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Geology Honors Thesis

Precipitation Intensity Required for Landslide Initiation in Rwanda

Submitted to

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By

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Abstract

Rwanda has a high density of landslides, heavy precipitation events and a shortage of resources to study them, making it an excellent candidate for study using satellite-based remote sensing data. To assess landslide hazards countrywide, I first built a landslide inventory of 254 landslides and used a statistical methodology. Using logistic regression on 24 test variables, I determined that slope and population density are statistically most relevant to landslide occurrence in Rwanda. A preliminary predictive hazard map for Rwanda was produced, with an overall predictive accuracy of 79.6%. Second, I worked to define a relationship between precipitation intensity and landslide density for a landslide-prone study area in western Rwanda. In the 1180 km² study area, I mapped 577 landslides, using CNES/Astrium and WorldView satellite imagery in Google Earth over a study period of 2000 to 2015. One 400 km² part of the study area has a high landslide density of 1.4 landslides/km², while another 780 km² part with identical geology, soils, land-use, and vegetation has a much lower landslide density. To identify possible triggering events for these landslides, I analyzed a 16 year record of TRMM (Tropical Rainfall Measuring Mission) satellite precipitation data. The high landslide density region and the low landslide density region were not notably different in rainfall, as quantified by recurrence interval analysis. A relationship between precipitation and landslide density could therefore not be developed, and the null hypothesis cannot be ruled out. This apparent lack of connection could result from a variety of factors including TRMM grid size, satellite imagery temporal resolution, antecedent soil moisture, or vegetation regrowth rates.

Approval

Dr. Adam Booth, Thesis Advisor

Date

Dr. Martin J. Streck, Department Chair

Date

1 Introduction

Landslides in the United States cause more than \$1 billion in damages and 50 deaths per year (USGS 2014). Globally, figures are much more grave- between 2004 and 2010, 32,322 fatalities from landslides were recorded (Petley 2012). Monitoring, mapping and forecasting of these hazards are less than adequate in many parts of the world. In this study, “landslide” is a general term used for a variety of types of mass movement, including rock and soil falls, topples, slides, and flows. Landslides have a distinctive appearance when viewed from satellite or aerial photographs- the land is deformed and shows evidence of slippage. There is often a clear shape of a head scarp, hummocky slide, and a bulging toe (Ritter et al. 2011). Recent slides are visible as patches of bare earth, where land cover has been disrupted.

Landslide hazards lead to more economic losses and casualties than commonly recognized, due in part to casualties from slope failure being higher in developing nations (Guzetti et al. 1999). Research into rainfall induced landslides is often highly localized and relies on in situ rain gages. Methods based on high resolution spatial and temporal data and adequate ground data do not scale well to regional assessment (Kirschbaum 2009). Rapidly evaluating slope stability in response to storms, over a regional or larger scale is invaluable in a developing nation like Rwanda. Remotely sensed surface and atmospheric data provides an opportunity to assess landslide hazard at a regional scale (Kirschbaum 2012).

1.1 Rwanda

Rwanda is a 26,338 km² country located in eastern Africa (Figure 1) with a population of approximately 11 million (CIA 2015, NISR 2014). This is the highest population density in mainland Africa (UNEP 2011). Seventy-five percent of the population of Rwanda earns a living from farming, mostly subsistence, and the landscape is ninety percent anthropogenic (eSoko

2015). Rwanda has a nickname of “land of a thousand hills”, and the country’s steep slopes are prone to landslides (UNEP 2011).

Figure 1. The country of Rwanda. Rwanda is 26,338 km², about the size of the state of Vermont. It is located in Eastern Africa and has a population of approximately 11 million people

1.2 Causes of landslides

Material on a hillslope will remain stable as long as the shear stress does not exceed the shear strength of the slope materials (Ritter et al. 2011). When water fully saturates the soil, it pushes the sediment particles apart, which reduces the effective normal stress, and thereby decreases the frictional shear strength, leading to a possible failure surface (Terzaghi 1950). Studies have shown that an increase in pore pressure will initiate or increase the speed of a landslide, and a decrease in pore pressure will slow or stop a landslide (Iverson 2005). Even small differences in soil porosity influence landslide initiation and landslide rates (Iverson et al. 2000; Montgomery et al. 2002). Slope stability analysis is complex and involves many factors, but water plays a key role.

In Rwanda, landslides are often associated with heavy precipitation events and flash floods. Conversely, landslides can cause flood events when the flow of a river is blocked temporarily by a landslide. When this natural dam collapses, large volumes of water can be released without warning, presenting a threat to settlements, people, and agriculture in the valleys (UNEP 2011).

1.3 Precipitation

In Rwanda there are two rainy seasons and two dry seasons: one long rainy season in February–May representing 48 percent of annual rainfall, one long dry season from June to mid-September, a second rainy season in September–December representing 30 percent of annual rainfall, and a second short dry season in January–February, representing 22 percent of annual rainfall (UNEP 2011) (Figure 2). Rwanda receives an average of 1,200 mm of precipitation annually, but the annual average ranges from 2,000 mm in the west and north-western highlands to 600 mm in the eastern savannah (UNEP 2011). Available data suggests Rwanda experiences irregular and unpredictable rainfall patterns. Erratic rainfall data is observed in Kigali, one of the few locations where continuous rainfall data is measured. In seasons where excessive rainfall events are observed, they are not evenly spread throughout the season- instead, heavy rain typically falls in less than 3 days, sometimes over just one day (UNEP 2011). Landslides in Rwanda are often associated with heavy precipitation events and flash floods.

Figure 2. One year of TRMM data for Rwanda. This year shows the annual pattern of high rainfall in February through May, dry in June to mid-September, briefly rainy again, then dry in January and February.

In the most thoroughly documented instance, extreme precipitation (over 140 mm in 3 days) in Ruhengeri prefecture resulted in catastrophic debris avalanches, torrents, and earthflows 24 hours later (Byers 1992). This study describes 3 days of heavy rain, a small (4.5 magnitude, located 150 km north in Uganda) earthquake, and then 24 hours later, on a day with low rainfall (1.6 mm), landsliding and debris flows began. The following day, there was heavy rain again, leading to continuing debris flows. It is possible that the earthquake had an adverse effect on slope stability, however, witnesses stated that the landslide activity actually began 24 hours after the small quake. Based on the available data, the landslide event appears to be directly related to soil moisture and infiltration capacity (Byers 1992).

1.4 Storm Events

Relative magnitude of a precipitation event can be quantified by calculating a recurrence interval. This is a statistical calculation of the probability that an event will be equaled or exceeded in any given year. For example, recurrence intervals are commonly used in flood hazard analysis in referring to a “100 year flood plain” or a “100-year storm”. This means that there is a 1 in 100 chance that a “100-year storm” will be equaled or exceeded in any given year.

1.5 Determining Landslide Hazard

There are many methods to assess landslide hazards, but van Westen et al. (2006), Dai et al. (2002) and others categorize these methods into four general approaches: inventory, heuristic, statistical, and deterministic. A landslide inventory is critical to investigations of where and when landslides have occurred (Kirschbaum et al. 2015). An inventory is often the first step for many of the other landslide susceptibility mapping methodologies (Dai et al. 2002). A heuristic approach uses expert opinions to estimate landslide hazard based on variables. This method may be remote, or based on direct, in-the-field observations (Metternicht et al. 2005). Weighting of variables may be subjective in this method (Dai et al. 2002). A statistical model generally takes the form of bivariate or multivariate statistical analyses of landscape characteristics that have been present in areas where landslides occurred (Metternicht et al. 2005). Statistical analysis estimates future landslide hazard for areas currently free of landslides but with similar conditions to areas with landslides (Dai et al. 2002). This method is used remotely, and requires the collection of large amounts of data. It is considered to be most suitable for landslide hazard prediction at a medium scale (1:25,000 – 1:50,000) (Metternicht et al. 2005). A deterministic approach is based on slope stability analysis, and therefore is best used in small areas, when conditions are fairly uniform across the study area, and the landslide types are known and easy to analyze (Dai et al. 2002). These models often provide the most detailed results, but the data requirements can be prohibitive (Dai et al. 2002).

It is also important to differentiate between “risk” and “hazard”. Varnes (1984) defines risk as “the expected number of lives lost, persons injured, damage to property and disruption of economic activity due to a particular damaging phenomenon for a given area and reference period”. Risk is highly specific, and only practical to assess on a small scale. Hazard, one

component of risk, is something to be determined on a larger scale (van Westen 2006).

Therefore, this study focused on identifying landslide hazard, not landslide risk.

The global landslide catalog, produced by Kirschbaum et al., (2015), only contains four landslides for the entire country of Rwanda, but a cursory review of Google Earth imagery shows that there are numerous undocumented landslides.

In this thesis I will lay out a methodology for determining study areas and building a landslide inventory. I will describe the statistical methods used to determine which variables are statistically most relevant to landslide hazard in Rwanda, and the satellite data products used for remote sensing. I provide a preliminary hazard map for landslides in Rwanda and an accuracy assessment. I will then investigate the relationship between precipitation and landslide initiation in a specific region of Rwanda with abundant recent landslides, and discuss the implications of my results.

2 Study Areas

2.1 General Rwanda Landslide Study

The Area of Interest (AOI) selected was the entire country of Rwanda, plus some of Southern Uganda, to capture landslides close to the border of both countries.

