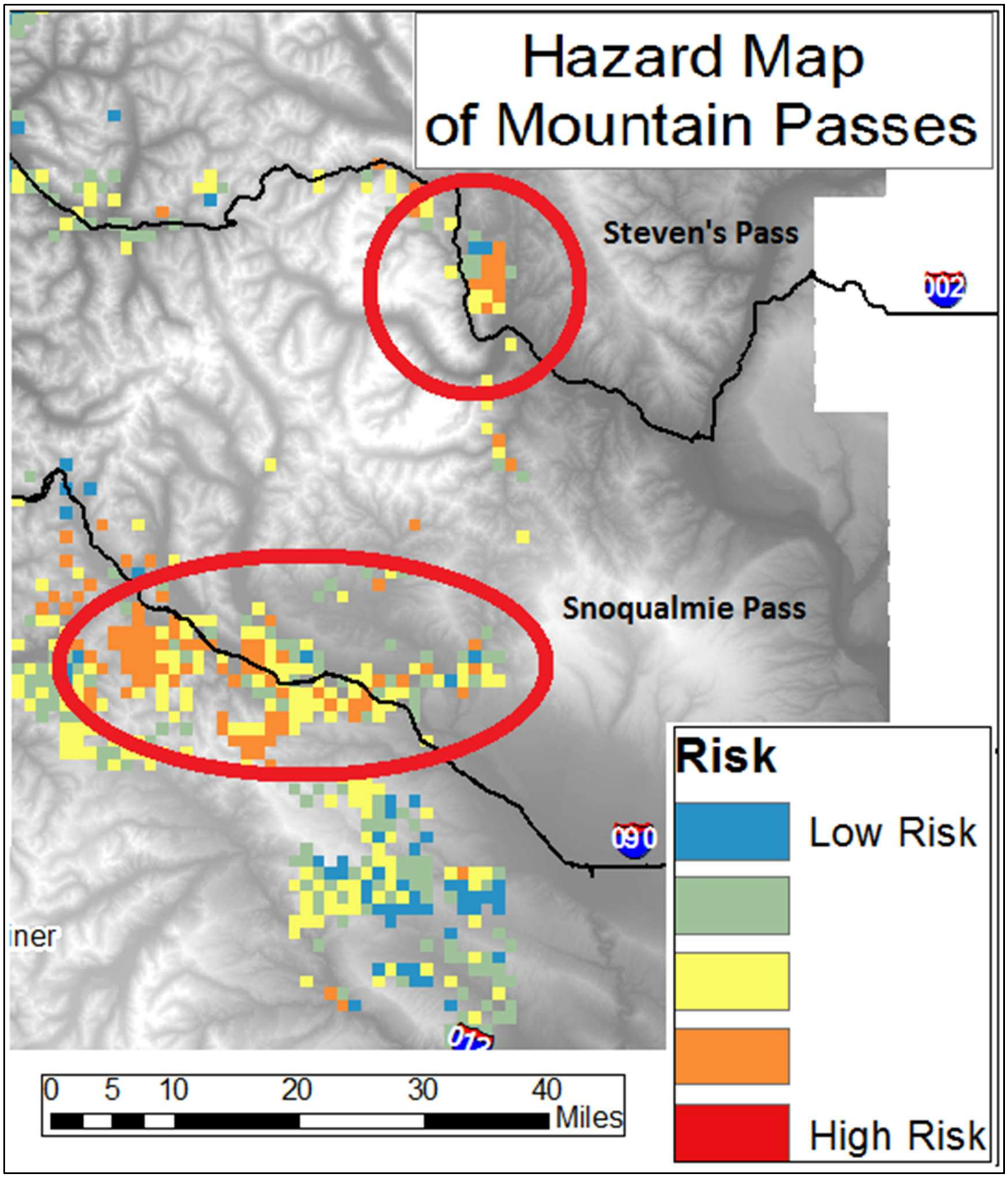


Figure 4-2 Landslide Hazard risk in mountain passes in Washington State. The northern pass is Steven's Pass while the Southern is Snoqualmie Pass.

4.2 Relative risk Map

Landslides are a natural phenomenon and are not considered a hazard in the natural environment devoid of human settlements. The potential for damage to the built environment and populations is what define landslides as geohazards. In order to test the LRAM and as part of the a proof of concept for this study, the relative risk map was generated in order to refine the hazard map, by including parcel and demographic information for the state through the inclusion of the dasymetric map as described in section 3.3.2. Figure 4.3 is the refined hazard map, now considered a relative risk map.

The resulting relative risk map shows a decreased number of higher risk or vulnerable areas, which shifted to encompass more populated places as defined by total population, and places with locations where there is a large amount of built infrastructure. Both mountain passes previously described scored high in this analysis, as did the northwestern portion of the state near the Canadian border. The coastline adjacent to Western Puget Sound and the Straights of Juan de Fuca are indicated as highly vulnerable. The Southwestern zone now exhibits moderate relative risk versus the high and highest risk previously indicated in Figure 4-2. The relative risk map is considered more useful than the hazard map for landslide hazard mitigation. While the initial hazard map does allow for a limited amount of anthropogenic influence through the land cover analysis, its primary purpose is to examine vegetation density while the land use map included in the relative risk map scores areas by the degree of anthropogenic change to the landscape. This landscape alteration combined with dasymetric mapping allows a relative risk map defining the susceptible region and its population.

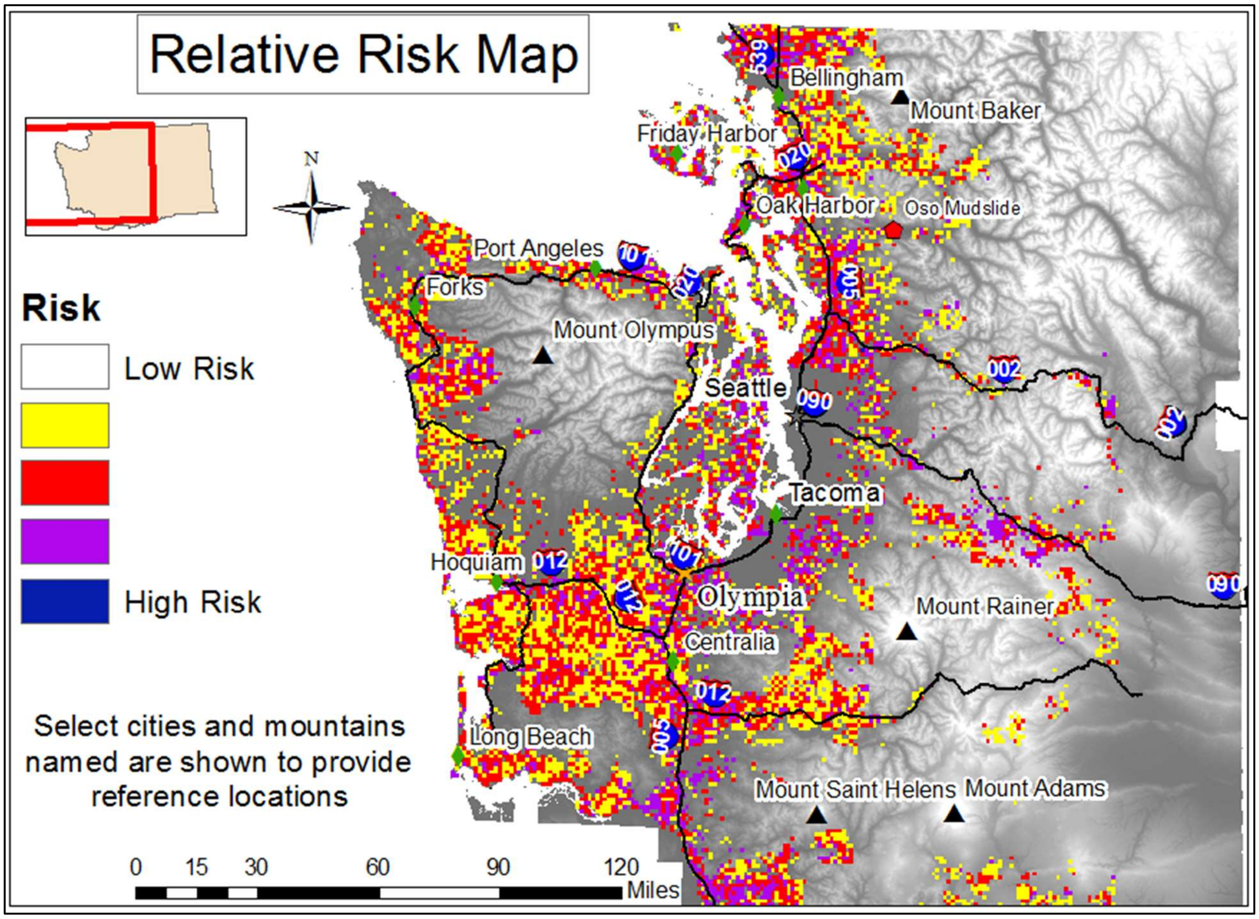


Figure 4-3 Relative risk map including parcel and population data.

4.3 Relative risk and Precipitation

The Relative risk was further refined by adding 15-day antecedent and 72 hour forecast precipitation data into the analysis. In order to test the LRAM and as part of the proof of concept for this study, 15-day antecedent precipitation for the 2-week period of October 28, through November 11, 2015, is presented in Figure 4.4. Figure 4.5 includes this data plus the total precipitation forecasted over the next 72 hours (November 12, through November 15, 2015).

