Debris Flow Landslide Susceptibility Modeling in Western North Carolina Using Suitability Analysis

Davis M. Mann

Auburn University Montgomery

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By

Davis Mann

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Approved by

Dr. Hoehun Ha
Thesis Director

Dr. Chelsea Ward
Second Reader

Dr. Gabriel Costa
Third Reader

Dr. Matthew Ragland
Associate Provost

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Abstract

Within the Blue Ridge Mountains of North Carolina in the Appalachian Mountain Chain, debris flow landslides are the most common type of landslides that occur in the region. With hundreds of debris flows occurring every decade, being able to identify where these landslide events are most likely to occur is in the best interest of developers and citizens alike. Using a suitability modeling approach, this project will use past research on landslide susceptibility modeling to construct a debris flow landslide susceptibility model. Data covering a landslide inventory, land cover, slope steepness, rainfall and hydrology was collected. The data was gathered in raster data format and were the main components for detecting susceptibility for the model. Slope and hydrology raster data was developed from processing Digital Elevation Models (DEMs) collected from United States Geological Survey (USGS) in ArcGIS to obtain the data. land cover data was gathered from the Major Resolutions LandCover Consortium (MRLC) in the form of their National Land Cover Database (NLCD). Rainfall data used for this project shows the annual rainfall for all areas in North Carolina. Each of these raster layers needed to be reclassified to reflect how each value impacted susceptibility. For land cover data this entailed giving unique values to every land cover type to reflect how values such as different levels of vegetation or urban build-up impacted susceptibility to landslides. With the data reclassified a raster calculation could be written that takes the reclassified data and creates a suitability layer using Weighted Linear Combination. This output raster layer is called the susceptibility raster which identifies areas based on debris flow susceptibility. After successful creation of the first draft of the susceptibility raster, a model was created to automate the process. The model finds that areas along steep slopes and mountain roads with little vegetation and moderate to high rainfall are among the most susceptible in the Blue Ridge Mountains and surrounding area.

I: Introduction

A landslide is a natural hazard that is defined as a downslope movement of debris under the force of gravity and is in many cases aided by other weathering factors such as heavy rainfall. Landslides can move rapidly or slowly and are commonly associated with high relief, steep areas where the influence of gravity is strongest, though they are known to occur at many different elevations if the proper conditions exist (Varnes 1978). Landslides are a type of mass wasting and the terms are sometimes used interchangeably. The debris present in any mass wasting event consist typically of soil content or rock but there are several forms a landslide can take depending on the conditions in the area they occur. According to Varnes (1978), A debris flow, also known as a mudslide, is typically fast moving and made up of a mass of unconsolidated soil and water mixed with other debris. This type of landslide can be highly destructive leading to loss of life as well as being costly to local infrastructure. Therefore, researching methods of evaluating landslide susceptibility is an important and worthwhile pursuit. Using Geographic Information Systems (GIS), a model can be produced which assesses the landslide susceptibility of a study area by calculating the weighted influence of all the factors that are involved in a debris flow landslide occurrence in that study area. The Blue Ridge Mountains within the Appalachian Mountain Chain of Western North Carolina will be used as the study area to assess susceptibility to debris flow landslides. Using probability models for landslide prediction is common practice but the quality of the model will depend on the data and how well it represents the properties of a study area. These models also assume that more landslides will occur in the area under similar conditions to previous landslides (Goetz 2015). With this in mind, the characteristics of the study area needed to be investigated thoroughly. Debris flow landslides were chosen in the interest of relevancy to the study area and for usefulness in application. Many landslide susceptibility models in the past have not specified the type of landslide or structured their data gathering process around a specific type, making the relevancy and usefulness of these models questionable (Reichenbach 2018). By specifically modeling debris flow susceptibility this project hopes to curb any ambiguity pertaining to the usefulness of the model.

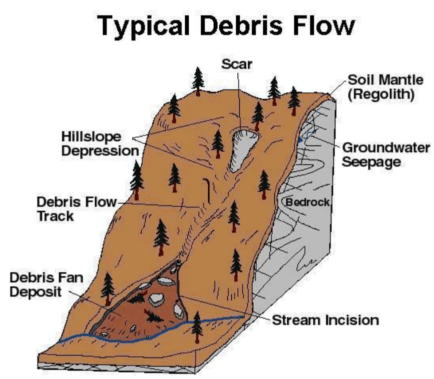

Figure 1-1: Diagram of a typical debris flow showing the path one takes from an initiation point to the debris fan. This is the common form of a debris flow in the Appalachian Mountains (Image courtesy of the North Carolina Geological Survey, 2003).