2.2 Focused Landslide Study

To isolate the effects of precipitation on landslides in Rwanda, this study looks at a smaller region of the country. I am looking at two defined locations, one with a high density of landslides, and one with a low density of landslides. Other factors that affect landsliding, such as slope, soil properties, bedrock geology, etc. are relatively constant across these two locations, but precipitation varies. This serves as a natural experiment, and I hypothesized that precipitation

was the most important variable that could vary between the two sites. Focusing on a specific region of Rwanda allows for analysis of landslides and precipitation.

The first characteristic I used to identify potential study areas was a high density of landslides. Using the landslide inventory of Rwanda generated in the General Landslide Study, I identified several high density areas. Ideally the area would also have a minimum of two satellite images available within one year, to allow landslides to be dated to the nearest year.

Now that this general region was identified, the AOI needed to be limited to a geologic unit and a soil unit. The soil type and lithology for the majority of high landslide density areas were Umbric Acrisol and metasedimentary, respectively. I produced a map of all areas with this same soil and lithology type to identify an overlap (Figure 3). I further limited the location by considering land cover (Figure 4). The dominant land covers in the region of overlapping soil type and lithology are cropland, grassland, and forest, and I limited landslide mapping to cropland and grassland. Based on these criteria I selected a 400 km² high landslide density study region, along with a 780 km² (one TRMM grid square) low landslide density area (Figure 5).

Rwanda: Umbric Acrisol and Metasedimentary Lithology

Figure 3. Map of Umbric Acrisol soils (gray striped area) and Metasedimentary lithology (blue shading) in Rwanda. Red points are areas of high landslide density identified in the General Rwanda Study. This figure demonstrates that most high density areas occur where this soil and lithology type coincide.

Rwanda: Landcover

Figure 4. Map of landcover types in Rwanda. Points represent areas of high landslide density that are possible sites for study.

The gray shaded area represents all areas where Umbric Acrisol and metasedimentary lithology overlap (from Figure 3).

Landcover types found within this shaded area are grassland, cropland, and forestland. The high landslide density study area was selected from this image.

Figure 5. Overview map of the Focused Study area. Colored squares each represent a 0.25 x 0.25 degree TRMM pixel and the central gridded area shows the study area with landslide polygons in red. The black outlined box shows the low landslide density area.

3 Methods

3.1 Remote Sensing Products

Remote sensing data is invaluable in a developing nation that faces challenges in tracking, cataloging, and predicting the numerous landslides that occur each year. This is not unique to Rwanda- SERVIR (a joint development initiative of the National Aeronautics and

Space Administration (NASA) and the United States Agency for International Development (USAID)) has completed a similar inventory and statistical analysis of landslides in El Salvador, as well as GIS (Global Information System) based hazard mapping in many other regions globally (SERVIR 2015). Remote sensing data makes it possible to study landslides in areas that are costly or otherwise inaccessible, as well as cover large areas.

3.1.1 Tropical Rainfall Measuring Mission (TRMM)

The remote sensing satellite TRMM launched in late November 1997, and gathered near-real-time precipitation estimates until April 15, 2015 (GSFC 2016). This mission was flown by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) to improve our quantitative knowledge of the 3D distribution of precipitation in the tropics. The satellite had a passive microwave radiometer, a precipitation radar, and a visible-infrared scanner, among other instruments (GSFC 2016). The product used for this analysis is 3B42 V7 (Daily TRMM and Others Rainfall Estimate). This product has a daily temporal resolution, and is provided on a global $0.25^{\circ} \times 0.25^{\circ}$ grid over the latitude band 50° N-S (GSFC 2016). Data is available from January 1, 1998 – May 2, 2015.

3.1.2 Digital Elevation Model

Digital elevation models (DEMs) used in this study are constructed using elevation data from stereo aerial photos, digitized contour maps, or global positioning systems (GPS). The NASA Shuttle Radar Topography Mission (SRTM) datasets result from a collaboration between NASA, the National Geospatial Intelligence Agency (NGA), and the German and Italian space agencies. The SRTM instrument was a specially modified radar system that gathered global elevation data over 11 days in 2000. The original SRTM DEM has a spatial resolution of 90 meters (3 arc second), and recently 30 meter (1 arc second) data has been made available

(LPDAAC 2014). Datasets were generated from Shuttle Radar Topography Mission (SRTM) 1-Arc second Digital Elevation Models (DEM). The source for the 90 m DEM is CGIAR, and the 30 m DEM was collected from LPDAAC.

3.1.3 High-resolution satellite imagery

Google Earth, as an aggregator of images, was the source for images used to build the landslide catalog for the General Study and the Focused Study. In the study areas, Google Earth provides CNES/Astrium and WorldView satellite imagery.

3.2 Mapping

When viewed from satellite images, landslides are visible as regions of bare earth with a rough and hummocky texture. As seen in Figure 6, the color usually contrasts with surrounding vegetation or cultivated land. The slide has a “natural” shape, as opposed to a more rectangular region of land cleared for farming or construction. Human intervention in mapping is important, otherwise farms, mining operations, and even flocks of sheep can be inadvertently identified as landslides.

Figure 6. Examples of two recent landslides in the study area shown in WorldView/Google Earth satellite imagery. The color of the bare earth and the texture of the landslide scar stands out in contrast to the surrounding farmland or other ground cover.

3.2.1 General Study Mapping

The first step in a statistical approach to estimating relative landslide hazard is gathering enough points representing landslide locations to produce a meaningful analysis. First, existing catalogs were consulted. Feldman and Byxbe (2014) produced a catalog for Rwanda and Uganda using an automated process to identify environmental and spectral characteristics indicative of landslides. Fifty-two points from this catalog were included in this study. The Global Landslide Catalog (GLC) was consulted next. The GLC methodology is to compile information from newspaper reports, published articles, aerial photographs, and other sources (Kirschbaum et al. 2015). The catalog contains 5741 points, but only 4 points in Rwanda. Additionally, GLC landslides can be cataloged as a point with a several kilometer radius of accuracy based on a news report rather than a visual sighting. Because of this methodology, these points were not usable in this study as they couldn't be matched to an exact point on a satellite image.

The inventory of landslides for Rwanda was built using visual interpretation of high resolution remote sensing images from 2000–2015. 2000 was chosen as the start year because at the time of this study, Google Earth contained no images for Rwanda before that date. As the spectral characteristics of landslides can be similar to other objects, like exposed rocks, roads, and settlements, a visual interpretation method is preferable to a fully automated information extraction method (Xu 2015). Of the 254 total points, the remaining 202 were selected this way (Ballard, 2015).

For logistic regression purposes (section 3.3.2) I generated not-landslide points within the AOI, semi-randomly. Based on the work of Dai et al. (2003) and Koutsias et al. (1998), the sampling size for this set was approximately the same as the landslide points set. I produced

these points by importing the Google Earth kml file for the landslide inventory into ArcMap, building a 2km buffer around each landslide point, and erasing study area contained in that buffer layer. Using the tool “Create Random Points” I created points over the remaining area of the AOI. These points then had to be imported into Google Earth and visually inspected; I discarded any points located within landslides, bodies of water, and cloudy or otherwise obscured areas. The first 253 of the remaining not-landslide points were retained.

3.2.2 Focused Study Mapping

For this study, I mapped all landslides that could be recognized at an eye altitude of approximately 1830 meters from the currently available satellite images, starting from my existing landslide inventory of Rwanda and adding additional points by locating patches of exposed soil in landslide scars and runout tracks (Figure 6). Similar to the General Study (Section 3.2.1) I built this inventory using visual interpretation of high resolution remote sensing images. To ensure no regions of the study area were overlooked, I used a grid overlay on the study area. I outlined each landslide with a polygon so that the area could be calculated (Figure 7) (see section 4.2 below).

Figure 7. Example of polygons marking landslides in Google Earth. Each area identified as a landslide scar is outlined with a polygon to approximate the shape and area covered by the slide. Largest landslide is about 181 meters across, and 170 meters top to bottom

3.3 Analysis

3.3.1 General Study

I completed a general study of landslide hazards in Rwanda in August 2015, with the assistance of SERVIR, a joint development initiative of the National Aeronautics and Space Administration (NASA) and the United States Agency for International Development (USAID). This study focused on the development of a landslide inventory and a statistical methodology for assessing landslide hazards. Using logistic regression on 23 test variables (Table 1) and a sample of over 254 landslides, I determined which variables were statistically most relevant to landslide occurrence in Rwanda.

I derived thirteen of the variables from SRTM (Shuttle Radar Topography Mission-generated DEMs (Digital Elevation Models) and tested them at both 30 meter and 90-meter resolution. The source for the 90 meter DEM is CGIAR, and the 30 meter DEM was collected from LPDAAC. As most previous research would have been completed with a 90 meter DEM,

both 30 meter and 90 meter were used in this study to see if 30 meter data universally provided a superior regression result. Potentially influential variable ideas were drawn from the literature review, including Dai and Lee (2002), Dai et al. (2002), van Westen (2006), and Anderson (2012). All datasets were projected to WGS84 UTM35S.

The remaining 10 variables were collected from sources such as the Regional Centre for Mapping of Resources for Development (RCMRD), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), the Consultative Group for International Agricultural Research (CGIAR), and the Rwandan government. All datasets were projected to WGS84 UTM35S (Ballard 2015).

3.3.2 Logistic regression

Logistic regression is useful for finding the relationship between a list of independent variables and a binary dependent variable (Dai and Lee 2002). In this case the dependent variable is presence of a landslide (0 = no, 1 = yes) and the independent variables are the variables selected and researched for each landslide point (Table 1). A Logistic Regression method pairs well with a geospatial (GIS) methodology. A statistical method, combined with landslide inventory maps, may provide the best risk assessment for the available input data over larger areas (van Westen 2006).