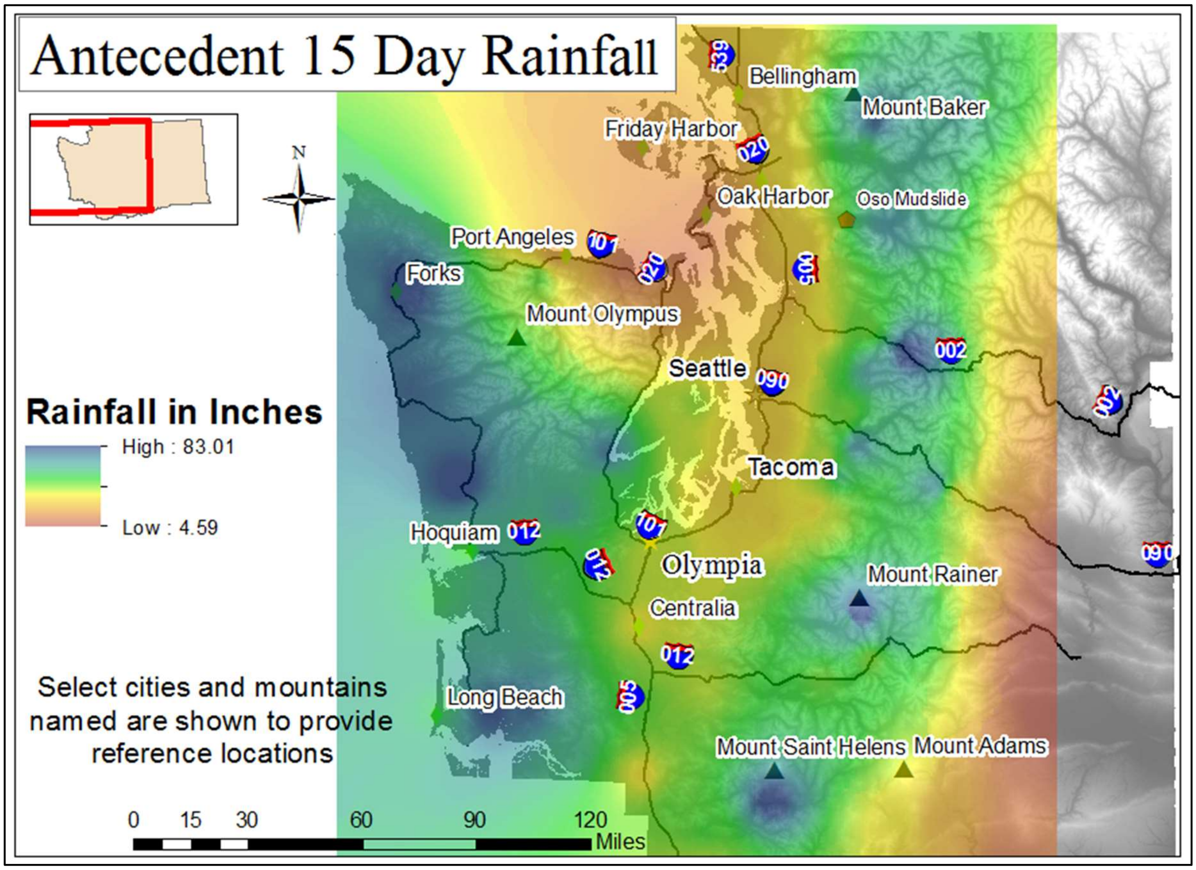


Figure 4-4 Antecedent 15 day rainfall for USGS Zone 10 (NDFD 2015).

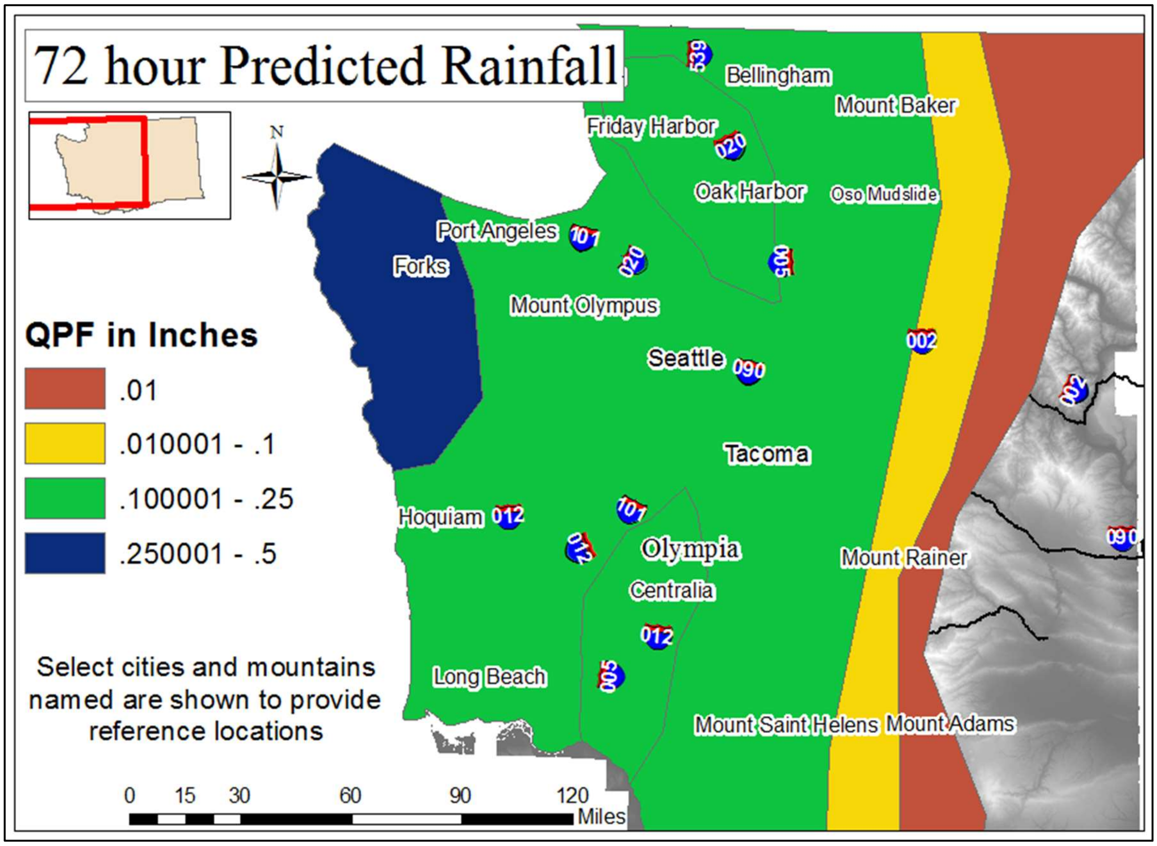


Figure 4-5 Forecasted precipitation from November 12, through November 15, 2015.

4.4 Final Precipitation Triggered Relative Risk Map

Figure 4-6 shows the relative risk of Western Washington when considering all of the previous variables (the Relative Risk Map) and the increased risk in areas where precipitation has surpassed the threshold as described by Chleborad (2003). In Figure 4-6, there is only one location that scored higher than "low." This location is located along State Highway 2 about 45 miles northeast of Seattle and 50 miles southeast of Oso, Washington. The nearest populated towns are Goldbar and Sultan. This location is along the Skykomish River in the foothills of the Cascade Range. This area is vulnerable to ground water flooding, has a high moisture retention rate with low percolation rates, and the soil is scored moderate low on soil sheer strength. These factors combined with an elevated precipitation level result in high potential landslide score.

Overall, we see repeat patterns throughout each analysis stage that become more precise as more data is incorporated. Mountain lowlands and passes are the highest risk areas, followed by coastal dunes, high population (urban areas) and then suburban locations with large amount of anthropogenic alteration of the landscape and a nearby hydrology network. The final analysis identifies a location in the mountain lowlands of the Cascade Range with similar geography and geomorphology as the recent Oso Mudslide