The geologic, geomorphic and meteorological characteristics of a region influence the landslide susceptibility of the region (Wooten 2016). As mentioned above, high relief areas with steep slopes are commonly associated with landslides including debris flows. Debris flow conditions favor loose sediment that is easily pushed along by water under gravity's influence. The meteorological characteristic refers to weather events that can influence and change the surface by weathering away at surface features. Weathering effects are a major triggering factor of landslide events, common triggering factors of debris flow are rainfall and ice melt. Debris flows begin their path at an elevated initiation site when a triggering factor such as rainfall weakens the soil mantled slopes and slope failure takes place resulting in the beginning of a debris flow. The debris flow continues its main track downward via a drainage way or stream channel (Wooten 2016). Typically a landslide will leave behind evidence of its occurrence in the form of a scar at the initiation point and a fan at the deposit zone. There may also be a visible track left behind by the flow of sediment. Many factors are at play and working together in landslide events so being able to recognize the influencing factors is an important first step in modeling landslide susceptibility (Westen 2008). In addition, how the influencing factors can be measured in terms of their influence on landslide susceptibility within a GIS program needed to be addressed as well.

1.1 Literature Review

Wang et al. (2013) emphasizes the importance of selecting appropriate training data points in the creation of a landslide susceptibility model for Mizunami city in Gifu prefecture, Japan. Appropriate landslide points were chosen as training data by a fuzzy c-means algorithm. FCM clusters data points so that those in the same cluster are similar to each other. The distinction between fuzzy and non-fuzzy clustering is that in fuzzy clustering, data points can belong to two different clusters whereas in non-fuzzy clustering they cannot (Wang 2013). The FCM pattern was first developed by Dunn (1973) and is widely used in the creation of soil mapping due to being capable of capturing the “fuzzy” nature of soil content properties and landscapes in general. By using FCM the researchers could consider the inter-relationships of data points and choose appropriate, high membership data points to be used as the training dataset.

Five different combinations of *m* (the fuzzy component) and *c* (the number of clusters) were developed and used in conjunction with a logistic regression model to determine the degree of accuracy that each combination could provide to a landslide susceptibility model. Each yielded different results for the model, it was found that *m* had much more impact than *c* and those where $m = 1.9$ produced susceptibility rasters with higher accuracies (indicated by spatial distribution of landslide affected areas and the areas determined by the model to be at risk) than those that did not. In the conclusions section of this study, it was suggested that triggering factors such as intense rainfall, snow melt or earthquake aftershocks could have influences on the probability of landslides occurring in this study area (Wang 2013).

The research by Wang et al. (2013) encourages discretion in choosing landslide points for use in a regression model. By identifying points that are more likely to be involved in landslide events due to varying degrees of validity functions that contribute toward susceptibility. This research made use of buffers to weigh proximity to these landslide points as well as proximity to rivers and faults. Being more discreet when it came to the *m* value seemed to have produced the most accurate results. Perhaps, as suggested in the conclusion, the inclusion of triggering factor data may have yielded even more accurate results (Wang 2013).

The research conducted by Nandi and Shakoor (2009) describes a study done in the Cuyahoga river watershed of northeastern Ohio that attempts to create a landslide susceptibility model using bivariate and multivariate statistical models. With both models, factors that contribute to landslides in the area are used in the evaluation and the accuracy of each model type is compared. Ultimately this study is trying to determine which model type is superior to use in modeling landslide susceptibility. The factors that the study chose for this experiment were slope angle, soil type, soil erodibility, soil liquidity index, precipitation, land cover, and proximity to streams.

In the bivariate model, each of the factors were treated individually and given a ranking of 0.0 to 1.0 based on their effect on landslides. The ones where landslides were dominant were given the highest ranking of 1.0. Two of the factors, soil type and landcover were divided into five classes and given a weight value in increments of 0.2. Each of the class values were reclassified with a new value reflecting their influence on landslides and this information was used in ArcGIS to create seven different grid maps (one for each factor) of numerically ranked data. A bivariate statistical analysis was then performed on these grids where all seven grids were used to calculate landslide susceptibility in grid format.

In the multivariate model however, instead of the variables being independent, all susceptibility factors were taken together so that their interactions could be used to determine landslide susceptibility. The multivariate model put more emphasis on how each factor affects landslide susceptibility when taken together as a whole. In order to accomplish a multivariate model the researchers made use of logistic regression analysis. The author notes that logistic regression analysis was chosen based on the nature of the data in the study containing categorical data such as land cover as well as continuous data such as slope angle and soil erodibility that would be difficult to use in any other multivariate model. This method produced landslide susceptibility maps that ranked the probability of landslides occurring on a scale of 0 to 1.0.

Nandi and Shakoor (2009) conclude that the multivariate process is superior in constructing a landslide susceptibility model after comparing the results of the bivariate and multivariate methods. They determined the accuracy of each method by comparing the results to known landslide locations and by testing them using Relative Operating Characteristics (ROC) curves. ROC curves are a method of determining the quality of a predictive model by using the Area under the ROC curve (AUC) values ranging from 0.5 to 1.0 to indicate accuracy. The closer to 1.0 the model scores, the more accurate it is. When testing the AUC value of the ROC curve for the bivariate model, it scored only a 0.59 with an estimated error of 0.11, while the multivariate model's AUC value of the ROC curve was found to be 0.81 with an estimated error of 0.07. This clearly indicates the advantage in using a multivariate approach to landslide susceptibility modeling. In summing up why this approach is superior, the authors express that the bivariate approach is a rudimentary way of analyzing susceptibility due to the fact that it diminishes the role that relevant factors play in a landslide susceptibility model while a multivariate approach using the logistic regression method indicates that factors such as slope angle, proximity to streams and soil erodibility are significant in promoting slope movements in the study area. Every independent factor that might have direct influence on landslides should be investigated.