The logistic regression test will show which variable is the most significant for predicting landslides in Rwanda. A statistical approach is based on the assumption that landslides are likely to occur under the same conditions as those which the occurred in the recent past (vanWesten et al. 2006).

The general form of a logistic regression equation is

$$Y = Ax_1 + Bx_2 + Cx_3 + \cdots Zx_n , \quad (1)$$

where $x_1, x_2, x_3, \dots, x_n$ are the collected variable values for each landslide, and A, B, C ... Z are the coefficients calculated for all landslide points.

Table 1. Twenty-Three variables used for Logistic Regression.

30 year rainfall	Land Cover
Aspect*	Lithology
Curvature(overall)*	Population Density
Curvature (plan)*	Slope*
Curvature(profile)*	Soil Moisture
Distance from Populated Area	Soil Type
Distance to Fault	Sediment Power Index*
Distance to Road	Sediment Transport Index*
Drainage Density*	Surface Roughness*
Earthquake Hazard (PGA)	Topographic Wetness Index*
Elevation*	Vertical Distance to Drainage*
Horizontal Distance to Drainage*	

*Note: Thirteen variables with * are SRTM DEM derived and were tested at both 30 meter and 90 meter resolution.*

I collected values for each variable for each landslide point using Multi Values to Points and Spatial Join tools in ArcMap. Values were compiled in Excel, then imported into the statistics program for logistic regression testing.

The logistic regression calculations were produced using the statistics program MYSTAT, a student version of SYSTAT. This program was chosen for its graphical user interface and low cost (free). First, a correlation check is performed. A “Pearson’s product moment correlation coefficient” method was used. Correlation is calculated by dividing the covariance of two variables by the product of their standard deviations (SYSTAT 2007). Any variables with correlations of 0.5 or higher are not run in combination with each other.

Using MYSTAT, I tested all variables, one at a time. A binary dependent variable called “Landslide”, with a value of 0 for no landslide and 1 for yes, landslide, was tested along with a constant and each of the 23 independent variables. This compares the performance, and informs future decisions of which variables to pair. Next, variables are run in pairs of two. Again, a binary dependent variable is set equal to the constant and independent variables, and coefficients are calculated. The metrics I used to measure statistical significance are Akaike Information Criterion (AIC), p-value, McFadden’s Rho-squared, and Area under the Receiver Operating Characteristic (ROC Curve). McFadden’s Rho-squared was used as the main indicator of quality, and remaining metrics were used to break any “ties”.

The coefficients for the variables with the best statistical significance were inserted into Equation 1 to produce the model for landslide hazard. Coefficients represent the change in logit of each unit change in predictor (SYSTAT 2007).

I produced a hazard map using the coefficients for the variables selected from the Logistic Regression. The layers for the variables selected as “best” (highest McFadden’s Rho-squared) were opened in ArcMap, and converted to raster files. I used the tool “Raster Calculator” to build a new layer using the model found in the logistic regression. In order to create a map with values for each pixel ranging from 0 to 1, the values must be normalized, using the equation

$$\frac{e^{[logistic\ regression\ model]}}{1+e^{[logistic\ regression\ model]}} \quad (2)$$

This transformation is more thoroughly described by Peng et al (2002) in Anderson (2012). A pixel value of 0 means low hazard, and 1 means very high hazard. “Low” “Medium” and “High” categories were assigned evenly to resulting values.

3.3.3 Accuracy Test

A logistic regression model is of little use without a metric for its accuracy. To this end, thirty percent of all points, landslide and not-landslide, were selected randomly and withheld from the logistic regression tests. This set is the “reference set”. These points were not used in the logistic regression test; instead I used them to assess the accuracy of the model built using the remaining 70%- the “response set”. The 152 points in the reference set and the hazard map were opened in ArcMap, and the “Extract Values to Points” tool was used to check the calculated hazard value for each point. Values of 0.5 and greater were considered to be landslides, and values less than 0.5 were considered to be non-landslides.

3.3.4 Focused Landslide Study

I downloaded TRMM precipitation data from REVERB for all dates available (1/1/1998–5/2/2015). TRMM data is provided as binary files containing data from 50 N to 50 S latitude. I developed a MATLAB script to interpret the TRMM files and pull out specifically the data for my study area (Appendix). Since the high landslide density area spans 4 different TRMM grid squares, I pulled data for each pixel and combined it using a weighted average (Figure 5). I designed the script to combine the thousands of individual daily files into one array, calculated the recurrence interval and exceedance probability of storms with a given total precipitation amount, and generated time series and recurrence interval plots.

To produce a recurrence interval, each precipitation value must be given a rank, in order from largest to smallest. If n represents the number of measurements, the formula is

$$recurrence\ interval = 100 * \frac{rank}{n+1} . \quad (3)$$

The formula for exceedance probability is

$$exceedance\ probability = \frac{n+1}{rank} . \quad (4)$$

The nearby TRMM grid square with a low density of landslides, but otherwise similar to the main study area was identified for comparison. I ran the script to generate time series and storm recurrence interval plots for this region as well. ArcGIS was used to calculate area of each slide, and total landslide density for the study area.

4 Results and Discussion

4.1 General Study Results

The pair of variables that significantly predicted locations of slope failures was slope (calculated with a 30-meter resolution SRTM DEM) and population density (2002). In general, the 30 meter DEM variables consistently performed better than the 90 meter DEM variables. The slope and population density pair have a McFadden's R^2 of 0.388. McFadden's R^2 ranges from 0 to 1, with a higher value indicating more significant results. A McFadden's R^2 value between 0.2 and 0.4 is very satisfactory (SYSTAT 2007). The logistic regression equation found for these two variables was

$$Y = -4.639061 + (10.030704 * Slope30) + (0.003977 * PopDen). \quad (5)$$

I used the “reference set” of points to assess the accuracy of the model built using the “response set”. There were more false positives than false negatives, which means most error is on the side of over-predicting landslides. The overall accuracy, determined by cross-validation, was 79.6% (Table 2).

		Predicted		Total	Correctly Classified
		Yes	No		
Observed	Yes	67	12	79	84.8%
	No	19	54	73	74.0%
Total		86	66	152	
Overall					79.6%

Table 2. Accuracy assessment for hazard map built using slope and population density (Piller 2015). Values in table are the total number of landslides in each category.

I produced a preliminary predictive hazard map for Rwanda using equation (5) (Figure 8). Although population is represented in the hazard map, this does not become an assessment of risk to population or property. Population density is included in the map because it was a significant result in the logistic regression, which suggests that some aspect of human presence is related to landslide occurrence in Rwanda. The map shows a high hazard in the area surrounding Kigali, which is the area that has the highest population density in Rwanda. The western part of the country that shows a high hazard is near the Albertine rift of the Great Rift Valley.

Figure 8. Landslide Hazard Map for Rwanda, based on slope and population density (Piller 2015).

4.1.2 General Study Discussion

This hazard map, in the context of Rwanda's topography, seems reasonable. The areas marked as a very high hazard are in fact on steep hillsides or mountain tops. The larger green areas are flat plateaus. With a flat enough slope, sediment transport is minimal and can't really be considered a "landslide". It is not unexpected that slope would be found as a crucial variable in landslide prediction.

Human impact is significant, and also not entirely unexpected, as 90% of the country's landscape is anthropogenic. Much of this is farming, but small-scale mining is also impacting the environment through river bank ripping and landslides (Dusková 2014).

One large high hazard area is found in the area of Kigali, the capital city of Rwanda. The city has a high population, and it is difficult to observe landslides as they are quickly cleaned up, but large numbers of landslides are reported in this area, so it is reasonable to see this area marked as a high hazard.

There is a difference in data granularity between the two variables used to produce this hazard map (Figure 9). Population density was calculated per district, a relatively large political unit. Data is available to calculate this variable by smaller units, called cells, but it is unclear if this would lead to any change in accuracy of the hazard map without analyzing the calculated coefficients provided by the logistic regression tests. Slope is at a 30 meter resolution, which is still much higher than population density, but using population cells will improve the overall granularity of the hazard map.

Figure 9. Granularity Differences between Slope 30 meter (left) and Population Density 30 meter (right)

Another spatial imprecision in this study may exist between the landslide points created in Google Earth and their respective locations on the DEM layers. Although all layers were projected to the same coordinate system, no analysis was performed to check the accuracy of

locations. If possible, a coregistration process to ensure the layers were aligned would have helped. Another method to avoid error would be to use a 3 square sampling method when collecting the DEM-derived variable data- where the neighboring pixels around each landslide point are also sampled and averaged into the final value.

A solution to this would be crowd-sourcing the data collection. If a landslide reporting phone app or call-in number was made available to the public, GPS locations and times of landslides could be collected as they are observed. Another way to achieve this could be scraping social media, like Twitter, for references to landslides in Rwanda.

A statistical methodology does have some unique limitations. There is a tendency to simplify the factors of landslides, by only choosing variables that can be relatively easily mapped or derived from a DEM (van Westen 2006). In this study, 50+ variables were initially considered, but that list was narrowed due to keep the project within time constraints. Variables removed were duplicates by different names, variables that may have an unclear link to landslides, and variables that would be difficult to acquire or calculate data for. This leads to some bias in variable selection.

Another limitation is assuming that all landslides occur under the same combination of conditions throughout the study area (van Westen 2006). This is a tradeoff between doing a time consuming but highly specific set of studies and providing an estimate for a larger region. In this study, this limitation is offset by the relatively small area of Rwanda. Any detrimental error is checked for in the accuracy assessment step.