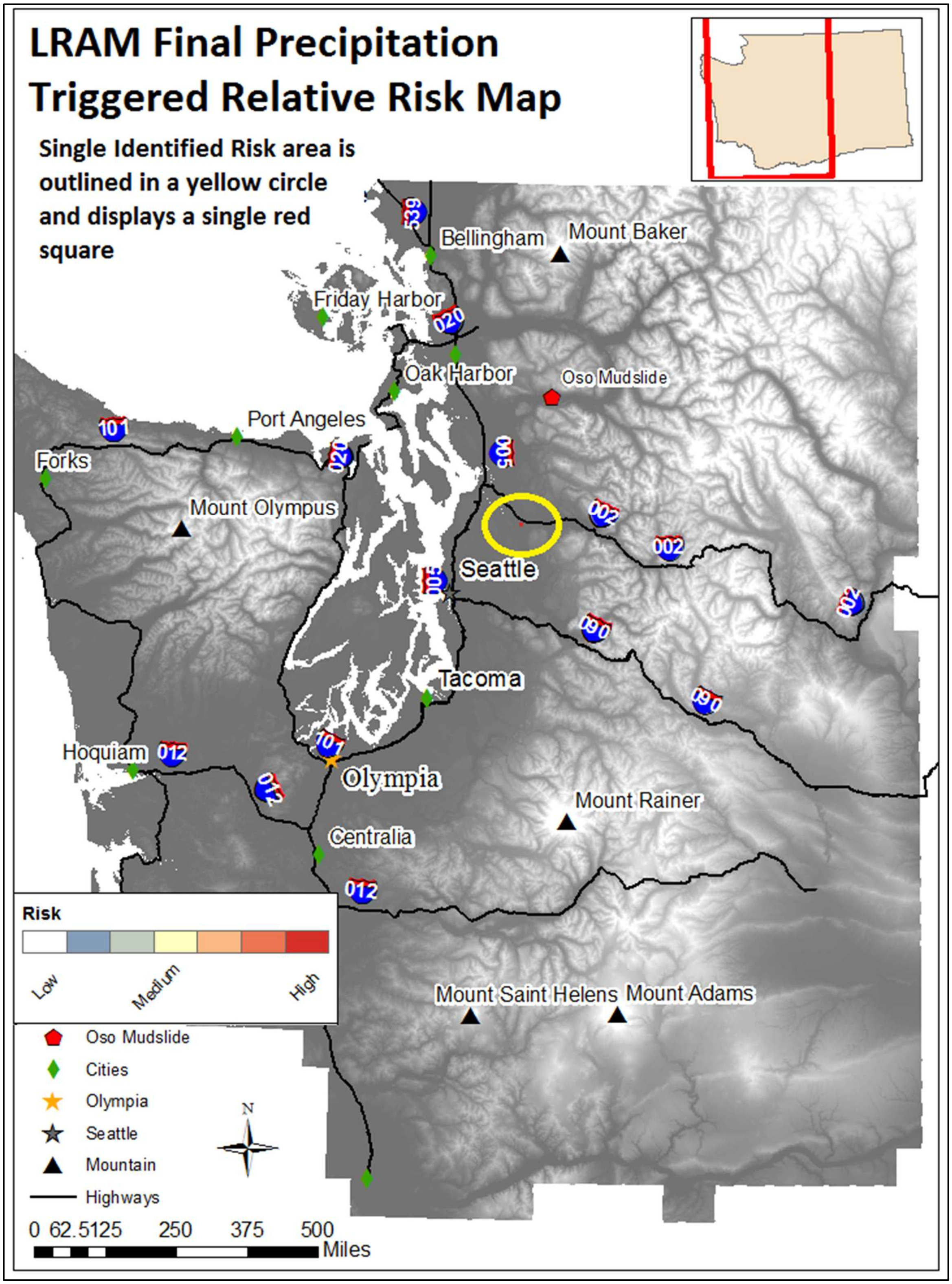


Figure 4-6 Relative risk map with scored monthly total precipitation. This analysis was run on the evening of December 17th 2015 making its prediction range December 18th – 20th.

4.5 LRAM Validation

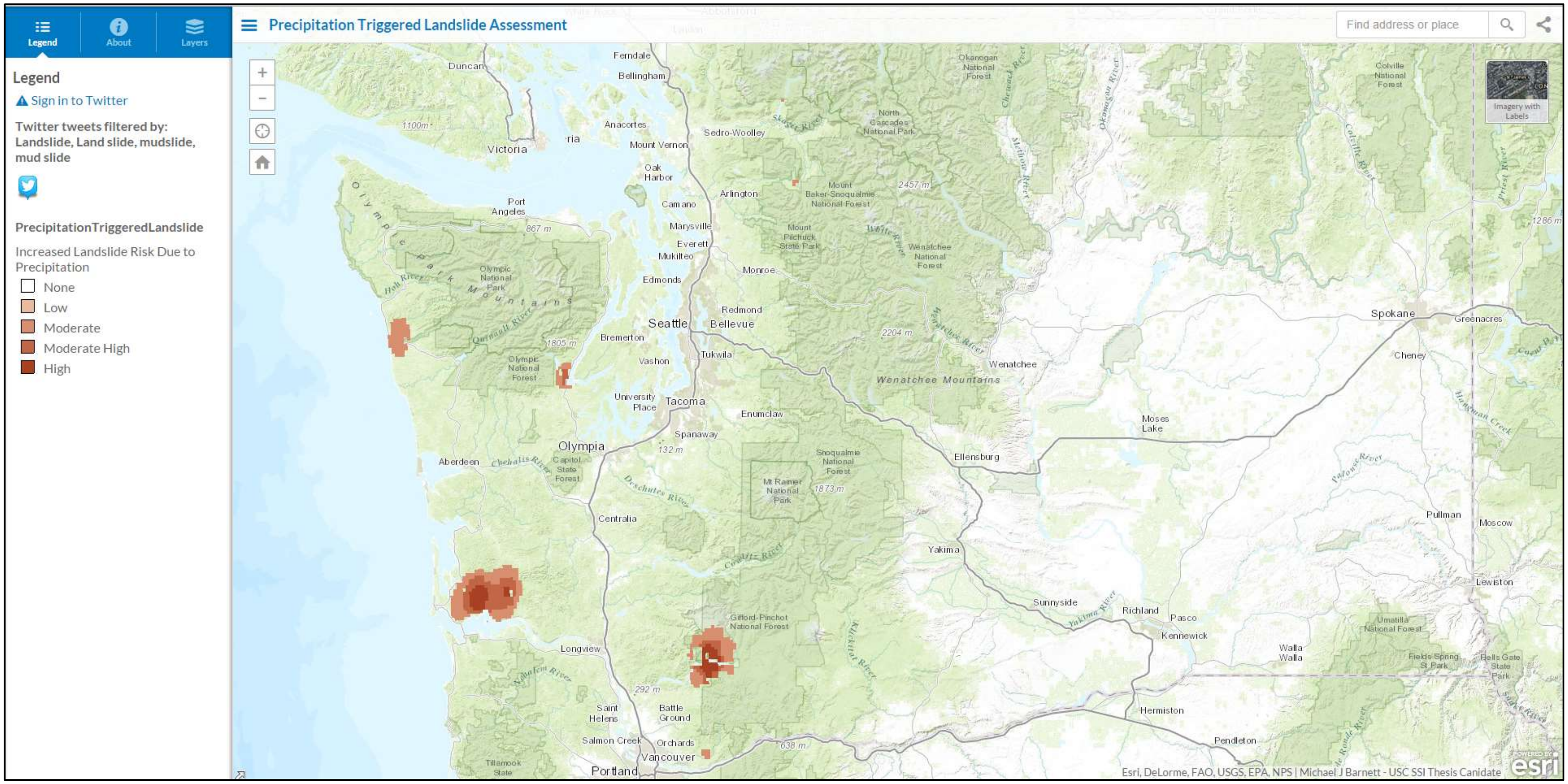
At 4:55 am on December 18, 2015, a small landslide was reported to the Snohomish County Sheriff's Office and reported in a local newspaper. This landslide occurred in the geographic area of the analysis at 47.852978, -121.775830. This location is within the analysis raster's identified high risk area (Monitor 2016).

4.6 Web Map Application Environment

To provide an example of disseminating the LRAM output, a landslide risk map was published as an interactive Web mapping application[6]. The landslide risk map discussed in Chapter 4 was uploaded to and Esri ArcGIS.com-based application, intended as a proof of concept. At the time of this writing, the LRAM output data are hosted through ArcGIS.com as an interactive map application built using Esri Web AppBuilder[7]. The current Web map application is shown in Figure 4-7. Incorporates the most recent precipitation data captured on December 18, 2015, and shows five discreet high-risk landslide zones. These high-risk areas agree with previous tests of the LRAM for both the risk and vulnerability maps discussed in Chapter 4. In the future, this basic Web map application will be moved to a dedicated personal website for further development.

[6] http://uscssi.maps.arcgis.com/home/item.html?id=f821d0d849a345a492e74732d5937cfd
[7] http://doc.arcgis.com/en/web-appbuilder/

Figure 4-7 Web map application of the LRA model



Chapter 5 Discussion

This landslide risk assessment model, LRAM, was constructed as a proof of concept for predicting and analyzing landslides in large geographic areas with similar geologic and geographic environments. The LRAM successfully integrated statistical rainfall as a triggering variable into a relative risk map. The model has been validated for Western Washington State and should be scalable to any region with similar environmental conditions. The LRAM is unable, at this time, to be modified into an absolute risk model to accurately and quantitatively predict landslides due to the requirement of more detailed engineering properties of soil typically gathered through field reconnaissance and subsequent laboratory testing of soils. The true value of this model is the use of publicly available data to create a scalable ordinal relative risk model that has been regionally validated.

5.1 Consequences of the Qualitative Soil Data Gap

In order to accurately gauge the amount of rainfall necessary to trigger a landslide, quantitative data on soil depth, soil texture, soil percolation, soil moisture capacity, and soil drainage is required. While many of the datasets used in this study included the required information, the available soil moisture capacity data was previously aggregated into ordinal ranges referred to as low, medium, and high. This lack of numerical data prohibits the model from functioning as an absolute risk model. The final published version of the model is an accurate and validated ordinal risk model. Ordinal risk models are important as they provide a low-cost approach to informing many interested communities such as researchers and land use planners about the relative landslide risk to a region, while not requiring government agencies to invest in expensive soil analysis studies.

Washington State's publically available geologic data is a limited feature set that is less robust than desired for a landslide hazard assessment. At this time, it is unknown what effect the interpolation of the limited dataset had on the region and its geology in terms of scoring the hazard map. While hazard maps can be created without geologic data, the result will be much more accurate if bedrock structure, weathering, and erosion are known, as the soil is a direct result of these processes. The Washington State data only contained limited bedrock structure, slope information, and excluded all erosion and weathering data. As such, the hazard model was missing a 5 point scale from the original model, bringing the original hazard map score to a modified score range of 7 to 35 as opposed to the original 12 to 40 (Hadi 2004). This data is particularly important when analyzing mountain areas and other rocky slopes where rockslides are the dominant form of land movement. Results that are more accurate could be obtained from a landslide assessment in areas surrounding mountain passes and on foothills if this data was included.

NOAA's DEGRIB application works well in conjunction with the Wget script to fetch and encode precipitation data into useable shapefiles. However, during testing, more than 50% of the precipitation data fetched through Wget and DEGRIB returned empty. At this time, a binary file is written to the file transfer protocol site at a regular interval whether or not data is present in the file. The Wget application has no way of verifying if data is present in the downloaded file, only that there is a new file to download. Future work will include testing of new versions of DEGRIB, which coding changes that may address this problem. A potential solution would be to configure an intermediate data quality control script that would filter out incomplete precipitation data prior to feeding into LRAM.

5.2 Future Work

Further research needs to be performed on the costs and benefits of collecting complete soil attributes for areas where landslides are common. It has been proven in small specific studies that rainfall triggered landslides can be partially predicted by analyzing soil loading and the point of critical failure. LRAM demonstrates that readily available input data and processes can interpolated to a larger geographic area as long as valid input data is utilized.