The information in these next studies relate to how suitability models have been used in the past and the general principles of their utilization. In a study on dengue infection rates in Africa, Suitability analysis was used to locate areas that were at high risk of infection based on known characteristics of areas that developed the infection. Variables related to elevation, temperature, precipitation and population density were found to be good indicators of infection activity (Attaway 2016). In their research, certain data variables such as elevation had to be weighted based on min max thresholds as established by prior literature on the subject. A similar weighting had to be done with the teams temperature data. Studies on what temperature ranges Dengue thrives in were used to assign weights for this variable. Variables such as population density and precipitation; however, could be weighted higher based purely on sheer quantity as Dengue thrives more the higher the population and precipitation are (Attaway 2016). Similar to how a landslide inventory is used in landslide susceptibility analysis, the researchers used Dengue case data points to confirm the relevance of the data gathered as well as the suitability layer that was created.

Using the four data classifications of Elevation & land cover, pop Density, temperature and precipitation as parameters, the researchers constructed their suitability layer using ArcGIS Predictive Analysis tools. Areas that met the highest weighted value for each parameter were ranked as highly suitable for infection by the

Dengue virus. The Researchers note that the suitability approach using raster data limits spatial bias that can result from using presence points (test points) as the basis for suitability, though previous research data can be used to validate the model output (Attaway 2016).

Another example of risk assessment using suitability analysis relates specifically to landslide susceptibility. In the research by Bathrellos et al. (2017), a suitability analysis was conducted in the drainage basin of the Xerias stream in Peloponnesus, Greece. This analysis combines the outputs of several other suitability assessments on different types of natural hazards in the area to create a final suitability raster that locates where the safest and most at risk areas are for urban development. Hazards mapped by the individual suitability maps covered flood, seismic and landslide susceptibility. Like in the research by Attaway et al., a landslide inventory was assembled, consisting of 41 landslide events in the area and used for verification of the data.

The factors used in the landslide suitability analysis were slope, rainfall, lithology, distance from active faults, land use, distance from roads and distance from streams. Each of these factors had a weight rating assigned to different levels or classes. Certain factors such as slope, distance from streams and rainfall were assigned their rating in correlation to how high or low their level was in an area, using standard deviations to separate the classes. Other factors such as lithology and land use had their rating assigned based on literature about how each individual value impacted susceptibility (Bathrellos 2017). A landslide suitability map was created using the Weighted Linear

Combination method in GIS and overlaid with the landslide inventory gathered earlier. Overlaying the landslide inventory was the researchers primary method of verification of the output results of the suitability analysis. With this verification method, the researchers were able to determine that 20% of the past landslides are located in the very high areas of susceptibility, 46% were in the high areas, 27% in moderate, 5% in low and 2% in very low areas. The majority of landslides were detected in the high and very high zones (Bathrellos 2017).

In the conclusion of the study Bathrellos et al. (2017) stated that the suitability maps that were created showed high correlation with past landslide and flood events. The authors felt that this implies that the suitability model is a reliable method of mapping areas and their susceptibility to natural hazards (Bathrellos 2017).

The potential for spatial bias is a possible weakness in other predictive models such as the fuzzy c-means and logistic regression models. By using a suitability model the possibility of this bias occurring in the landslide susceptibility model can be diminished (Attaway 2016). Using the multivariate principal presented by Nandi and Shakoor (2009) that all factors contributing to a landslide event must be investigated and treated as a whole, this study intends to use Suitability analysis to find where these factors interact the most.

The question of LULC (Land use land cover) and its influence on landslide susceptibility has been of particular interest to landslide researchers. Shu et al. (2019) conducted a study in Val d'Aran, Spain to determine how LULC changes would affect landslide activity in the area based on a 2013 landslide inventory. In this study, they first determined that areas with a land use classification of grassland were the most affected and shaped by landslides. In contrast, the landslide density of areas covered by forest and shrubbery was much lower. 52% of the study area that consisted of grassland was affected by landslides while only 15% of the forest land was affected and 23% of shrub land was affected.

This research supports the idea that vegetation stabilizes slopes and aids in the prevention of landslides. This is due to the shear affecting force of root systems that vegetation provides, which help to coalesce soil and give resistance against downslope forces such as those that occur during heavy rainfall (kuriakose 2006). The researchers also cite and agree with the research of Goetz et al. (2015) which proposes that deforestation plays a major role in destabilizing slopes against landslides. This research found that forestry activity in Vancouver Island, Canada contributed to an increase in landslide activity during an intense rainstorm in November of 2006. The research notes that open forest was more susceptible to landslides than sparse or more dense forest. Forests that had been recently disturbed by forestry activity was found to be more susceptible to landslides than they had previously been (Citation Goetz 2015).