Lastly, precipitation is an important variable, but not appropriately addressed in this general study. Therefore, this was examined in the more focused landslide study.

4.2 Focused Study Discussion

TRMM data for 16 years plotted as a time series indicated a yearly pattern of intense precipitation events (Figure 11). Precipitation ranged from zero up to a maximum of approximately 68 mm/day in 2010 in the low landslide density part of the study area. The time series clearly show the seasonal pattern of rainfall with two broad rainy periods each year separated by periods of no or low precipitation (Figure 10). The time series for the low landslide density pixel has its five highest peaks in 2001, 2003, 2009, 2010, and 2012 (

Table 3).

Figure 10. Daily precipitation in Low Landslide Density study area- precipitation values in mm/day are shown for 16 years of available TRMM data. The maximum precipitation value was 68.08 mm/day (red dot-dashed line), and the mean was 3.37 mm/day (green dot-dashed line).

In the high landslide density part of the study area, the precipitation ranged from zero up to a maximum of approximately 56 mm/day in 2001 (Figure 11). The seasonal pattern of rainy and dry seasons can again be seen. The time series for the high landslide density area has its five largest peaks in 1999, 2001, 2007, 2010, and 2013 (

Table 3).

Figure 11. Daily precipitation in the High Landslide Density study area - precipitation values in mm/day are shown for 16 years of available TRMM data. The maximum precipitation value was 56.07 mm/day (red dot-dashed line), and the mean was 2.93 mm/day (green dot-dashed line).

Table 3. Top five precipitation values for high and low landslide density areas

High Landslide Density		
Date	Precipitation (mm/day)	Precipitation in Low Landslide Density Region on this day (mm/day)
4/21/1999	45.53	17.34
10/30/2001	56.07	12.85
9/15/2007	49.65	34.25
2/28/2010	50.91	68.08
4/2/2013	46.62	44.13

Low Landslide Density		
Date	Precipitation (mm/day)	Precipitation in High Landslide Density Region on this day (mm/day)
9/24/2001	61.54	13.04
2/8/2003	50.23	5.173
5/3/2009	45.21	7.58
2/28/2010	68.08	50.91
11/1/2012	63.12	41.05

The high landslide density region has precipitation peaks that don't match the peaks in the low landslide density region. The one peak they both have in common is 2/28/2010. To compare and see if there is a corresponding peak in landslide occurrence, I produced a plot of number of landslides per year (Figure 12). Landslides are classified by the year they were first observed in satellite imagery. This shows that the majority of landslides mapped occurred in 2014 or 2015, and a few in earlier years. There are large gaps in time where no landslides were mapped, and the peak precipitation dates in

Table 3 don't correlate to dates for landslides that were mapped. This is most likely because satellite imagery is not available for all years. Satellite data is not available for most of the years identified by TRMM as having a peak rainfall value.

Figure 12. Number of landslides mapped per year. Landslides are classified by the year they first appeared in satellite images. This means they occurred this year, or earlier. Years not shown either had no landslides, or no suitable satellite imagery available on Google Earth.

The areas of mapped landslides range from 1 to 317,900 m². I split the areas of landslides into bins of 1000 m² size, and plotted the distribution on a log-log scale (Figure 13). Landslide areas generally ranged from 0 to 3500 m², with several extremely large (>100,000 m²) slides. The data are approximately power-law distributed, which indicates that relatively rare but very large events may play an important role in setting the landslide erosion rate.

Figure 13. Distribution of Landslide Area in square meters. 577 mapped landslides in the high density area are split into 1000 m² bins and plotted. The majority of landslides mapped are between 0 and 3500 m² in area and the largest landslide mapped is 317,900 m². The few extremely large landslides leads to a long tail distribution.

In one more attempt to compare or contrast precipitation for the high density landslide area and the low landslide density area, I plotted precipitation versus recurrence interval for each region (Figure 14). The largest storm events for the high density and the low density regions occurred on different dates, and were a variety of sizes, but when the precipitation versus recurrence interval plots are shown on the same axis, it is clear that they are extremely similar. Despite the different dates for the storm events, the overall precipitation distribution is very similar for both the high density and low density regions.

Figure 14 Recurrence Interval vs. precipitation for low and high landslide density areas. Despite the fact that dates for storms were different, the overall precipitation pattern for the two regions is very similar.

4.3 Focused Study Discussion

The high landslide density region and the low landslide density region are not notably different in rainfall- overall, the time series for both regions look very similar. A relationship between precipitation and landslide density was not developed and the null hypothesis cannot be ruled out. This apparent lack of connection could result from several aspects of the available data and nature of the study area.

First, perhaps the grid size (0.25° by 0.25°) for the TRMM data is too large for this type of study, and relevant rainstorms are going “unseen” as they are smaller than the grid. This would assume that concentrated weather events that are more likely to trigger landslides are smaller than 0.25° by 0.25° (approximately 780 km^2 in the study area). This is also a problem that Turner et al. (2010) encountered in their study of landslide densities in Washington state. The TRMM data was not sufficiently accurate to capture rainfall amounts for the landslides they

studied. This could be addressed by finding a different source of rainfall data with a smaller spatial grid, designing and deploying a rain gage system, or by interpreting precipitation through other related variables, like type of groundcover or measuring soil moisture, which can be estimated remotely via NASA's Soil Moisture Active Passive (SMAP) mission. SMAP was not used for this study because the google earth images available covered (2006 – mid 2015) and SMAP data is only consistently available after November, 2015. Soil Moisture can also be approximated from surface temperature and vegetation index, which can in turn be sourced from satellite data (Holzman et al. 2014).

While the spatial grid for TRMM was larger than desired, the temporal resolution (daily) was excellent, much better than the satellite imagery currently available. In contrast to this, high resolution topographic data from techniques such as airborne LIDAR would be excellent spatially, but not sufficient temporally due to cost and logistical constraints.

Satellite imagery could also be affecting the results because the temporal resolution is approximately yearly to decadal. In this study area, there were no satellite images for the years in which peak rainfall occurred, so landslides triggered by those storms might not be visible in the more recent imagery. Most of the study area is in agricultural land, and landslide scars are often re-planted or otherwise obscured within a few years of the landslide. It is likely that landslides are being promptly cleaned up and vegetation quickly grows back over or is replanted in landslide areas. Some landslides will not show up on satellite imagery unless they were very recent. But not all landslides in Rwanda seem to act this way- some landslides continue to be visible in many years of satellite imagery.

Landslides mapped as occurring in 2014 or 2015 could have occurred in earlier years. This could be addressed by purchasing satellite imagery for specific years after analyzing the precipitation data for a study area.

Alternatively, an unconsidered factor could be more significant, such as antecedent soil moisture. This could be a reason why a landslide would not tie directly to a storm event, but instead lag after, or not be triggered until a second storm event.

A change in data quality, be it satellite imagery or mapping technique, could also be relevant. Some years of satellite imagery are very dark images, and some years are better resolution than others. A landslide is more likely to be spotted on a lighter image with higher contrast than a darker, low contrast image. Especially combined with questionable image quality, mapping bias can lead to a lower quality landslide inventory than field mapping, even when conducted by experts (Van Den Eeckhaut 2005).

5 Conclusions and Implications

Landslide hazard in Rwanda is largely dependent on the slope of the topography and anthropogenic factors. Considering only these two factors, landslide hazard can be predicted with about an 80% accuracy. Water plays a large role in landsliding in Rwanda, with high intensity precipitation events of 40-50 mm/day occurring annually. The specific mechanism of how water is triggering landslides is difficult to determine from freely available satellite imagery and precipitation data.

In general, the effects of landslides are more significant in Rwanda than they would be in another location, all other factors being the same. It is estimated that 90% of urban housing is met through “informal settlements”, cheap unplanned housing in inappropriate locations with steep slopes and poor drainage (UNEP 2011).

While a complete picture of precipitation for the country of Rwanda is not available, this focused study shows a relationship between storm size and widespread land sliding. Available data suggests Rwanda experiences irregular and unpredictable rainfall patterns. One predicted effect of climate change is an increase in the kind of extreme rainfall events that cause flooding and landslides (UNEP 2011). This means conditions will continue or worsen, and landslide hazard mapping and landslide prediction are more crucial now than ever.