The largest difficulty in disseminating natural hazard risk information is discovering a way to awaken public interest before a disaster occurs. The best way to survive a natural disaster is to be prepared for one (FEMA 2015b). Being prepared for a landslide requires foreknowledge of a geographic risk and susceptibility to major landslide triggering events, such as rainfall and earthquakes. Even if the risk information is not qualitatively certain the value of knowing where disasters are likely to occur could be enough to save lives. A validated model can mean the difference between ignorance and informed awareness.

LRAM was validated against a single landslide incident in Washington State. While this study's validation provides confirmation of the accuracy of the analysis for a single location, it is nonetheless considered inadequate for quantitative damage estimation of loss of life and property, beyond a proof of concept model. A confusion matrix or error matrix is well suited for a future series of model validations. By creating a raster of all possible rainfall triggered events in the study area and comparing the outputs of a confusion matrix (false positives, false negatives, true positives, and true negatives) the researcher would be able to assess a confidence interval to the model and determine its statistical viability. Future development of a large geographic area landslide prediction model will require substantial resource investment in acquiring soil data and subsequent validation.

5.2.1. *Web Map Application*

In the future, the web map application could be hosted within a landslide assessment website to disseminate information about Washington State and provide an example of how the LRAM can assist planners, developers, municipal and state employees, and the public. The model could be published through a server hosting GIS and web mapping software, as a Web map application that includes a geoprocessing service that runs the LRAM in real time, behind the scenes using server resources[8]. The output data from running the geoprocessing service (LRAM) would look the same or similar to Figure 4-7, provided to the end user as a template for online map construction. The user could be given written or video tutorial guidance on how to prepare and utilize their own local input data into LRAM in order to obtain localized landslide risk and vulnerability map results.

5.3 Conclusions

The deployment of a functional model, LRAM, and the safety planning measures it can provide is considered a successful proof of concept. Though the technology is readily available, detailed critical input information to allow computation of quantitative damage estimates is not. With more complete soil data, geology and strong validation techniques the current model may be adaptable from an ordinal risk model to an absolute risk model. The model was validated with a single predicted slide event at the time of writing and could be further validated with an error matrix as described in section 5.2. Providing a model of this utility to the public will require a significant investment of time and resources and therefore should be provided by the agency

[8] http://server.arcgis.com/en/server/latest/publish-services/windows/what-is-a-geoprocessing-service-.htm

which governs the geographic area the model covers. This could probably be easily managed by a county or state.

The overall goal of this study was to create a landslide risk and relative risk assessment model and resultant map, to automate as much of the computations as possible, and to publish the results in a publically available Web mapping application. While LRAM did not incorporate the quantitative prediction assessment, loss and damage estimation tools originally desired, it did succeed in meeting other goals of this thesis project, including the creation of a scalable and easily portable model that can determine landslide hazard, relative risk, and has a regionally validated rainfall triggered assessment model. Furthermore, this model requires no fieldwork on behalf of the researcher and utilizes primary data sources typically collected by municipal and federal agencies. The framework for this model is easily expandable and when applied with quantitative data sources the model itself could, with validation, accurately predict landslides in the time frame for the region of interest.