In every attempt at modeling landslide susceptibility, data must be gathered that covers a range of classifications. There have been data gathering models created in the interest of providing a standard to the data gathering process that assures that all of the relevant data has been acquired by the researchers for landslide testing. Often dividing the data into classifications based on what realm of influence it has on landslide susceptibility. Westen et al. (2008) in their research on spatial data relating to landslide risk and hazard modeling created a data gathering schematic that provides a criteria for data gathering for landslide risk research that can be easily applied to susceptibility research. The model divides data into four classifications: environmental factors, triggering factors, landslide inventory and elements at risk.

Environmental factors cover the unique natural characteristics of the study area such as morphology, soil and hydrology as well as land cover. Essentially, the state of the land in the study area as it is without any disruption. The selected data in this classification that is used in the project should depend on the type of landslide that is being researched (Westen 2008). Triggering factors consist of the weather or other natural events that can play a role in a landslide triggering such as precipitation and earthquakes. Similar to environmental data, the data collected in this classification can be varied depending on the type of landslide and especially on the study area. The landslide inventory is the third classification. The researchers refer to this as the data on past landslide events that have occurred within the study area (Westen 2008). Finally, they include an Elements at Risk classification. This classification is for data that will be used in assessing the risk factor of a landslide such as buildings, land use and census data. Although this data classification does not strictly apply to the landslide susceptibility analysis of this thesis, data on infrastructure and land use can be useful as these can have effects on susceptibility (Shu 2019). A full visualization of the Westen et al. schematic can be seen in the methods section.

Expanding on landslide Inventories, a landslide inventory is a record of past landslide events and can be visualized in GIS as a spatial layer showing initiation points, flow paths and deposits. In order for a landslide susceptibility map to be as reliable as possible, it needs to not only be able to give insight into the spatial distribution of past landslides events of the area it covers, but also to be relevant in terms of context to past landslides. Therefore a landslide inventory that is as complete as possible should be compiled before a susceptibility analysis is conducted (Westen 2008). Westen also describes having a proper landslide inventory that is complete in terms of space and time as essential to having insight on the spatial and temporal frequencies of landslide events in the study area . The spatial and temporal elements of the landslides in the inventory are desired as well as classifications for the types of landslide. Information pertaining to the landslide’s specific triggering factors can be helpful in determining what triggering factors to consider. It is widely accepted that establishing a landslide inventory should be the first step in a landslide susceptibility study (Westen 2008).

As stated, the research in this section had the most influence and provided the most guidance in how to approach the model creation process. Other research that is referenced in this paper serve to support the methods and claims of these researchers. Landslide modeling using a suitability analysis was decided on as the method used in the model due to the advantages it offers over regression analysis approaches. It also allows for multivariate principals to be applied by weighting factors differently in regard to overall contribution to susceptibility. Research on how land cover impacts susceptibility was crucial to understanding how to apply weights to the land cover data values. How vegetation affects susceptibility was important to understand so that different types of vegetation land cover could be weighed accurately. The unique perspectives offered by all of the researchers on the creation of landslide susceptibility models is much appreciated and built the foundation for how this study was approached and performed.

II: Methods

Western North Carolina was chosen as the study area due to the region's history of debris flow events. In the Southern Appalachian mountains, debris flows are the most common type of landslide with a majority of them occurring in the Blue Ridge Mountain province of Appalachia, a sizeable portion of which lies within Western North Carolina (Wooten 2016). This region provides suitable conditions for the mechanics of a debris flow, namely, that it is a highly elevated region with steep slopes that receive moderate to high amounts of rainfall per year. High rainfall occurs particularly in the southern sections of North Carolina's Blue Ridge Mountains where annual rainfall averages over 90 inches per year, making it one of the rainiest regions in the United States (NCCO 2019). According to Wooten et al. (2016), storms that trigger hundreds of debris flows occur every 9 years in the SAH (Southern Appalachian Highlands) between North Carolina and Tennessee and storms that trigger thousands of events will happen every 25 years (Wooten 2016). The death toll of debris flows was at least 200 in the 20th century and much damage was caused to the many acres of local farmland and forests (Scott 1972). This region is touched by man-made infrastructure. With Many roads and small communities found throughout the mountains, man-made infrastructure would have to be considered in addition to that of the natural features of the study area. This study will not calculate risk to infrastructure as part of susceptibility, it only considers the potential of infrastructure to influence landslide susceptibility. Although the primary study area was the Blue Ridge mountains within North Carolina, surrounding areas to the east that are within the piedmont region were also included in the study area to test the results of utilizing the model in a lower elevation area. Figure 2-1 below shows a map of the Appalachian mountain chain and the various regions.