There are processes in place to improve some of Rwanda's land management practices, including buffers on farming and building, moving populations from the most dangerous locations, and green practices. However, they are not well enforced, and it is a slow process to get these to a level where they make a difference. Environmental governance is strong, though, and good policies have been established- destructive flooding and landslides, droughts and food insecurity have not gone unnoticed. Decentralization of government has also allowed regional communities to have a larger voice in environmental governance (UNEP 2011)

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Appendix A: Landslide Inventory for Focused Study

Appendix B: Matlab Script

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
1	2015	539.125661	-2.028604	29.567261	
2	2015	236.92899	-2.028811	29.567405	
3	2015	7173.678658	-2.029197	29.567697	
4	2015	598.927618	-2.029278	29.566756	
5	2015	101.168661	-2.027119	29.567356	
6	2015	156.2059	-2.028641	29.566082	
7	2015	412.203142	-2.027925	29.566068	
8	2015	155.664567	-2.028482	29.565933	
9	2015	470.428732	-2.027105	29.566132	
10	2015	1239.082116	-2.024025	29.566251	
11	2015	752.180507	-2.022613	29.566691	
12	2015	260.168472	-2.023064	29.566895	
13	2015	82.050746	-2.023118	29.566462	
14	2015	7749.290889	-2.022528	29.565684	
15	2015	979.297688	-2.021347	29.565737	
16	2015	3491.979157	-2.021154	29.565272	
17	2015	127.354558	-2.026888	29.564455	
18	2015	370.341859	-2.026109	29.565204	
19	2015	98.547386	-2.025811	29.565282	
20	2015	958.141349	-2.025754	29.566156	
21	2015	366.064807	-2.026247	29.566239	
21	2015	150.628973	-2.025573	29.566594	
22	2015	145.933746	-2.025715	29.566726	
23	2015	3121.359719	-2.026215	29.56739	
24	2015	2404.261381	-2.025447	29.567275	
25	2015	241.29347	-2.025809	29.570409	
26	2014	402.296679	-2.020398	29.569499	and 2015
27	2014	4911.71597	-2.020845	29.569962	and 2015
28	2015	340.814179	-2.021666	29.570663	
29	2015	23955.18473	-2.015543	29.572446	
30	2015	3750.092038	-2.030634	29.567938	
31	2015	215.710425	-2.030657	29.566253	
32	2015	1905.490242	-2.005745	29.573828	
33	2015	334.369729	-1.995215	29.561609	
34	2015	503.641659	-1.994989	29.561811	
35	2015	49.288274	-1.995527	29.561254	
36	2015	138.56606	-2.042492	29.563964	
37	2015	807.248678	-2.02933	29.579075	
38	2015	150.756345	-2.023017	29.578714	
39	2015	163.136565	-2.023379	29.579396	
40	2015	588.108088	-2.01676	29.594005	
41	2015	3703.565082	-2.010219	29.586061	
42	2014	2994.984557	-2.000861	29.597718	
43	2014	5920.57838	-2.000724	29.599124	
44	2014	317859.5599	-1.998161	29.601806	
45	2014	187.609066	-1.995767	29.602294	
46	2014	374.711407	-1.995548	29.602255	
47	2014	1060.949284	-1.995023	29.602124	
48	2014	782.913619	-1.994352	29.601427	
49	2014	2081.693589	-1.994341	29.60095	
50	2014	1116.876015	-1.993782	29.60081	
51	2014	54.049036	-1.993518	29.600686	
52	2014	129.379695	-1.994046	29.600526	
53	2014	19745.47216	-1.994342	29.597824	
54	2014	11360.22353	-1.991121	29.59687	
55	2014	3557.685817	-1.993077	29.598021	
56	2014	1006.398639	-1.992961	29.599214	
57	2014	137.737199	-1.992778	29.599361	
58	2014	174.967966	-1.992548	29.599365	
59	2014	1679.961678	-1.992288	29.597825	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
60	2014	11153.2399	-1.988014	29.601006	
61	2014	258.999625	-1.989334	29.59919	
62	2014	206.334238	-1.988924	29.598896	
63	2014	398.5662	-1.986035	29.600249	
64	2014	837.156768	-1.985263	29.599853	
65	2014	2712.352529	-1.987575	29.604423	
66	2014	419.967901	-1.99309	29.60958	
67	2014	7038.60939	-1.985195	29.596043	
68	2014	4902.299026	-1.986652	29.596242	
69	2011	6382.690435	-1.986382	29.597854	and 2014
70	2014	3160.17886	-1.995753	29.606446	
71	2014	1079.084765	-2.017914	29.603753	
72	2014	222.529013	-2.016622	29.597572	
73	2015	882.139249	-2.024047	29.571281	
74	2015	849.17498	-2.012795	29.570846	
75	2015	364.002969	-2.011933	29.570538	
76	2014	6327.868677	-2.011736	29.585698	looks older
77	2014	242.409995	-2.043804	29.600785	
78	2014	1203.888111	-2.041811	29.597189	
79	2014	186.955279	-2.02385	29.615983	
80	2014	90.22386	-2.023442	29.631857	
81	2014	288.902814	-2.014284	29.624983	
82	2014	219.91366	-2.015525	29.615917	
83	2014	28.262073	-2.010895	29.631583	
84	2014	275.071084	-1.997739	29.628861	
85	2014	274.121166	-2.002926	29.628007	
86	2014	11372.40679	-1.978833	29.617738	
87	2014	1188.482634	-1.986394	29.631285	
88	2014	208.710596	-1.990926	29.623742	
89	2014	91.980959	-1.987616	29.579747	
90	2014	146.078996	-1.987051	29.580088	
91	2014	79.661488	-1.986736	29.579655	
92	2014	115.741526	-1.986621	29.579734	
93	2014	81.571111	-1.98645	29.57978	
94	2014	142.05696	-1.983741	29.590187	
95	2014	2646.215047	-1.980184	29.595329	
96	2014	410.084362	-1.975975	29.562988	
97	2015	955.593252	-1.976266	29.572052	
98	2015	921.003641	-1.97652	29.572191	
99	2015	339.437331	-1.979397	29.570507	
100	2015	61.290744	-1.987839	29.574214	
101	2015	481.844741	-1.988456	29.562708	
102	2015	60.047511	-1.948026	29.571985	
103	2015	671.503334	-1.945951	29.563657	
104	2015	483.186676	-1.986251	29.56182	
105	2015	289.396923	-1.986721	29.561509	
106	2015	405.810595	-1.957717	29.56801	
107	2015	230.726429	-1.981198	29.559253	
108	2015	366.79361	-1.98126	29.5594	
109	2014	686.402283	-2.020783	29.551611	
110	2014	593.272197	-2.020512	29.551856	
111	2014	83.764581	-2.020492	29.552039	
112	2014	33903.72826	-2.018671	29.550718	
113	2014	517.973992	-2.019297	29.55173	
114	2014	182.935514	-2.019177	29.551393	
115	2015	541.667011	-2.020133	29.550615	
116	2014	417.878769	-2.022123	29.54816	
117	2014	195.691399	-2.022016	29.547613	
118	2014	163.44081	-2.0279	29.55275	
119	2014	56.396134	-2.028366	29.550329	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
120	2014	69.421082	-2.02792	29.548657	
121	2015	55.959335	-2.028083	29.545502	
122	2014	8330.70205	-2.003462	29.551113	
123	2015	3001.350495	-2.002717	29.549532	
124	2015	5761.418147	-1.995628	29.543946	
125	2015	116.832083	-1.993027	29.555298	
126	2015	161.624913	-1.993237	29.554903	
127	2015	2008.649055	-1.989672	29.556741	
128	2015	133.796854	-1.985351	29.552441	
129	2015	279.366336	-1.990169	29.556005	
130	2015	1170.315411	-2.029867	29.55428	
131	2015	251.392124	-2.044639	29.546596	
132	2015	165.157855	-2.044705	29.546805	
133	2014	53.760219	-1.971352	29.603501	
134	2014	935.375833	-1.970043	29.602345	
135	2014	3418.383439	-1.973088	29.592634	
136	2014	302.245021	-1.969709	29.591746	
137	2014	1127.441854	-1.969826	29.584354	
138	2014	500.374535	-1.969039	29.584828	
139	2014	196.756307	-1.97023	29.583747	
140	2014	254.831315	-1.96897	29.58705	
141	2014	102.068382	-1.961704	29.589933	
142	2014	94.328078	-1.961785	29.589517	
143	2014	77.235774	-1.960148	29.58752	
144	2015	58.994851	-1.973214	29.573503	
145	2015	38.088711	-1.973013	29.573021	
146	2015	311.305763	-1.972987	29.572761	
146	2015	159.173148	-1.973601	29.573527	
147	2015	75.858663	-1.973473	29.572954	
148	2015	278.871881	-1.973071	29.574211	
149	2015	39.717911	-1.972997	29.574483	
150	2015	24.219851	-1.973964	29.574352	
151	2015	367.073588	-1.974176	29.560112	
152	2015	17556.65862	-1.970569	29.571383	
153	2015	2421.225191	-1.971306	29.571958	
154	2015	1116.691313	-1.969731	29.572507	
155	2015	535.684134	-1.961405	29.564043	
156	2015	1379.988312	-1.960294	29.559823	
157		3835.550238	-1.966124	29.563321	
158	2015	164.353425	-1.970446	29.577743	
159	2015	1103.687889	-1.965997	29.56153	
160	2015	416.12872	-1.965552	29.561771	
161	2014	106.31558	-1.965132	29.562204	
162	2014	55.332253	-1.965052	29.562269	
163	2015	140.477296	-1.97261	29.561389	
164	2011	464.6711	-1.968434	29.573069	
165	2015	3237.485948	-1.968694	29.572547	
166	2014	104.614529	-1.973731	29.576443	
167	2015	266.125595	-1.969981	29.558052	
168	2014	1063.445038	-1.95709	29.556319	
169	2015	380.510031	-1.960515	29.553468	
170	2015	3913.923582	-1.960605	29.549378	
171	2015	10853.81551	-1.959665	29.547435	
172	2015	345.17444	-1.966785	29.54486	
173	2014	318.261618	-1.972543	29.544234	
174	2014	202.295597	-1.96859	29.629105	
175	2014	517.040137	-1.961937	29.614611	
176	2014	3693.617387	-1.950651	29.629595	
177	2014	804.488433	-1.951992	29.630107	
178	2014	2643.375677	-1.94813	29.630305	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
179	2014	1118.563813	-1.947189	29.629646	
180	2014	424.218704	-1.945318	29.628429	
181	2014	1842.7764	-1.942029	29.629555	
182	2014	1022.794403	-1.943939	29.623732	
183	2014	2657.469544	-1.944103	29.623343	
184	2014	3181.018412	-1.939789	29.619363	
185	2014	331.333423	-1.952423	29.629762	
186	2014	34.578089	-1.950882	29.630771	
187	2014	7901.20508	-1.951228	29.631299	
188	2014	1461.951946	-1.948603	29.629795	
189	2014	1924.640936	-1.949052	29.629212	
190	2014	766.391059	-1.949368	29.629897	
191	2014	466.288782	-1.95009	29.629719	
192	2014	1538.396146	-1.947552	29.631556	
193	2014	652.634989	-1.951171	29.630044	
194	2014	21028.34379	-1.934442	29.619138	
195	2014	125525.4435	-1.931336	29.615723	
196	2014	15004.10663	-1.936787	29.615972	
197	2014	2228.512631	-1.937466	29.615378	
198	2014	425.642936	-1.931918	29.626058	
199	2014	380.518819	-1.930748	29.626451	