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Appendix A: Python Code

```
# ---------------------------------------------------------------------------
# LRAM Final.py
# Created on: 2015-11-20 03:13:30.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: LRAM Final <DEM> <BlockPop> <Soilmap> <v72_Hour_Precipitation> <v8-
14_Day_Precipitation> <WaParcel> <Landcover> <v1-7_Day_Precipitation>
# Description:
# Local Landslide Risk Assessment model created by Michael Barnett. This project is to demonstrate the
availability of data and the ability of the model to create an accurate analysis.
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "D:\\data\\geodatabase\\LRA_Final.gdb"
arcpy.env.snapRaster = ""
arcpy.env.extent = "576751.629936263 81877.319960922 2551197.68005201 1355594.74889892"
arcpy.env.workspace = "D:\\data\\geodatabase\\LRA_Final.gdb"

# Script arguments
DEM = arcpy.GetParameterAsText(0)
if DEM == '#' or not DEM:
    DEM = "D:\\data\\geodatabase\\tenmeter\\zone10" # provide a default value if unspecified

BlockPop = arcpy.GetParameterAsText(1)
if BlockPop == '#' or not BlockPop:
    BlockPop = "D:\\data\\geodatabase\\LocalLRA.gdb\\BlockPop" # provide a default value if unspecified

Soilmap = arcpy.GetParameterAsText(2)
if Soilmap == '#' or not Soilmap:
    Soilmap = "D:\\data\\geodatabase\\LocalLRA.gdb\\soils" # provide a default value if unspecified

v72_Hour_Precipitation = arcpy.GetParameterAsText(3)
if v72_Hour_Precipitation == '#' or not v72_Hour_Precipitation:
    v72_Hour_Precipitation = "D:\\data\\geodatabase\\LRA.gdb\\Precipitation\\day13_2015111800" #
provide a default value if unspecified

v8-14_Day_Precipitation = arcpy.GetParameterAsText(4)
if v8-14_Day_Precipitation == '#' or not v8-14_Day_Precipitation:
    v8-14_Day_Precipitation = "D:\\data\\geodatabase\\LRA.gdb\\T97e1112" # provide a default value if
unspecified
```

```
WaParcel = arcpy.GetParameterAsText(5)
if WaParcel == '#' or not WaParcel:
    WaParcel = "D:\\data\\geodatabase\\LocalLRA.gdb\\WaParcel" # provide a default value if unspecified

Landcover = arcpy.GetParameterAsText(6)
if Landcover == '#' or not Landcover:
    Landcover = "D:\\data\\geodatabase\\LRA.gdb\\Landcover" # provide a default value if unspecified

v1-7_Day_Precipitation = arcpy.GetParameterAsText(7)
if v1-7_Day_Precipitation == '#' or not v1-7_Day_Precipitation:
    v1-7_Day_Precipitation = "D:\\data\\geodatabase\\LRA.gdb\\T97e1800" # provide a default value if
unspecified

# Local variables:
SoilTextRaster = Soilmap
SC_Tx = SoilTextRaster
Hz_Score = SC_Tx
LRAM_Final = Hz_Score
SoilStbRaster = Soilmap
Sc_Stb = SoilStbRaster
SoilDpRaster = Soilmap
Sc_Dp = SoilDpRaster
SoilDrRaster = Soilmap
Sc_Dr = SoilDrRaster
SlopeMap = DEM
SlopeScore = SlopeMap
c72HourPrecipitation_Clip = DEM
GreaterRaster = c72HourPrecipitation_Clip
v15day_Clip = DEM
Population_Raster = BlockPop
Sc_pop = Population_Raster
v72HrPrecipRaster = v72_Hour_Precipitation
v8-14DPrecipRaster = v8-14_Day_Precipitation
v15day = v8-14DPrecipRaster
LCRaster = Landcover
SC_Lc = LCRaster
WaParcelRaster = WaParcel
v1-7DPrecipRaster = v1-7_Day_Precipitation

# Process: 1-7DPrecipRasterCreate
arcpy.PolygonToRaster_conversion(v1-7_Day_Precipitation, "QPF", v1-7DPrecipRaster,
"CELL_CENTER", "NONE", "1200")

# Process: 8-14DPrecipRasterCreate
arcpy.PolygonToRaster_conversion(v8-14_Day_Precipitation, "QPF", v8-14DPrecipRaster,
"CELL_CENTER", "NONE", "1200")

# Process: 15dayMerge
arcpy.gp.RasterCalculator_sa("\"%1-7DPrecipRaster%\" + \"%8-14DPrecipRaster%\"", v15day)
```

```
# Process: 15dayPrecipClip
arcpy.Clip_management(v15day, "541707.539368356 47020.8082192693 1806223.53350932
1375478.46972344", v15day_Clip, DEM, "", "NONE", "NO_MAINTAIN_EXTENT")

# Process: 72HrPrecipRasterCreate
arcpy.PolygonToRaster_conversion(v72_Hour_Precipitation, "QPF", v72HrPrecipRaster,
"CELL_CENTER", "NONE", "1200")

# Process: CurrentPrecipClip
arcpy.Clip_management(v72HrPrecipRaster, "541707.539368356 47020.8082192693 1806223.53350932
1375478.46972344", c72HourPrecipitation_Clip, DEM, "", "NONE", "NO_MAINTAIN_EXTENT")

# Process: Greater Than Frequency
arcpy.gp.GreaterThanFrequency_sa(v15day_Clip,
"D:\\data\\geodatabase\\LRA_Final.gdb\\c72HourPrecipitation_Clip", GreaterRaster)

# Process: Soil_TextureRaster
arcpy.PolygonToRaster_conversion(Soilmap, "SOIL_TXTR_MDFR", SoilTextRaster,
"CELL_CENTER", "NONE", "5100")

# Process: SoilTextClass
arcpy.gp.Reclassify_sa(SoilTextRaster, "SOIL_TXTR_MDFR", "'SILT LOAM' 2;'GRAVELLY LOAM'
1;'STONY LOAM' 1;'V.BOULDERY LOAM' 1;'STONY SANDY LOAM' 1;'V.GRAVELLY SANDY
LOAM' 1;VF.SNDY.LOAM 3;LOAM 1;'GRAVELLY SILT LOAM' 1;'V.GRAVELLY LOAM'
1;'GRAVELLY SANDY LOAM' 1;'GRAVELLY LOAMY SAND' 1;F.SANDY.LOAM 2;'COBBLY
SILT LOAM' 2;MUCK 3;'VARIABLE VARIABLE' 1;'SANDY LOAM' 2;LOAMY.FN.SND
3;'XTR.GRAVELLY LOAMY SAND' 1;'V.STONY SILT LOAM' 1;'STONY SILT LOAM' 1;'STONY
LOAMY SAND' 1;SAND 2;'V.STONY LOAM' 1;'V.GRAVELLY SILT LOAM' 1;CRS.SND.LOAM
2;'XTR.STONY LOAM' 1;'VARIABLE SAND' 1;'SHALY LOAM' 2;SLT.CLY.LOAM 2;'STONY
F.SANDY.LOAM' 2;'V.COBBLY SANDY LOAM' 1;'XTR.GRAVELLY SANDY LOAM' 1;'LOAMY
SAND' 1;'GRAVELLY F.SANDY.LOAM' 1;PEAT 2;'V.COBBLY SILT LOAM' 1;'XTR.STONY
SANDY LOAM' 1;'BOULDERY LOAM' 1;'COBBLY LOAM' 1;VARIABLE 1;'V.COBBLY LOAM'
1;'V.BOULDERY SILT LOAM' 1;'BOULDERY F.SANDY.LOAM' 1;'COBBLY SANDY LOAM'
1;'V.STONY SANDY LOAM' 1;'XTR.STONY SILT LOAM' 1;'V.GRAVELLY LOAMY SAND'
1;'COBBLY LOAMY SAND' 1;'CLAY LOAM' 3;LOAM.CRS.SND 3;'MUCKY SILT LOAM' 2;SILT
2;'V.STONY LOAMY SAND' 1;'V.ROCKY SILT LOAM' 1;'OTHER MUCK' 1;'GRAVELLY
SLT.CLY.LOAM' 2;'MUCKY SLT.CLY.LOAM' 2;'MUCKY PEAT' 2;'STONY OTHER' 1;'CINDERY
SANDY LOAM' 1;'CINDERY F.SANDY.LOAM' 1;'COBBLY F.SANDY.LOAM' 1;'GRAVELLY
CLAY LOAM' 1;'BOULDERY SANDY LOAM' 1;'V.ROCKY SANDY LOAM' 1;'GRAVELLY
CRS.SND.LOAM' 1;'V.GRAVELLY LOAMY.FN.SND' 1;'V.BOULDERY LOAMY SAND'
1;'V.BOULDERY SANDY LOAM' 1;'V.COBBLY LOAMY SAND' 1;'XTR.GRAVELLY LOAM'
1;'ROCKY SANDY LOAM' 1;'MUCKY LOAM' 2;'SHOTTY LOAM' 2;'SILTY CLAY' 3;'V.CINDERY
LOAMY SAND' 2;'V.CINDERY SANDY LOAM' 2;'VARIABLE LOAM' 1;CLAY 3;'SANDY CLAY'
3;'CINDERY LOAMY SAND' 1;'V.CINDERY LOAM' 1;'V.GRAVELLY SLT.CLY.LOAM'
2;'V.ROCKY LOAMY SAND' 2;'XTR.CINDERY LOAMY SAND' 1;'ROCKY SILT LOAM'
2;'CINDERY LOAM' 1;'XTR.COBBLY LOAM' 1;'COBBLY VARIABLE' 1;'STONY CLAY LOAM'
2;NODATA 0", SC_Tx, "NODATA")

# Process: Soil_StabilityRaster
arcpy.PolygonToRaster_conversion(Soilmap, "SOIL_EROSION_POTNL", SoilStbRaster,
"CELL_CENTER", "NONE", "5100")
```

```
# Process: Soil_Stb_Class
arcpy.gp.Reclassify_sa(SoilStbRaster, "SOIL_EROSION_POTNL", "MEDIUM 2;LOW 1;HIGH 3;N/A
0;VARIABLE 1;NODATA 0", Sc_Stb, "NODATA")

# Process: Soil_DepthRaster
arcpy.PolygonToRaster_conversion(Soilmap, "SOIL_DPT", SoilDpRaster, "CELL_CENTER", "NONE",
"5100")

# Process: Soil_Dp_Class
arcpy.gp.Reclassify_sa(SoilDpRaster, "SOIL_DPT", "'>60 inches' 4;'40 - 60 inches' 3;'0 - 0 inches' 1;'20 -
40 inches' 1;'0 - 60 inches' 3;'20 - 60 inches' 3;'40 - 40 inches' 3;'10 - 20 inches' 1;'30 - 60 inches' 3;'8 - 14
inches' 1;'30 - 40 inches' 1;'4 - 20 inches' 1;'0 - 40 inches' 1;'30 - 50 inches' 3;'20 - 44 inches' 2;'6 - 20
inches' 1;'50 - 60 inches' 3;'20 - 36 inches' 2;'14 - 20 inches' 1;'10 - 60 inches' 2;'10 - 40 inches' 2;'0 - 10
inches' 1;'30 - 30 inches' 2;'20 - 30 inches' 2;'12 - 60 inches' 2;'25 - 40 inches' 3;'24 - 40 inches' 2;'12 - 20
inches' 1;'0 - 20 inches' 1;'18 - 18 inches' 1;'55 - 60 inches' 3;'20 - 35 inches' 2;'23 - 40 inches' 2;'20 - 20
inches' 2;'36 - 36 inches' 2;'30 - 55 inches' 3;'26 - 33 inches' 2;'48 - 48 inches' 3;'16 - 20 inches' 1;'8 - 20
inches' 1;'29 - 40 inches' 2;'4 - 10 inches' 1;'24 - 36 inches' 2;'5 - 10 inches' 1;'5 - 15 inches' 1;'4 - 12
inches' 1", Sc_Dp, "DATA")

# Process: Soil_DrainageRaster
arcpy.PolygonToRaster_conversion(Soilmap, "SOIL_DRAIN_RATE", SoilDrRaster, "CELL_CENTER",
"NONE", "5100")

# Process: Soil_Dr_Class
arcpy.gp.Reclassify_sa(SoilDrRaster, "SOIL_DRAIN_RATE", "'WELL Drained' 1;'MOD WELL
Drained' 1;'NO DATA Drained' 1;'SOME POOR Drained' 3;'SOME EXCESS Drained' 1;'POOR Drained'
4;'VERY POOR Drained' 5;'VARIABLE Drained' 3;'EXCESS Drained' 1;'N/A Drained' 1", Sc_Dr,
"NODATA")

# Process: Population to Raster
tempEnvironment0 = arcpy.env.newPrecision
arcpy.env.newPrecision = "SINGLE"
tempEnvironment1 = arcpy.env.autoCommit
arcpy.env.autoCommit = "1000"
tempEnvironment2 = arcpy.env.XYResolution
arcpy.env.XYResolution = ""
tempEnvironment3 = arcpy.env.XYDomain
arcpy.env.XYDomain = ""
tempEnvironment4 = arcpy.env.scratchWorkspace
arcpy.env.scratchWorkspace = "F:\\Barnett_Office\\Documents\\ArcGIS\\Default1.gdb"
tempEnvironment5 = arcpy.env.cartographicPartitions
arcpy.env.cartographicPartitions = ""
tempEnvironment6 = arcpy.env.terrainMemoryUsage
arcpy.env.terrainMemoryUsage = "false"
tempEnvironment7 = arcpy.env.MTolerance
arcpy.env.MTolerance = ""
tempEnvironment8 = arcpy.env.compression
arcpy.env.compression = "LZ77"
tempEnvironment9 = arcpy.env.coincidentPoints
arcpy.env.coincidentPoints = "MEAN"
```

```
tempEnvironment10 = arcpy.env.randomGenerator
arcpy.env.randomGenerator = "0 ACM599"
tempEnvironment11 = arcpy.env.outputCoordinateSystem
arcpy.env.outputCoordinateSystem = ""
tempEnvironment12 = arcpy.env.rasterStatistics
arcpy.env.rasterStatistics = "STATISTICS 1 1"
tempEnvironment13 = arcpy.env.ZDomain
arcpy.env.ZDomain = ""
tempEnvironment14 = arcpy.env.transferDomains
arcpy.env.transferDomains = "false"
tempEnvironment15 = arcpy.env.resamplingMethod
arcpy.env.resamplingMethod = "NEAREST"
tempEnvironment16 = arcpy.env.snapRaster
arcpy.env.snapRaster = ""
tempEnvironment17 = arcpy.env.projectCompare
arcpy.env.projectCompare = "NONE"
tempEnvironment18 = arcpy.env.cartographicCoordinateSystem
arcpy.env.cartographicCoordinateSystem =
"PROJCS['NAD_1927_UTM_Zone_10N',GEOGCS['GCS_North_American_1927',DATUM['D_North_
American_1927',SPHEROID['Clarke_1866',6378206.4,294.9786982]],PRIMEM['Greenwich',0.0],UNIT[
'Degree',0.0174532925199433]],PROJECTION['Transverse_Mercator'],PARAMETER['False_Easting',5