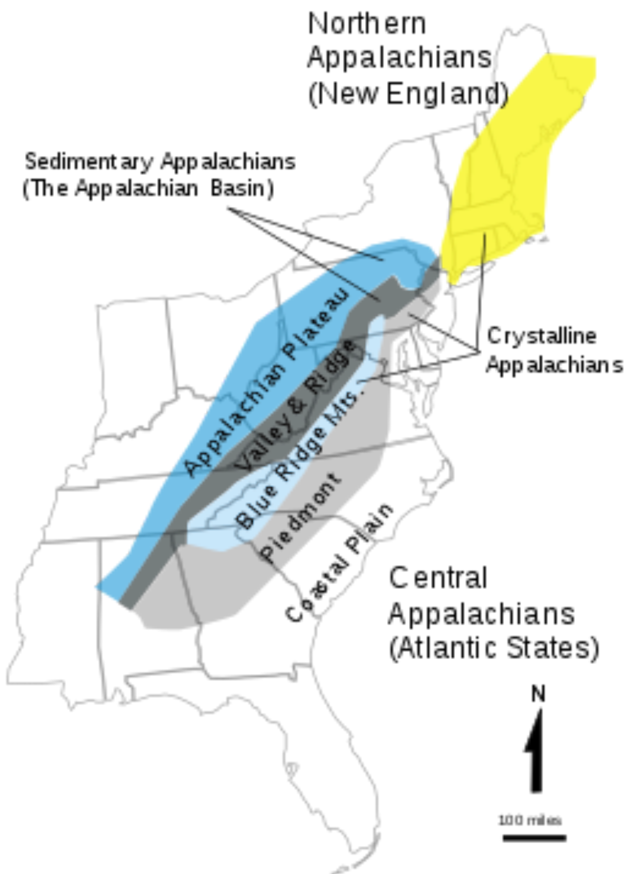

Figure 2-1: This figure shows a map of the Appalachian Mountain chain regions. As can be seen, the Blue Ridge Mountains and Piedmont regions make up a significant portion of Western North Carolina (Image Courtesy of USGS).

2.1: Data and Data Sources

All of the literature contributed to the spatial data gathering process of this research; however, Westen et al. (2008) presented the most influential schematic for landslide susceptibility data gathering. A visualization of this schematic is presented in Figure 2-2, specifically the factors that make up the “Hazard” factors in this model provided a basis for the data that was gathered. Elements at risk were not included for this project. Roughly following the data gathering process presented by Westen et al. (2008), data for this project was classified as landslide inventory, environmental factor or triggering factor

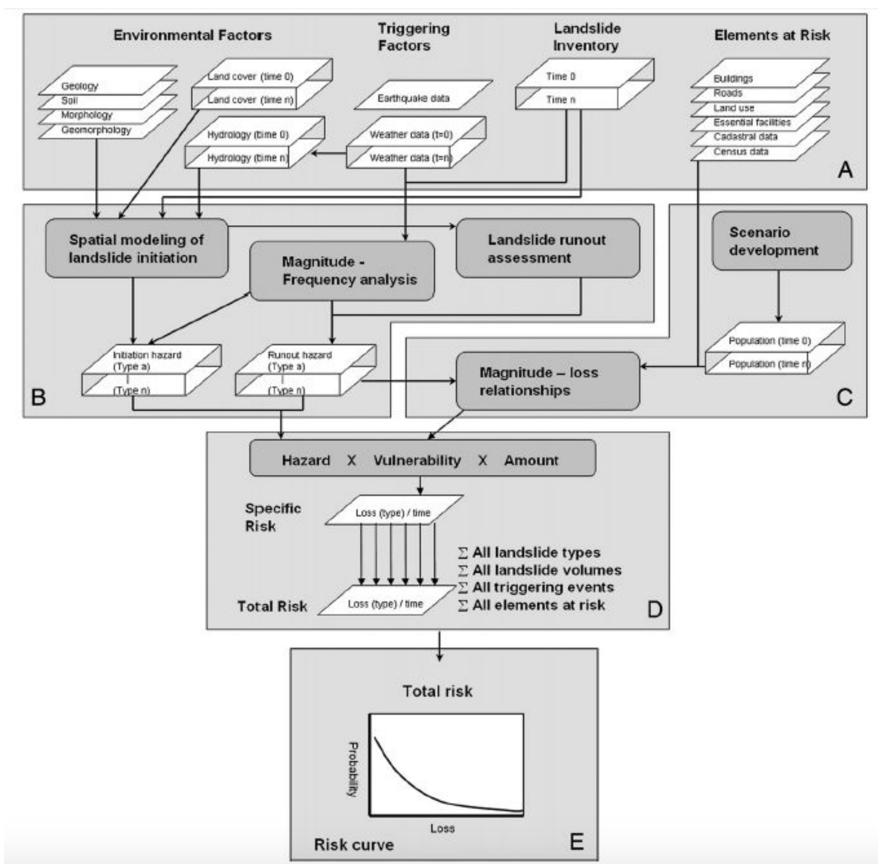

Figure 2-2: The data gathering model proposed by Westen et al (2008). in their paper on data necessary to build a landslide risk model. These categories informed the base components for the data used in this model.