200	2014	14631.8474	-1.9231	29.61764	
201	2014	6598.713412	-1.927926	29.61345	
202	2014	3926.978541	-1.927181	29.624886	
203	2014	3045.763948	-1.930933	29.611428	
204	2014	23051.82421	-1.928799	29.611941	
205	2014	19984.17262	-1.928449	29.605938	
206	2014	511.326528	-1.92608	29.605865	
207	2014	5839.381044	-1.926893	29.605043	
208	2014	357.686759	-1.9276	29.60337	
209	2014	397.970054	-1.934871	29.601179	
210	2014	169.029695	-1.934751	29.601885	
211	2014	2433.254153	-1.929898	29.607507	
212	2014	125.508961	-1.939213	29.602976	
213	2014	189.46336	-1.946405	29.599424	
214	2014	333.904189	-1.949338	29.61025	
215	2014	345.351893	-1.948329	29.611715	
216	2014	1360.284355	-1.952226	29.591595	
217	2014	182.532463	-1.952554	29.592902	
218	2014	129.748988	-1.952071	29.593078	
219	2014	68.376285	-1.95348	29.594979	
220	2014	52.31525	-1.954334	29.594641	
221	2014	408.767932	-1.953513	29.58303	
222	2014	967.084138	-1.944887	29.580053	
223	2014	249.818388	-1.945	29.579721	
224	2014	287.728802	-1.94416	29.579256	
225	2015	244.184012	-1.948218	29.554231	
226	2015	148.241621	-1.948423	29.55486	
227	2015	278.531882	-1.948247	29.554592	
228	2015	254.427562	-1.949253	29.55396	
229	2015	104.358936	-1.950525	29.548874	
230	2015	248.714336	-1.94959	29.548698	
231	2015	206.972095	-1.941106	29.553324	
232	2015	117.504318	-1.94004	29.549636	
233	2015	285.230034	-1.954609	29.558323	
234	2014	165.762635	-1.921788	29.595688	
235	2014	118.251375	-1.92172	29.586809	
236	2014	1649.76438	-1.922256	29.581737	
237	2014	230.322939	-1.923687	29.588591	
238	2015	1785.415614	-1.926219	29.556624	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
239	2015	243.854758	-1.934618	29.550806	
240	2015	2257.907811	-1.926135	29.545565	
241	2014	499.160516	-1.927891	29.544089	
242	2015	551.937905	-1.952436	29.534598	
243	2015	258.406974	-1.945501	29.532606	
244	2015	205.043275	-1.94507	29.532587	
245	2015	182.13322	-1.941302	29.527643	
246	2015	170.735336	-1.941448	29.527199	
247	2015	524.150682	-1.943583	29.531268	
248	2015	782.811801	-1.943409	29.531906	
249	2015	473.523064	-1.958725	29.536872	
250	2006	939.678098	-1.967937	29.52956	
251	2015	342.923118	-1.987427	29.526731	
252	2015	1596.24338	-1.988968	29.524876	
253	2015	315.817866	-1.989449	29.52448	
254	2015	2800.993294	-1.990338	29.527267	
255	2014	1120.871876	-2.000898	29.524492	
256	2014	312.803742	-2.000767	29.52973	
257	2014	1305.665583	-2.00358	29.531188	
258	2014	2144.177686	-1.996912	29.516948	
259	2014	1109.364765	-1.995266	29.516117	
260	2014	1317.46621	-1.994995	29.515512	
261	2014	925.05476	-1.995231	29.514696	
262	2014	156.320653	-1.994945	29.514546	
263	2014	88.887598	-1.994709	29.514107	
264	2014	133.705865	-1.994554	29.513946	
265	2014	198.708423	-1.995111	29.519441	
266	2014	444.213186	-1.994776	29.519075	
267	2014	277.028711	-1.977531	29.506472	
268	2014	371.544646	-1.977497	29.507078	
269	2014	3248.663068	-1.978027	29.507219	
270	2014	156.307791	-1.978611	29.5077	
271	2014	108.757982	-1.977598	29.507411	
272	2014	371.635227	-1.977372	29.507421	
273	2014	226.740514	-1.982353	29.518871	
274	2014	486.01856	-1.982423	29.518186	
275	2015	158.592207	-1.981476	29.518222	
276	2015	292.822712	-1.981315	29.517969	
276	2014	298.855258	-1.987775	29.515794	
277	2014	782.09506	-1.987548	29.515358	
278	2006	1165.994316	-1.993158	29.515035	
279	2015	840.733078	-1.99255	29.514008	
280	2006	1614.474759	-1.992125	29.513653	
281	2014	1492.704673	-1.974994	29.514576	
282	2014	712.679054	-1.975226	29.512767	
283	2014	446.738436	-1.975388	29.512483	
284	2014	535.3022	-1.975174	29.51193	
285	2006	1354.308259	-1.974861	29.511847	
286	2014	1544.899104	-1.974948	29.509642	
287	2014	610.245315	-1.97407	29.508123	
288	2014	990.484549	-1.973644	29.509062	
289	2014	368.068548	-1.973511	29.509984	
290	2014	271.599729	-1.973971	29.509973	
291	2006	208.668999	-1.973198	29.50928	
292	2006	1625.122674	-1.972498	29.507918	
293	2014	174.852604	-1.956254	29.508804	
294	2014	38.194644	-1.956033	29.50873	
295	2015	201.360646	-1.956442	29.508848	
296	2014	1091.533215	-1.955917	29.522273	
297	2014	359.47004	-1.952527	29.523998	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
298	2014	807.775875	-1.951494	29.524747	
299	2015	284.340715	-1.950265	29.529878	
300	2015	593.272852	-1.950898	29.521911	
301	2015	688.134189	-1.946967	29.51573	
302	2014	4702.033219	-1.947106	29.518861	
303	2014	965.062276	-1.947995	29.521357	
304	2015	481.803568	-1.945251	29.519911	
305	2014	604.008676	-1.941024	29.516105	
306	2014	423.369136	-1.939286	29.513797	
307	2014	119.027206	-1.940154	29.513697	
308	2015	169.704348	-1.941981	29.513231	
309	2014	574.551038	-1.946019	29.511029	
310	2015	90.34752	-1.945423	29.508397	
311	2014	1138.659359	-1.950003	29.504973	
312	2014	170.153083	-1.941455	29.501659	
313	2014	95.03419	-1.940461	29.499585	
314	2014	112.660962	-1.940462	29.499779	
315	2015	282.843239	-1.954947	29.519042	
316	2014	137.145975	-1.954741	29.518534	
317	2014	55.808413	-1.954884	29.518239	
318	2015	40.496312	-1.953058	29.518955	
319	2015	114.876181	-1.95273	29.507441	
320	2015	396.037439	-1.944562	29.523158	
321	2015	1515.53947	-1.948938	29.524178	
322	2015	115.186639	-1.945647	29.521938	
323	2015	513.126371	-1.950646	29.512695	
324	2014	54.809759	-1.933638	29.506889	
325	2014	265.043407	-1.921982	29.506905	
326	2015	87.926748	-1.916229	29.517438	
327	2015	2898.859638	-1.903754	29.51096	
328	2014	1285.73258	-1.90955	29.53974	
329	2014	1108.283365	-1.910358	29.53303	
330	2014	844.492147	-1.909544	29.532766	
331	2014	108.906184	-1.908058	29.557454	
332	2014	50.499126	-1.908137	29.557502	
333	2015	421.77205	-1.915725	29.55803	
334	2014	2438.971643	-1.915908	29.543283	
335	2006	139.430865	-1.918637	29.548691	
336	2015	5847.317924	-1.907589	29.564386	
337	2014	1720.099349	-1.908447	29.58803	
338	2014	2079.347611	-1.910427	29.588064	
339	2014	2092.646166	-1.904094	29.589933	
340	2006	292.754561	-1.91211	29.598197	
341	2014	360.988139	-1.912462	29.597937	
342	2014	254.347327	-1.912699	29.597234	
343	2014	92.297222	-1.912723	29.597603	
344	2014	845.103275	-1.912696	29.598716	
345	2014	157.043368	-1.912357	29.597173	
346	2014	726.93186	-1.910533	29.605509	
347	2014	110.900706	-1.910124	29.606053	
348	2014	567.826694	-1.909363	29.610294	
349	2014	287.082633	-1.907321	29.608687	
350	2014	171.4943	-1.907184	29.608164	
351	2014	9358.722503	-1.909257	29.612437	
352	2014	248.39119	-1.916356	29.598951	
353	2014	711.939427	-1.919073	29.628087	
354	2014	127.289109	-1.918823	29.623906	
355	2014	215.484968	-1.915641	29.623776	
356	2014	1736.152369	-1.896607	29.629881	
357	2014	194.656492	-1.898529	29.630264	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
358	2014	891.831565	-1.892633	29.598267	
359	2014	427.670762	-1.89275	29.598507	
360	2014	322.265483	-1.893112	29.598922	
361	2014	877.70554	-1.899538	29.601901	
362	2014	724.505063	-1.892888	29.596084	
363	2014	349.621675	-1.900553	29.60551	
364	2014	2701.285797	-1.885494	29.585233	
365	2014	13157.98815	-1.890537	29.583749	
366	2014	7629.94107	-1.89398	29.581136	
367	2014	683.543256	-1.90116	29.593078	
368	2014	116.230487	-1.894832	29.568979	
369	2015	89.713512	-1.894417	29.559893	
370	2014	114.344333	-1.893437	29.529181	
371	2015	2317.848798	-1.888208	29.527387	
372	2014	538.903801	-1.887614	29.526041	
373	2015	174.845637	-1.898993	29.533606	
374	2014	359.903716	-1.900134	29.535062	
375	2015	122.40605	-1.902586	29.507592	
376	2015	215.643385	-1.902456	29.507244	
377	2015	165.635064	-1.902152	29.507169	
378	2015	106.241964	-1.897648	29.506474	
378	2015	1463.69568	-1.890978	29.512346	
379	2015	41.502687	-1.890949	29.512765	
380	2014	419.832423	-1.889626	29.515106	
381	2015	565.341566	-1.888801	29.518614	
382	2015	379.885579	-1.895552	29.510133	
383	2015	530.752764	-1.895781	29.510564	
384	2014	336.252382	-1.879166	29.535074	
385	2015	367.039425	-1.8728	29.542599	
386	2014	609.911775	-1.867297	29.584917	
387	2014	50.008089	-1.871566	29.586527	
388	2014	781.038305	-1.875169	29.613213	
389	2014	280.614571	-1.881065	29.607464	
390	2014	143.516204	-1.877284	29.603322	
391	2014	42.558231	-1.877137	29.602823	
392	2014	87.79735	-1.868861	29.596485	
393	2014	55.389816	-1.869143	29.596487	
394	2014	105.585181	-1.869419	29.596715	
395	2014	143.849072	-1.86909	29.596598	
396	2014	2566.356276	-1.872642	29.615269	
397	2015	820.336371	-1.990827	29.506219	
398	2015	1749.849445	-1.990139	29.503133	
399	2015	333.237376	-1.991414	29.502135	
400	2015	216.592556	-1.984983	29.494863	
401	2015	594.820668	-1.97723	29.506106	
402	2015	2951.542271	-1.971109	29.506674	
403	2014	207.367435	-1.957539	29.498376	
404	2014	238.831829	-1.957791	29.498656	
405	2014	147.572247	-1.966292	29.500551	
406	2014	200.794296	-1.966459	29.501024	
407	2014	121.893212	-1.966607	29.501248	
408	2014	193.591	-1.968292	29.502726	
409	2014	77.136877	-1.968058	29.502284	
410	2015	73.242702	-1.936347	29.496153	
411	2015	96.254186	-1.934071	29.49078	
412	2015	1990.538464	-1.931289	29.490978	
413	2015	168.099047	-1.930644	29.490462	
414	2015	245.239023	-1.928386	29.495892	
415	2015	1148.071866	-1.927984	29.495331	
416	2015	4736.044284	-1.926951	29.494101	