00000.0],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-
123.0],PARAMETER['Scale_Factor',0.9996],PARAMETER['Latitude_Of_Origin',0.0],UNIT['Meter',1.0]
],VERTCS['Unknown
VCS',VDATUM['Unknown'],PARAMETER['Vertical_Shift',0.0],PARAMETER['Direction',1.0],UNIT['
User_Defined_Unit',0.1]]"
tempEnvironment19 = arcpy.env.configKeyword
arcpy.env.configKeyword = ""
tempEnvironment20 = arcpy.env.outputZFlag
arcpy.env.outputZFlag = "Same As Input"
tempEnvironment21 = arcpy.env.qualifiedFieldNames
arcpy.env.qualifiedFieldNames = "true"
tempEnvironment22 = arcpy.env.tileSize
arcpy.env.tileSize = "128 128"
tempEnvironment23 = arcpy.env.parallelProcessingFactor
arcpy.env.parallelProcessingFactor = ""
tempEnvironment24 = arcpy.env.pyramid
arcpy.env.pyramid = "PYRAMIDS -1 NEAREST DEFAULT 75 NO_SKIP"
tempEnvironment25 = arcpy.env.referenceScale
arcpy.env.referenceScale = ""
tempEnvironment26 = arcpy.env.extent
arcpy.env.extent = "DEFAULT"
tempEnvironment27 = arcpy.env.XYTolerance
arcpy.env.XYTolerance = ""
tempEnvironment28 = arcpy.env.tinSaveVersion
arcpy.env.tinSaveVersion = "CURRENT"
tempEnvironment29 = arcpy.env.nodata
arcpy.env.nodata = "NONE"
tempEnvironment30 = arcpy.env.MDomain
arcpy.env.MDomain = ""
tempEnvironment31 = arcpy.env.spatialGrid1
```

```
arcpy.env.spatialGrid1 = "0"
tempEnvironment32 = arcpy.env.cellSize
arcpy.env.cellSize = "MAXOF"
tempEnvironment33 = arcpy.env.outputZValue
arcpy.env.outputZValue = ""
tempEnvironment34 = arcpy.env.outputMFlag
arcpy.env.outputMFlag = "Same As Input"
tempEnvironment35 = arcpy.env.geographicTransformations
arcpy.env.geographicTransformations = "NAD_1927_To_NAD_1983_NADCON"
tempEnvironment36 = arcpy.env.spatialGrid2
arcpy.env.spatialGrid2 = "0"
tempEnvironment37 = arcpy.env.ZResolution
arcpy.env.ZResolution = ""
tempEnvironment38 = arcpy.env.mask
arcpy.env.mask = ""
tempEnvironment39 = arcpy.env.spatialGrid3
arcpy.env.spatialGrid3 = "0"
tempEnvironment40 = arcpy.env.maintainSpatialIndex
arcpy.env.maintainSpatialIndex = "false"
tempEnvironment41 = arcpy.env.workspace
arcpy.env.workspace = "F:\\Barnett_Office\\Documents\\ArcGIS\\Default1.gdb"
tempEnvironment42 = arcpy.env.MResolution
arcpy.env.MResolution = ""
tempEnvironment43 = arcpy.env.derivedPrecision
arcpy.env.derivedPrecision = "HIGHEST"
tempEnvironment44 = arcpy.env.ZTolerance
arcpy.env.ZTolerance = ""
arcpy.PolygonToRaster_conversion(BlockPop, "P0010001", Population_Raster, "CELL_CENTER",
"NONE", "0.014")
arcpy.env.newPrecision = tempEnvironment0
arcpy.env.autoCommit = tempEnvironment1
arcpy.env.XYResolution = tempEnvironment2
arcpy.env.XYDomain = tempEnvironment3
arcpy.env.scratchWorkspace = tempEnvironment4
arcpy.env.cartographicPartitions = tempEnvironment5
arcpy.env.terrainMemoryUsage = tempEnvironment6
arcpy.env.MTolerance = tempEnvironment7
arcpy.env.compression = tempEnvironment8
arcpy.env.coincidentPoints = tempEnvironment9
arcpy.env.randomGenerator = tempEnvironment10
arcpy.env.outputCoordinateSystem = tempEnvironment11
arcpy.env.rasterStatistics = tempEnvironment12
arcpy.env.ZDomain = tempEnvironment13
arcpy.env.transferDomains = tempEnvironment14
arcpy.env.resamplingMethod = tempEnvironment15
arcpy.env.snapRaster = tempEnvironment16
arcpy.env.projectCompare = tempEnvironment17
arcpy.env.cartographicCoordinateSystem = tempEnvironment18
arcpy.env.configKeyword = tempEnvironment19
arcpy.env.outputZFlag = tempEnvironment20
arcpy.env.qualifiedFieldNames = tempEnvironment21
```

```
arcpy.env.tileSize = tempEnvironment22
arcpy.env.parallelProcessingFactor = tempEnvironment23
arcpy.env.pyramid = tempEnvironment24
arcpy.env.referenceScale = tempEnvironment25
arcpy.env.extent = tempEnvironment26
arcpy.env.XYTolerance = tempEnvironment27
arcpy.env.tinSaveVersion = tempEnvironment28
arcpy.env.nodata = tempEnvironment29
arcpy.env.MDomain = tempEnvironment30
arcpy.env.spatialGrid1 = tempEnvironment31
arcpy.env.cellSize = tempEnvironment32
arcpy.env.outputZValue = tempEnvironment33
arcpy.env.outputMFlag = tempEnvironment34
arcpy.env.geographicTransformations = tempEnvironment35
arcpy.env.spatialGrid2 = tempEnvironment36
arcpy.env.ZResolution = tempEnvironment37
arcpy.env.mask = tempEnvironment38
arcpy.env.spatialGrid3 = tempEnvironment39
arcpy.env.maintainSpatialIndex = tempEnvironment40
arcpy.env.workspace = tempEnvironment41
arcpy.env.MResolution = tempEnvironment42
arcpy.env.derivedPrecision = tempEnvironment43
arcpy.env.ZTolerance = tempEnvironment44

# Process: PopulationClassify
tempEnvironment0 = arcpy.env.newPrecision
arcpy.env.newPrecision = "SINGLE"
tempEnvironment1 = arcpy.env.autoCommit
arcpy.env.autoCommit = "1000"
tempEnvironment2 = arcpy.env.XYResolution
arcpy.env.XYResolution = ""
tempEnvironment3 = arcpy.env.XYDomain
arcpy.env.XYDomain = ""
tempEnvironment4 = arcpy.env.scratchWorkspace
arcpy.env.scratchWorkspace = "F:\\Barnett_Office\\Documents\\ArcGIS\\Default1.gdb"
tempEnvironment5 = arcpy.env.cartographicPartitions
arcpy.env.cartographicPartitions = ""
tempEnvironment6 = arcpy.env.terrainMemoryUsage
arcpy.env.terrainMemoryUsage = "false"
tempEnvironment7 = arcpy.env.MTolerance
arcpy.env.MTolerance = ""
tempEnvironment8 = arcpy.env.compression
arcpy.env.compression = "LZ77"
tempEnvironment9 = arcpy.env.coincidentPoints
arcpy.env.coincidentPoints = "MEAN"
tempEnvironment10 = arcpy.env.randomGenerator
arcpy.env.randomGenerator = "0 ACM599"
tempEnvironment11 = arcpy.env.outputCoordinateSystem
arcpy.env.outputCoordinateSystem = ""
tempEnvironment12 = arcpy.env.rasterStatistics
arcpy.env.rasterStatistics = "STATISTICS 1 1"
```

```
tempEnvironment13 = arcpy.env.ZDomain
arcpy.env.ZDomain = ""
tempEnvironment14 = arcpy.env.transferDomains
arcpy.env.transferDomains = "false"
tempEnvironment15 = arcpy.env.resamplingMethod
arcpy.env.resamplingMethod = "NEAREST"
tempEnvironment16 = arcpy.env.snapRaster
arcpy.env.snapRaster = ""
tempEnvironment17 = arcpy.env.projectCompare
arcpy.env.projectCompare = "NONE"
tempEnvironment18 = arcpy.env.cartographicCoordinateSystem
arcpy.env.cartographicCoordinateSystem =
"PROJCS['NAD_1927_UTM_Zone_10N',GEOGCS['GCS_North_American_1927',DATUM['D_North_
American_1927',SPHEROID['Clarke_1866',6378206.4,294.9786982]],PRIMEM['Greenwich',0.0],UNIT[
'Degree',0.0174532925199433]],PROJECTION['Transverse_Mercator'],PARAMETER['False_Easting',5
00000.0],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-
123.0],PARAMETER['Scale_Factor',0.9996],PARAMETER['Latitude_Of_Origin',0.0],UNIT['Meter',1.0]
],VERTCS['Unknown
VCS',VDATUM['Unknown'],PARAMETER['Vertical_Shift',0.0],PARAMETER['Direction',1.0],UNIT['
User_Defined_Unit',0.1]]"
tempEnvironment19 = arcpy.env.configKeyword
arcpy.env.configKeyword = ""
tempEnvironment20 = arcpy.env.outputZFlag
arcpy.env.outputZFlag = "Same As Input"
tempEnvironment21 = arcpy.env.qualifiedFieldNames
arcpy.env.qualifiedFieldNames = "true"
tempEnvironment22 = arcpy.env.tileSize
arcpy.env.tileSize = "128 128"
tempEnvironment23 = arcpy.env.parallelProcessingFactor
arcpy.env.parallelProcessingFactor = ""
tempEnvironment24 = arcpy.env.pyramid
arcpy.env.pyramid = "PYRAMIDS -1 NEAREST DEFAULT 75 NO_SKIP"
tempEnvironment25 = arcpy.env.referenceScale
arcpy.env.referenceScale = ""
tempEnvironment26 = arcpy.env.extent
arcpy.env.extent = "DEFAULT"
tempEnvironment27 = arcpy.env.XYTolerance
arcpy.env.XYTolerance = ""
tempEnvironment28 = arcpy.env.tinSaveVersion
arcpy.env.tinSaveVersion = "CURRENT"
tempEnvironment29 = arcpy.env.nodata
arcpy.env.nodata = "NONE"
tempEnvironment30 = arcpy.env.MDomain
arcpy.env.MDomain = ""
tempEnvironment31 = arcpy.env.spatialGrid1
arcpy.env.spatialGrid1 = "0"
tempEnvironment32 = arcpy.env.cellSize
arcpy.env.cellSize = "MAXOF"
tempEnvironment33 = arcpy.env.outputZValue
arcpy.env.outputZValue = ""
tempEnvironment34 = arcpy.env.outputMFlag
```

```
arcpy.env.outputMFlag = "Same As Input"
tempEnvironment35 = arcpy.env.geographicTransformations
arcpy.env.geographicTransformations = "NAD_1927_To_NAD_1983_NADCON"
tempEnvironment36 = arcpy.env.spatialGrid2
arcpy.env.spatialGrid2 = "0"
tempEnvironment37 = arcpy.env.ZResolution
arcpy.env.ZResolution = ""
tempEnvironment38 = arcpy.env.mask
arcpy.env.mask = ""
tempEnvironment39 = arcpy.env.spatialGrid3
arcpy.env.spatialGrid3 = "0"
tempEnvironment40 = arcpy.env.maintainSpatialIndex
arcpy.env.maintainSpatialIndex = "false"
tempEnvironment41 = arcpy.env.workspace
arcpy.env.workspace = "F:\\Barnett_Office\\Documents\\ArcGIS\\Default1.gdb"
tempEnvironment42 = arcpy.env.MResolution
arcpy.env.MResolution = ""
tempEnvironment43 = arcpy.env.derivedPrecision
arcpy.env.derivedPrecision = "HIGHEST"
tempEnvironment44 = arcpy.env.ZTolerance
arcpy.env.ZTolerance = ""
arcpy.gp.Reclassify_sa(Population_Raster, "VALUE", "0 54 1;54 205 2;205 481 3;481 1127 4;1127 2314
5", Sc_pop, "DATA")
arcpy.env.newPrecision = tempEnvironment0
arcpy.env.autoCommit = tempEnvironment1
arcpy.env.XYResolution = tempEnvironment2
arcpy.env.XYDomain = tempEnvironment3
arcpy.env.scratchWorkspace = tempEnvironment4
arcpy.env.cartographicPartitions = tempEnvironment5
arcpy.env.terrainMemoryUsage = tempEnvironment6
arcpy.env.MTolerance = tempEnvironment7
arcpy.env.compression = tempEnvironment8
arcpy.env.coincidentPoints = tempEnvironment9
arcpy.env.randomGenerator = tempEnvironment10
arcpy.env.outputCoordinateSystem = tempEnvironment11
arcpy.env.rasterStatistics = tempEnvironment12
arcpy.env.ZDomain = tempEnvironment13
arcpy.env.transferDomains = tempEnvironment14
arcpy.env.resamplingMethod = tempEnvironment15
arcpy.env.snapRaster = tempEnvironment16
arcpy.env.projectCompare = tempEnvironment17
arcpy.env.cartographicCoordinateSystem = tempEnvironment18
arcpy.env.configKeyword = tempEnvironment19
arcpy.env.outputZFlag = tempEnvironment20
arcpy.env.qualifiedFieldNames = tempEnvironment21
arcpy.env.tileSize = tempEnvironment22
arcpy.env.parallelProcessingFactor = tempEnvironment23
arcpy.env.pyramid = tempEnvironment24
arcpy.env.referenceScale = tempEnvironment25
arcpy.env.extent = tempEnvironment26
arcpy.env.XYTolerance = tempEnvironment27
```