Environmental factors include data relating to the geomorphological and hydrological characteristics of the study area as well as the land cover i.e. land use. In general, environmental factors in a susceptibility assessment are determinant upon the type of landslide being researched, the type of terrain, and the availability of data resources. This means that the way certain factors are weighted in a susceptibility model will be determined by the fact that the model will be detecting debris flow susceptibility (Westen 2008). Much of the geomorphological data relates to the physical features of the earth, specifically how they have been shaped by weathering processes that mold the surface resulting in the distinctive landscapes of a region (BSG 2014). The topography of a region is directly influenced by geomorphological processes and has a role in landslide susceptibility. Digital Elevation Models (DEMs), are a reliable source of elevation data which can be processed to gain topological and morphology data (Fabbri 2003). Models that use DEMs to analyze slope and aspect have been found to be superior to those that do not (Reichenbach 2018). The land cover factors denote the primary “cover” of an area i.e. vegetation, forest, urban etc. Depending on the primary land cover characteristic, a slope can be more or less susceptible to debris flows (Goetz 2015).

The DEMs that were collected for this study come from the United States Geological Survey (USGS) Earthexplorer website, a public database for satellite imagery. These DEMs are of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) type which is available for all regions that are 83 degrees north and south latitude at 1-arc-second

(30m) spatial resolution (Gesch, 2018). ASTER GDEMs were chosen primarily for their 30m spatial resolution because for the purposes of assessing landslide susceptibility, a highly detailed DEM is desired in order to find the most susceptible slopes in any given study area. Six DEMs covering areas of western North Carolina were collected in all and information on the elevation and slope data was collected.

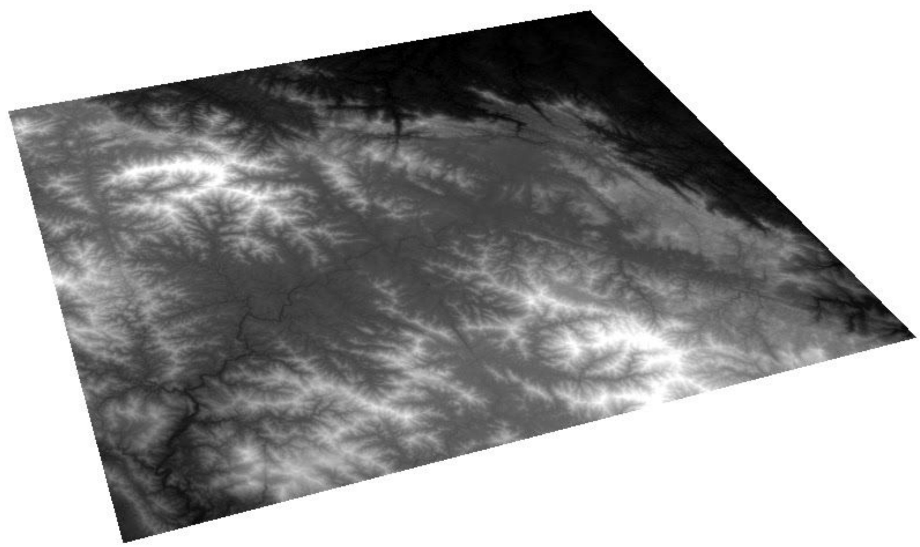

Figure 2-3: An example of one of the USGS ASTER DEMs. This particular DEM is known as Asheville_DEM in the data. Named after the city of Asheville within the DEMs area. ArcScene was used to orient this DEM and create the image.

Land cover data was downloaded from the Multi-Resolution Land Characteristics Consortium (MRLC). The MRLC is composed of federal agencies that collaborate and produce land cover data of the entire United States as part of the National Land Cover Database (NLCD). Specifically, the data that was used for this research is the NLCD 2016 Land Cover (CONUS). This data is at a 30m spatial resolution making it easy to use in conjunction with data derived from the DEMs. The NLCD follows a classification system that identifies various types of vegetation, urban areas, and water bodies. NLCD data was clipped to each DEM within ArcGIS so as to focus on the area of the DEM and the broader study area.

The Hydrology of the Blue Ridge Mountains indicates the downslope paths a debris flow could take. Paths with the highest flow accumulation will contribute to the overall susceptibility of a slope. For this factor, the DEMs are used to analyze the hydrology of an area by performing flow direction and flow accumulation functions using GIS operations (Pan 2012).

ArcToolbox possesses tools for deriving flow accumulation and stream data. The final version of the processed DEMs (five in total) shows the flow accumulation levels of each cell that will be used to weight influence on debris flow landslide susceptibility. Details on the processing of the DEMs to gather the flow accumulation data are covered later.