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Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
417	2015	1765.85269	-1.919157	29.499617	
418	2015	467.804534	-1.918275	29.497472	
419	2015	5586.12759	-1.916138	29.497619	
420	2015	1621.480381	-1.917278	29.498329	
421	2015	385.494949	-1.914453	29.493098	
422	2015	2269.713708	-1.911503	29.48837	
423	2015	306.117243	-1.918402	29.493118	
424	2015	147.344242	-1.894606	29.492597	
425	2015	802.553162	-1.888142	29.490927	
426	2015	764.899185	-1.88771	29.489272	
427	2015	746.353758	-1.892983	29.501652	
428	2015	208.580582	-1.891204	29.502129	
429	2015	135.189913	-1.896735	29.503863	
430	2015	638.776761	-1.88792	29.487177	
431	2015	182.342672	-1.886324	29.487947	
432	2015	85.915889	-1.886015	29.487939	
433	2015	754.364529	-1.8852	29.480113	
434	2015	132.010453	-1.889547	29.480352	
435	2015	89.42936	-1.890457	29.474453	
436	2015	31.34196	-1.891261	29.474237	
437	2015	117.340871	-1.894747	29.473326	
438	2015	245.172109	-1.885451	29.470034	
439	2015	281.703072	-1.889273	29.459208	
440	2015	57.064446	-1.889041	29.459467	
441	2015	46.725769	-1.888888	29.459381	
442	2015	29.72723	-1.888746	29.459321	
443	2015	116.337677	-1.889944	29.461928	
444	2015	93.119053	-1.889716	29.461618	
445	2015	68.870832	-1.889762	29.461712	
446	2015	383.547143	-1.889883	29.460006	
447	2006	965.01074	-1.889335	29.460868	
448	2006	11512.58635	-1.894147	29.465826	
449	2006	3526.092188	-1.899689	29.463143	
450	2006	2806.058886	-1.899779	29.461831	
451	2006	4290.374898	-1.900733	29.466988	
452	2015	553.620911	-1.880371	29.496272	
453	2015	1056.517822	-1.870927	29.488209	
454	2015	328.103274	-1.884328	29.484148	
455	2015	89.23789	-1.881302	29.478415	
456	2006	2268.833917	-1.878172	29.470267	
457	2015	10908.08468	-1.879237	29.468219	
458		969.339479	-1.879132	29.466636	
459	2015	406.164568	-1.878691	29.465836	
460	2006	1899.703328	-1.86818	29.46568	
461	2015	1755.361673	-1.874734	29.465087	
462	2015	182.66606	-1.875645	29.46372	
463	2006	97.208271	-1.880229	29.464541	
464	2006	52.838546	-1.879878	29.464619	
455	2015	308.250798	-1.879228	29.463662	
456	2015	400.306376	-1.880013	29.463785	
457	2015	956.907763	-1.880222	29.463397	
458	2015	247.586999	-1.880663	29.462971	
459	2015	535.386541	-1.880003	29.465258	
460	2015	223.342581	-1.881535	29.465368	
461	2015	7965.463437	-1.873574	29.462631	
462	2015	3190.901347	-1.873323	29.461242	
463	2015	2281.212578	-1.874818	29.461161	
464	2015	160.300772	-1.874427	29.460666	
456	2006	1448.28768	-1.870364	29.457179	
457	2006	346.186182	-1.87015	29.45778	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
458	2006	1758.080331	-1.870012	29.456311	
459	2006	62.176083	-1.869817	29.455839	
460	2006	74.410048	-1.869749	29.455694	
461	2015	224.623055	-1.870017	29.453105	
462	2015	879.837308	-1.86961	29.45307	
463	2015	216.870124	-1.869523	29.453505	
464	2015	4097.469286	-1.869705	29.453958	
465	2015	1784.050494	-1.87169	29.453086	
466	2015	987.742973	-1.872696	29.455124	
467	2015	1945.589627	-1.873177	29.454426	
468	2015	109.051551	-1.874545	29.454372	
469	2015	93.09637	-1.87438	29.455275	
470	2015	171.6392	-1.874334	29.454978	
471	2015	269.900105	-1.874054	29.454315	
472	2015	95.226877	-1.874372	29.455479	
473	2015	159.894253	-1.874743	29.455151	
474	2015	43.597108	-1.874576	29.45564	
475	2015	54.207238	-1.874621	29.455708	
476	2015	518.325813	-1.87466	29.45553	
477	2015	49.604476	-1.875361	29.455682	
478	2015	29.130368	-1.875394	29.45579	
479	2015	79.717982	-1.875256	29.456002	
480	2015	65.430726	-1.875173	29.456228	
481	2015	718.795155	-1.874971	29.455995	
482	2015	1519.843864	-1.873793	29.45623	
483	2015	847.622061	-1.874001	29.456748	
484	2015	1796.694833	-1.874037	29.457221	
485	2015	1998.247388	-1.874391	29.457656	
486	2015	207.613144	-1.873967	29.457994	
487	2015	79.567262	-1.873698	29.457717	
488	2015	45.262565	-1.874082	29.458164	
489	2015	890.635761	-1.874092	29.458477	
490	2015	623.710667	-1.876314	29.457189	
491	2015	273.950592	-1.880205	29.462087	
492	2015	680.460866	-1.879717	29.452375	
493	2015	222.836614	-1.880036	29.4533	
494	2015	1130.951733	-1.869662	29.455266	
495	2015	78.720729	-1.869696	29.456656	
496	2015	78.191034	-1.879407	29.460749	
497	2015	84.139548	-1.879639	29.460532	
498	2015	165.447342	-1.879894	29.460503	
499	2015	271.676827	-1.877926	29.465552	
500	2015	532.314654	-1.914668	29.46315	
501	2015	3183.845921	-1.916546	29.459128	
502	2015	817.677557	-1.915923	29.458599	
503	2015	162.735653	-1.910865	29.45397	
504	2015	346.085043	-1.905603	29.455978	
506	2006	358.435142	-1.903035	29.452508	
505	2006	354.284385	-1.903504	29.452609	
507	2006	173.126528	-1.902789	29.45283	
508	2006	125.226984	-1.902531	29.452275	
509	2006	597.750947	-1.901522	29.452406	
510	2006	283.82975	-1.906676	29.452531	
511	2006	289.563795	-1.903975	29.45258	
512	2006	159.522504	-1.904219	29.462995	
513	2015	1104.560348	-1.907902	29.462102	
514	2015	107.815273	-1.908466	29.462892	
515	2015	338.480755	-1.914066	29.478361	
516	2015	600.87535	-1.910991	29.478579	
517	2015	764.121933	-1.912224	29.486626	