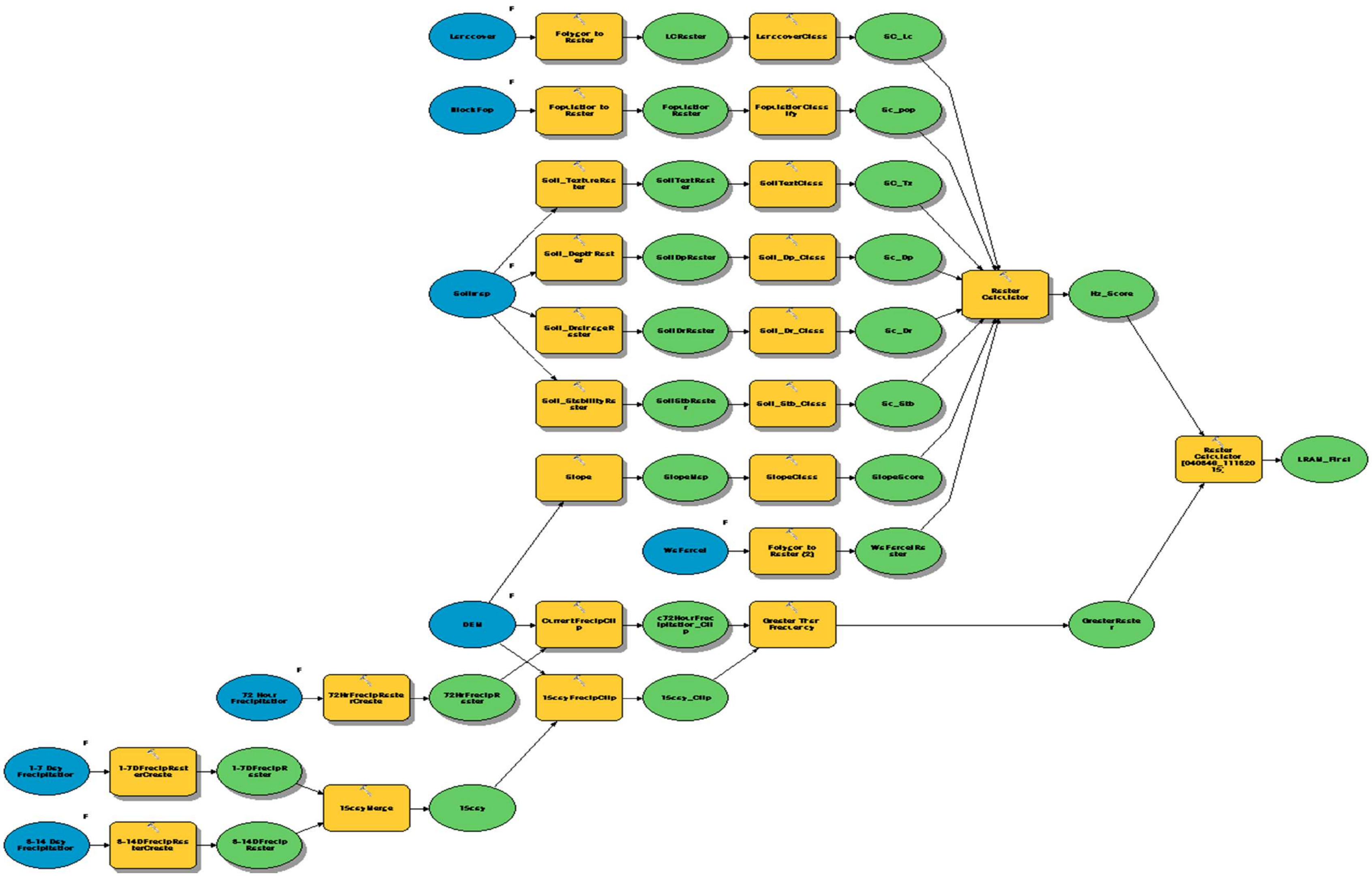
```
arcpy.env.tinSaveVersion = tempEnvironment28
arcpy.env.nodata = tempEnvironment29
arcpy.env.MDomain = tempEnvironment30
arcpy.env.spatialGrid1 = tempEnvironment31
arcpy.env.cellSize = tempEnvironment32
arcpy.env.outputZValue = tempEnvironment33
arcpy.env.outputMFlag = tempEnvironment34
arcpy.env.geographicTransformations = tempEnvironment35
arcpy.env.spatialGrid2 = tempEnvironment36
arcpy.env.ZResolution = tempEnvironment37
arcpy.env.mask = tempEnvironment38
arcpy.env.spatialGrid3 = tempEnvironment39
arcpy.env.maintainSpatialIndex = tempEnvironment40
arcpy.env.workspace = tempEnvironment41
arcpy.env.MResolution = tempEnvironment42
arcpy.env.derivedPrecision = tempEnvironment43
arcpy.env.ZTolerance = tempEnvironment44

# Process: Slope
arcpy.gp.Slope_sa(DEM, SlopeMap, "DEGREE", "0.1")

# Process: SlopeClass
arcpy.gp.Reclassify_sa(SlopeMap, "Value", "0 8 1;8 15 2;15 25 3;25 45 4;45 100 5", SlopeScore,
"NODATA")

# Process: Polygon to Raster
arcpy.PolygonToRaster_conversion(Landcover, "Landuse", LCRaster, "CELL_CENTER", "NONE",
"5100")

# Process: LandcoverClass
arcpy.gp.Reclassify_sa(LCRaster, "VALUE", "0 1 5;1 2 3;2 3 3;3 4 5;4 5 2;5 6 4;6 7 1;7 8 1;8 9 1",
SC_Lc, "NODATA")

# Process: Polygon to Raster (2)
arcpy.PolygonToRaster_conversion(WaParcel, "LU", WaParcelRaster, "CELL_CENTER", "NONE",
"5100")

# Process: Raster Calculator
arcpy.gp.RasterCalculator_sa("Hazard = \"%SC_Tx%\" + \"%Sc_Stb%\" + \"%Sc_Dp%\" +
\"%Sc_Dr%\" + \"%Sc_pop%\" + \"%SlopeScore%\"  + \"%SC_Lc%\" + \"%WaParcelRaster%\"",
Hz_Score)

# Process: Raster Calculator [040846_11182015]
tempEnvironment0 = arcpy.env.newPrecision
arcpy.env.newPrecision = "SINGLE"
tempEnvironment1 = arcpy.env.autoCommit
arcpy.env.autoCommit = "1000"
tempEnvironment2 = arcpy.env.XYResolution
arcpy.env.XYResolution = ""
tempEnvironment3 = arcpy.env.XYDomain
arcpy.env.XYDomain = ""
```

```
tempEnvironment4 = arcpy.env.scratchWorkspace
arcpy.env.scratchWorkspace = "D:\\data\\geodatabase\\LocalLRA.gdb"
tempEnvironment5 = arcpy.env.cartographicPartitions
arcpy.env.cartographicPartitions = ""
tempEnvironment6 = arcpy.env.terrainMemoryUsage
arcpy.env.terrainMemoryUsage = "false"
tempEnvironment7 = arcpy.env.MTolerance
arcpy.env.MTolerance = ""
tempEnvironment8 = arcpy.env.compression
arcpy.env.compression = "LZ77"
tempEnvironment9 = arcpy.env.coincidentPoints
arcpy.env.coincidentPoints = "MEAN"
tempEnvironment10 = arcpy.env.randomGenerator
arcpy.env.randomGenerator = "0 ACM599"
tempEnvironment11 = arcpy.env.outputCoordinateSystem
arcpy.env.outputCoordinateSystem =
"PROJCS['NAD_1983_HARN_StatePlane_Washington_South_FIPS_4602_Feet',GEOGCS['GCS_North
_American_1983_HARN',DATUM['D_North_American_1983_HARN',SPHEROID['GRS_1980',637813
7.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['
Lambert_Conformal_Conic'],PARAMETER['False_Easting',1640416.666666667],PARAMETER['False_
Northing',0.0],PARAMETER['Central_Meridian',-
120.5],PARAMETER['Standard_Parallel_1',45.83333333333334],PARAMETER['Standard_Parallel_2',4
7.33333333333334],PARAMETER['Latitude_Of_Origin',45.33333333333334],UNIT['Foot_US',0.30480
06096012192]]"
tempEnvironment12 = arcpy.env.rasterStatistics
arcpy.env.rasterStatistics = "STATISTICS 1 1"
tempEnvironment13 = arcpy.env.ZDomain
arcpy.env.ZDomain = ""
tempEnvironment14 = arcpy.env.transferDomains
arcpy.env.transferDomains = "false"
tempEnvironment15 = arcpy.env.resamplingMethod
arcpy.env.resamplingMethod = "NEAREST"
tempEnvironment16 = arcpy.env.snapRaster
arcpy.env.snapRaster = ""
tempEnvironment17 = arcpy.env.projectCompare
arcpy.env.projectCompare = "NONE"
tempEnvironment18 = arcpy.env.cartographicCoordinateSystem
arcpy.env.cartographicCoordinateSystem =
"PROJCS['NAD_1983_HARN_StatePlane_Washington_South_FIPS_4602_Feet',GEOGCS['GCS_North
_American_1983_HARN',DATUM['D_North_American_1983_HARN',SPHEROID['GRS_1980',637813
7.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['
Lambert_Conformal_Conic'],PARAMETER['False_Easting',1640416.666666667],PARAMETER['False_
Northing',0.0],PARAMETER['Central_Meridian',-
120.5],PARAMETER['Standard_Parallel_1',45.83333333333334],PARAMETER['Standard_Parallel_2',4
7.33333333333334],PARAMETER['Latitude_Of_Origin',45.33333333333334],UNIT['Foot_US',0.30480
06096012192]]"
tempEnvironment19 = arcpy.env.configKeyword
arcpy.env.configKeyword = ""
tempEnvironment20 = arcpy.env.outputZFlag
arcpy.env.outputZFlag = "Same As Input"
tempEnvironment21 = arcpy.env.qualifiedFieldNames
```

```
arcpy.env.qualifiedFieldNames = "true"
tempEnvironment22 = arcpy.env.tileSize
arcpy.env.tileSize = "128 128"
tempEnvironment23 = arcpy.env.parallelProcessingFactor
arcpy.env.parallelProcessingFactor = ""
tempEnvironment24 = arcpy.env.pyramid
arcpy.env.pyramid = "PYRAMIDS -1 NEAREST DEFAULT 75 NO_SKIP"
tempEnvironment25 = arcpy.env.referenceScale
arcpy.env.referenceScale = ""
tempEnvironment26 = arcpy.env.extent
arcpy.env.extent = "360475 5038305 733345 5431525"
tempEnvironment27 = arcpy.env.XYTolerance
arcpy.env.XYTolerance = ""
tempEnvironment28 = arcpy.env.tinSaveVersion
arcpy.env.tinSaveVersion = "CURRENT"
tempEnvironment29 = arcpy.env.nodata
arcpy.env.nodata = "NONE"
tempEnvironment30 = arcpy.env.MDomain
arcpy.env.MDomain = ""
tempEnvironment31 = arcpy.env.spatialGrid1
arcpy.env.spatialGrid1 = "0"
tempEnvironment32 = arcpy.env.cellSize
arcpy.env.cellSize = "MAXOF"
tempEnvironment33 = arcpy.env.outputZValue
arcpy.env.outputZValue = ""
tempEnvironment34 = arcpy.env.outputMFlag
arcpy.env.outputMFlag = "Same As Input"
tempEnvironment35 = arcpy.env.geographicTransformations
arcpy.env.geographicTransformations = "NAD_1927_To_NAD_1983_NADCON"
tempEnvironment36 = arcpy.env.spatialGrid2
arcpy.env.spatialGrid2 = "0"
tempEnvironment37 = arcpy.env.ZResolution
arcpy.env.ZResolution = ""
tempEnvironment38 = arcpy.env.mask
arcpy.env.mask = ""
tempEnvironment39 = arcpy.env.spatialGrid3
arcpy.env.spatialGrid3 = "0"
tempEnvironment40 = arcpy.env.maintainSpatialIndex
arcpy.env.maintainSpatialIndex = "false"
tempEnvironment41 = arcpy.env.workspace
arcpy.env.workspace = "D:\\data\\geodatabase\\LocalLRA.gdb"
tempEnvironment42 = arcpy.env.MResolution
arcpy.env.MResolution = ""
tempEnvironment43 = arcpy.env.derivedPrecision
arcpy.env.derivedPrecision = "HIGHEST"
tempEnvironment44 = arcpy.env.ZTolerance
arcpy.env.ZTolerance = ""
arcpy.gp.RasterCalculator_sa("(\"%GreaterRaster%\" * 3) + \"%Hz_Score%\"", LRAM_Final)
arcpy.env.newPrecision = tempEnvironment0
arcpy.env.autoCommit = tempEnvironment1
arcpy.env.XYResolution = tempEnvironment2
```

```
arcpy.env.XYDomain = tempEnvironment3
arcpy.env.scratchWorkspace = tempEnvironment4
arcpy.env.cartographicPartitions = tempEnvironment5
arcpy.env.terrainMemoryUsage = tempEnvironment6
arcpy.env.MTolerance = tempEnvironment7
arcpy.env.compression = tempEnvironment8
arcpy.env.coincidentPoints = tempEnvironment9
arcpy.env.randomGenerator = tempEnvironment10
arcpy.env.outputCoordinateSystem = tempEnvironment11
arcpy.env.rasterStatistics = tempEnvironment12
arcpy.env.ZDomain = tempEnvironment13
arcpy.env.transferDomains = tempEnvironment14
arcpy.env.resamplingMethod = tempEnvironment15
arcpy.env.snapRaster = tempEnvironment16
arcpy.env.projectCompare = tempEnvironment17
arcpy.env.cartographicCoordinateSystem = tempEnvironment18
arcpy.env.configKeyword = tempEnvironment19
arcpy.env.outputZFlag = tempEnvironment20
arcpy.env.qualifiedFieldNames = tempEnvironment21
arcpy.env.tileSize = tempEnvironment22
arcpy.env.parallelProcessingFactor = tempEnvironment23
arcpy.env.pyramid = tempEnvironment24
arcpy.env.referenceScale = tempEnvironment25
arcpy.env.extent = tempEnvironment26
arcpy.env.XYTolerance = tempEnvironment27
arcpy.env.tinSaveVersion = tempEnvironment28
arcpy.env.nodata = tempEnvironment29
arcpy.env.MDomain = tempEnvironment30
arcpy.env.spatialGrid1 = tempEnvironment31
arcpy.env.cellSize = tempEnvironment32
arcpy.env.outputZValue = tempEnvironment33
arcpy.env.outputMFlag = tempEnvironment34
arcpy.env.geographicTransformations = tempEnvironment35
arcpy.env.spatialGrid2 = tempEnvironment36
arcpy.env.ZResolution = tempEnvironment37
arcpy.env.mask = tempEnvironment38
arcpy.env.spatialGrid3 = tempEnvironment39
arcpy.env.maintainSpatialIndex = tempEnvironment40
arcpy.env.workspace = tempEnvironment41
arcpy.env.MResolution = tempEnvironment42
arcpy.env.derivedPrecision = tempEnvironment43
arcpy.env.ZTolerance = tempEnvironment44
```