Data classified as triggering factors does not usually have spatial importance but rather is of temporal importance (Westen 2008). For the purposes of landslide susceptibility modeling, Triggering factor data refers to factors such as rainfall and earthquake activity. With rainfall being a major triggering factor in the initiation of a debris flow landslide the susceptibility model will need to be able to weigh average rainfall over a given period of time. The higher the average rainfall of an area, the higher susceptibility to landslides (Witt 2005) and thus the higher that area will be weighted in its landslide susceptibility ranking. Depending on the date range of the rainfall data, the model could be used for analyzing seasonal changes in susceptibility. For this study, however, average annual rainfall data taken over a lengthy time period was desired to obtain a more general look into how rainfall impacts the landslide susceptibility in the Blue Ridge Mountains.

The ESRI ArcGIS library provided a point shapefile of past landslide initiation points. These origin points were dated from 1930 to 2005. This shapefile contained information not only on the dates that the landslides occurred, but also the landslides type, the known causes of the landslide and unique weather events, such as hurricanes, that the landslides were associated with. GIS data on the deposits of past landslides in the area is limited but the North Carolina Department of Environmental Quality (NC DEQ) produces landslide deposit maps for the counties Buncombe, Macon, Watauga and Henderson, all counties with the most landslide activity in North Carolina. These maps were used in conjunction with the landslide initiation points shapefile to compare with the results of the susceptibility model throughout its development. As these counties were the only ones that a full landslide deposit inventory had been created for, they were considered to be primary areas of interest while testing the model. The landslide inventory will be used for the verification of the results of this study.

This study forgoed including an “elements at risk” category for the data; however man-made infrastructure was important to include in the data in order to weigh the impact that it has on landslide susceptibility. The NLCD land use data acquired from the MRLC includes classifications for urban development. Roads that are found along the Blue Ridge Mountains are classified as developed, open space according to the NLCD

Legend. The NLCD clarifies that this classification refers to areas where impervious surfaces account for less than 20% of total cover. There are also multiple levels of urban classifications ranging from developed, low intensity to developed, high intensity. The level of classification is corresponding to how much the total cover of the area is made up of impervious surfaces and gives an idea of the type of infrastructure that is present. For example, high intensity areas that are made up of 80% to 100% impervious surfaces are most commonly associated with commercial or industrial districts, apartment complexes, and row houses. Figure 2-4 below shows the NLCD legend and the types of classifications it detects.

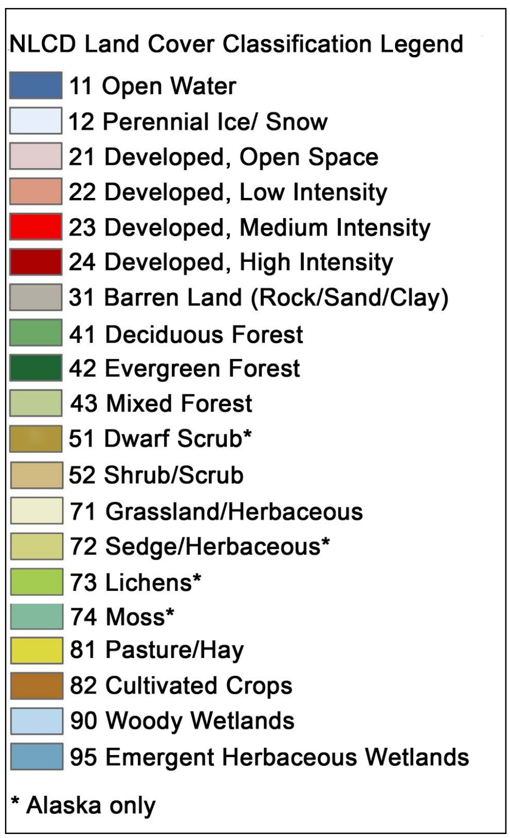

Figure 2-4: The NLCD Legend which classifies areas based on dominant land cover characteristics. Many types of vegetation and development levels are classified by this system.

2.2 Building the Model.

The model was created in ArcMap 10.6. A single model was built to produce a susceptibility raster layer using ArcGIS model builder. Before the model could be created in ArcGIS, the individual processes needed to be tested in ArcMap and determined to be suitable for obtaining the desired data. The data that needed to be developed in ArcMap in order to weight properly within the model included slope data, land use data, annual rainfall data and hydrology data.

2.2.1 Developing Slope Data

A slope analysis was performed first to reclassify the resulting slope raster layer using ArcToolbox. Using the elevation data in the 30m ASTER DEMs obtained from USGS, the slope tool was applied to identify the steepness of the slopes. The rate of change of the elevation value is calculated between all adjacent cells to identify the steepest downhill slope. This produces an output raster layer where the steepest slopes in the DEM can be clearly seen. An example of one of the output slope rasters is shown in Figure 2-5.