2016 Focused Study (Precipitation) Landslide Inventory

Name	Landslide Date	Area	Latitude (in decimal degrees)	Longitude (in decimal degrees)	Notes
518	2015	173.842684	-1.912211	29.486403	
519	2015	250.235444	-1.913183	29.48678	
520	2015	484.711238	-1.917118	29.485623	
521	2015	625.884044	-1.915029	29.471892	
522	2015	113.467443	-1.936665	29.488163	
523	2015	129.942293	-1.936543	29.487596	
524	2006	2694.747294	-1.952183	29.469232	
525	2006	428.220184	-1.952443	29.468887	
526	2006	130.443876	-1.952531	29.468681	
527	2015	460.958203	-1.951595	29.464215	
528	2015	262.22194	-1.942228	29.459777	
529	2015	575.386025	-1.942709	29.459973	
530	2015	1062.135271	-1.947214	29.454122	
531	2015	206.200704	-1.946211	29.452717	
532	2015	639.626328	-1.943205	29.454605	
533	2015	827.618284	-1.937926	29.475248	
534	2015	164.034604	-1.948217	29.477354	
535	2015	191.700539	-1.976255	29.469725	
536	2014	88.902612	-1.982612	29.472645	
537	2015	100.508432	-1.993319	29.476104	
538	2015	200.959428	-1.995372	29.488837	
539	2015	320.154447	-2.026337	29.488163	
540	2015	243.415042	-2.016513	29.482576	
541	2015	74.218207	-2.013842	29.477686	
542	2015	158.467072	-2.013965	29.452469	
543	2015	271.865045	-2.027519	29.457333	
544	2015	141.868884	-2.010715	29.46165	
545	2015	96.687019	-2.023274	29.468859	
546	2015	590.450659	-2.024863	29.467457	
547	2015	222.12665	-2.02965	29.45472	
548	2015	423.082423	-2.043355	29.477824	
549	2015	463.065191	-2.041049	29.481293	
550	2015	1623.426622	-2.041988	29.459399	
551	2015	976.918585	-2.043203	29.463938	
552	2002	4345.625143	-2.043205	29.463013	
553	2002	1342.95527	-2.043364	29.466003	
554	2015	113.940091	-2.042751	29.454663	

```
clear all;
close all;

% This program is to read a TRMM 3B42 daily binary file
% By Angela Piller May 2016
%
% Info about TRMM binary files:
%The file size is about 2.25 MB (uncompressed). The data are stored in
%flat binary, as 4-byte floating numbers. Users who download these data
%will need to execute byte swapping if working on a little endian machine.
%These data have the first grid cell at (0.125,-49.875) (lon,lat), and
%data are stored in rows of 1440 longitudes. The first row is at -49.875
%latitude. In standard matrix notation, the grid is sized (400,1440)
%(rows, columns).
%-----

%DATES (edit here if appropriate)

startyr= 1998; %years available are 1998 - 2015. Last date available is 5/2/2015.
endyr= 2015;

%LOCATION (edit here if appropriate)
%Here is code to define the study area and then calculate minlon and min lat
%(round these values to the nearest .25 degree)
%Values for low landslide density area
%north = -1.5;
%south = -1.75;
%east = 29.75;
%west = 29.50;

%rounded values for high landslide density (main study) area
north = -1.75;
south = -2.25;
east = 29.75;
west = 29.25;

nlat = (north * -4) + 200;
slat = (south * -4) + 200;

if east >=0
    elon = (east * 4);
else
    elon = (east * 4 + 1440);
end

if west >=0
    wlon = (west * 4);
else
    wlon = (west * 4 + 1440);
end
```

```
%Define the start and unit (1 day) for time ('0' or the 3rd dimension of matrix).  
%Time is measured in days. The first date for TRMM data was 1/1/1998 and  
%the last was 5/2/2015. 'minlat' and 'minlon' are 1 less than the minimums  
%of the study area. This is used to locate the locations in the matrix  
%that have my precipitation data in them (files contain data for the entire world).
```

```
firstday = 1;  
timedim = 1;
```

```
minlat = (nlat - 1); %(study area is south of the equator)  
minlon = (wlon - 1);
```

```
%Define the way calendar time works and use these rules to generate filenames  
%'fname' and array name 'aname' (Not using aname for anything right now).
```

```
basename = 'C:\Users\apiller\Documents\School\Honors\Thesis Work\data\Data for  
Rwanda\TRMM\3B42_daily.';
```

```
for i_fname = startyr:endyr %year 1998 - 2015  
    if i_fname == 2015 % Last date available is 5/2/2015  
        lastmonth = 5;  
    else  
        lastmonth = 12;  
    end
```

```
for j_fname = 1:lastmonth %month  
    if i_fname == 2000 && j_fname == 2 %leapyears  
        lastday = 29;  
    elseif i_fname == 2004 && j_fname == 2  
        lastday = 29;  
    elseif i_fname == 2008 && j_fname == 2  
        lastday = 29;  
    elseif i_fname == 2012 && j_fname == 2  
        lastday = 29;  
    elseif i_fname == 2015 && j_fname == 5 %Last date available is 5/2/2015  
        lastday = 2;  
    elseif j_fname == 2  
        lastday = 28;  
    elseif j_fname == 4  
        lastday = 30;  
    elseif j_fname == 6  
        lastday = 30;  
    elseif j_fname == 9  
        lastday = 30;  
    elseif j_fname == 11  
        lastday = 30;  
    else  
        lastday = 31;  
    end
```

```
for k_fname = 1:lastday
```

```
i_strfname = num2str(i_fname);
j_strfname = num2str(j_fname);
k_strfname = num2str(k_fname);

if j_fname < 10
    j_strfname = strcat('0',j_strfname);
end

if k_fname < 10
    k_strfname = strcat('0',k_strfname);
end

fname = strcat(basename, i_strfname, '.',j_strfname, '.',k_strfname, '.7.bin');
aname = strcat(i_strfname, j_strfname, k_strfname);
aname = str2num(aname);
timedim = timedim + 1; %for the 3rd dimension in the array

% Now read the information out of the TRMM files. Locate the file ID,
% change data from big endian to little endian, rotate contents of the
% array.
% Source: http://disc.sci.gsfc.nasa.gov/additional/faq/precipitation\_faq.html#matlab
%('lat' and 'lon' aren't currently being used)

fid = fopen(fname, 'r');
precipitation = fread(fid, [1440, 400], 'float', 'b');
fclose(fid);
precipitation = rot90(precipitation);

%for i_lat = 248:-1:216 %my addition- increase accuracy, though? to reflect exact study area
%for j_lon = 116:120 %my addition to reflect exact study area
for i_lat = (slat-1):-1:(nlat)
for j_lon = wlon:(elon-1)

    lat = 49.875 - 0.25*(i_lat - 1);
    if j_lon <= 720;
        lon = 0.125 + 0.25*(j_lon - 1);
    else
        lon = 0.125 + 0.25*(j_lon - 1) - 360.0;
    end

    daily_rain_total = precipitation(i_lat, j_lon);
    P((i_lat - minlat), (j_lon-minlon), timedim) = daily_rain_total;

end
end

close all

end
```

```
end
end

%ONLY FOR MAIN STUDY AREA COMMENT OUT AND USE LOW DENSITY VERSION
%Average values for all four TRMM pixels together, put them in a new matrix.
%Weight them 54% North pixel, 19.5% North2 pixel, 19.5% South pixel, 7%
%South2 pixel.

for i = 1:timedim
    Q(1,i) = (((P(1,1,i))*1.95) + ((P(2,1,i))*0.07) + ((P(1,2,i))*0.54) + ((P(2,2,i))*1.95));%[1,:]averaged precipitation value
end

%LOW DENSITY VERSION (next 3 lines)
%for i = 1:timedim
%    Q(1,i) = (P(1,1,i));
%end

%Determine the rank of each precipitation value "PR"
PR = sort(Q,'descend');

%Since interpolate won't work if there are multiple identical values, use
%"unique" to remove all but one zero. However, treat calculations as if the
%full number of records ('timedim') exist.
PR = unique(PR,'stable');

n=0;
PRdim = size(PR);

for j = 1:PRdim(1,2)
    PR(2,j) = n+1;%[2,:]Rank
    if PR(1,j) == 0;
        PR(2,j) = timedim;
    end
    n=n+1;
end

%Determine Exceedance Probability (Weibull method)
for k = 1:PRdim(1,2)
    PR(3,k) = 100 * ((PR(2,k)/(timedim+1))); %[3,:]Probability
    PR(4,k) = (1/((PR(3,k)/100))); %[4,:]Recurrence Interval
end

event = (1:(PRdim(1,2)));

Storm1 = interp1(PR(4,:),PR(1,:),event);
%Storm1 = interp1(PR(4,:),PR(1,:),event);
%%
plot(Storm1,event)
title('Precipitation vs Recurrence Interval - High Density')
```

```
xlabel('Daily Precipitation (mm)')
ylabel ('Recurrence Interval (days)')
%%
plot(Q)
%plot(squeeze(P(1,1,:)))
title('Daily Precipitation - High Density')
xlabel('Day')
ylabel('Daily Precipitation (mm)')
```