Appendix B: Python Model Graphic



Appendix C: Server Data Maintenance Code

- **NOAA Download 72 Hour** – Code used to fetch current 72 hour forecast data

Set the directory
cd C:\wget_Data_3
##Execute Wget to download weather data for Pacific Northwest Region.
wget http://weather.noaa.gov/pub/SL.us008001/ST.opnl/DF.gr2/DC.ndfd/AR.pacnwest/

- **NOAA Download 15 day** – Code used to fetch antecedent 15 day forecast

Set the directory
cd C:\wget_Data_15
##Execute Wget to download weather data for Pacific Northwest Region.
wget http://weather.noaa.gov/pub/SL.us008001/ST.opnl/DF.gr2/DC.ndfd/AR.pacnwest /VP.001-003/ds.qpf.bin

- **Deletion Script 72hour** – Code used to clean up server's old data files

Set the directory
cd C:\wget_Data_3
delete all data in the directory file with .bin or .txt file extensions.
del "C:\wget_Data*.BIN"
del "C:\wget_Data*.TXT"

- **Deletion Script 15day** – Code used to clean up server's old data files

Set the directory
cd C:\wget_Data_15
delete all files in the wget_Data_15 directory that are 16 days or older.
C:\wget_Data_15 forfiles /m *.BIN /c "cmd /c Del *.BIN " /d -16
C:\wget_Data_15 forfiles /m *.TXT /c "cmd /c Del *.TXT " /d -16

- **DEGRIB Convert Script –** Used to convert the binary data downloaded through Wget into a usable ESRI Shapefile

Set the directory
cd C:\wget_Data_3
execute degrib to select the .bin files and convert them to small polygon shapefiles
/degrib/bin/degrib "*.BIN" -C -msg 1 -Shp -poly small
Change the directory to wget_Data_15
cd C:\wget_Data_15
execute degrib to select the .bin files and convert them to small polygon shapefiles
/degrib/bin/degrib "*.BIN" -C -msg 1 -Shp -poly small