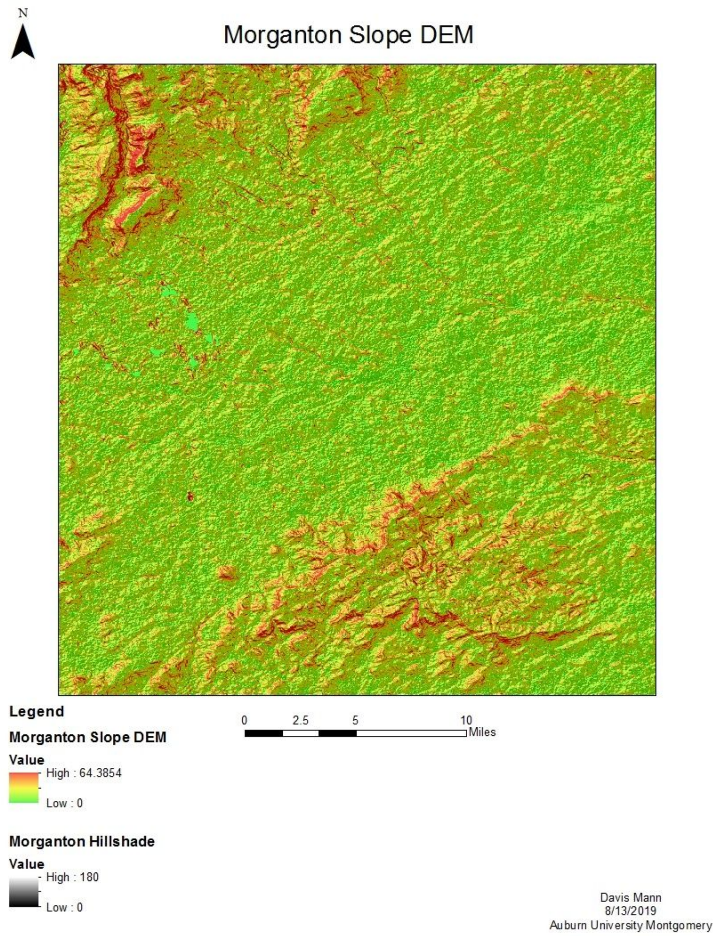

Figure 2-5: An example of a slope raster developed from one of the DEMs obtained from USGS Earthexplorer. Slope Steepness is one of the factors needed to build the landslide susceptibility raster. This layer will be reclassified as a weighted layer.

In order to weight the slope layer in the landslide susceptibility model, it needed to be reclassified. Using the reclassify tool, with the new slope layer as the input layer, the values could be reclassified with new values to reflect the influence on landslide susceptibility that each value has. The Higher the slope value was in the slope layer, the higher on a scale of 0-9 the value would be reclassified as in the new reclassified slope layer (Bathrellos 2017). The reclassified slope layer could now be used in the raster calculation to determine landslide susceptibility.

2.2.2 Developing Hydrology data

Data representing the hydrological flow mechanics in the study area was needed for the model to effectively calculate landslide susceptibility. For this, a drainage network needed to be detected. Debris flows can be highly influenced by local drainage networks; ideally, the data would have to assess the flow levels of each cell in a raster layer so that the cells could be weighted in the model based on their flow level. In order to get this data the USGS ASTER DEMs needed to be processed through several steps of flow detection analysis. The first step in the analysis was to fill any sinks in the data so that a depressionless DEM could be made (Pan 2012), beginning with identifying the sinks using the Sink tool in the ArcToolbox. This created a layer that identified how many sinks were in each layer. Now that sinks were identified the flow detection analysis could be started. Using the fill tool in ArcToolbox, the sinks in the raster data could be filled and the depressionless version of the DEM was created. Having a depressionless version of each DEM helped to avoid discontinuous data that would negatively impact the accuracy of the data when the drainage network is detected (Pan 2012).

A flow direction raster needed to be made from the filled DEM layers. This could be accomplished in the ArcToolbox by using the flow direction tool which produces an output layer by classifying each cell based on the direction of flow out of that cell. This is based on analysis of the elevation data of all the cells surrounding a single cell. In this analysis, higher elevation cells will flow into lower elevation cells. This tool produces an output raster layer where the directional flow of all areas in the DEM can be seen. However, this is not enough to make a drainage network layer from. The accumulated flow of each cell would need to be identified first. This part of the process was completed using the flow accumulation tool. Using the flow direction raster as the input layer, the flow accumulation tool determined the accumulated flow of each cell based on the number of total upslope cells that flow into it. This process is ideal for locating stream networks by identifying areas of concentrated flow but for the purposes of this project it will be used to create the drainage network layer. The final step in creating the drainage network layer was to perform a Log10 function on the new flow accumulation raster layer. The Log10 function will calculate the base 10 logarithm of cells in the raster data. The raster calculator was used to perform this calculation using a simple formula: Log10Flow_Acc = Log10(Flow_Accumulation). Performing this calculation gave a better visualization of the drainage network than the Flow_Accumulation layer. It also allows areas identified as 0 or negative to be classified as NoData. Having this visualization would be useful later when comparing how close highly susceptible areas follow a drainage pattern. The Layer has been placed over a hillshade layer and made transparent so that the relationship between the slopes and the drainage networks can be visualized (Figure 2-6).

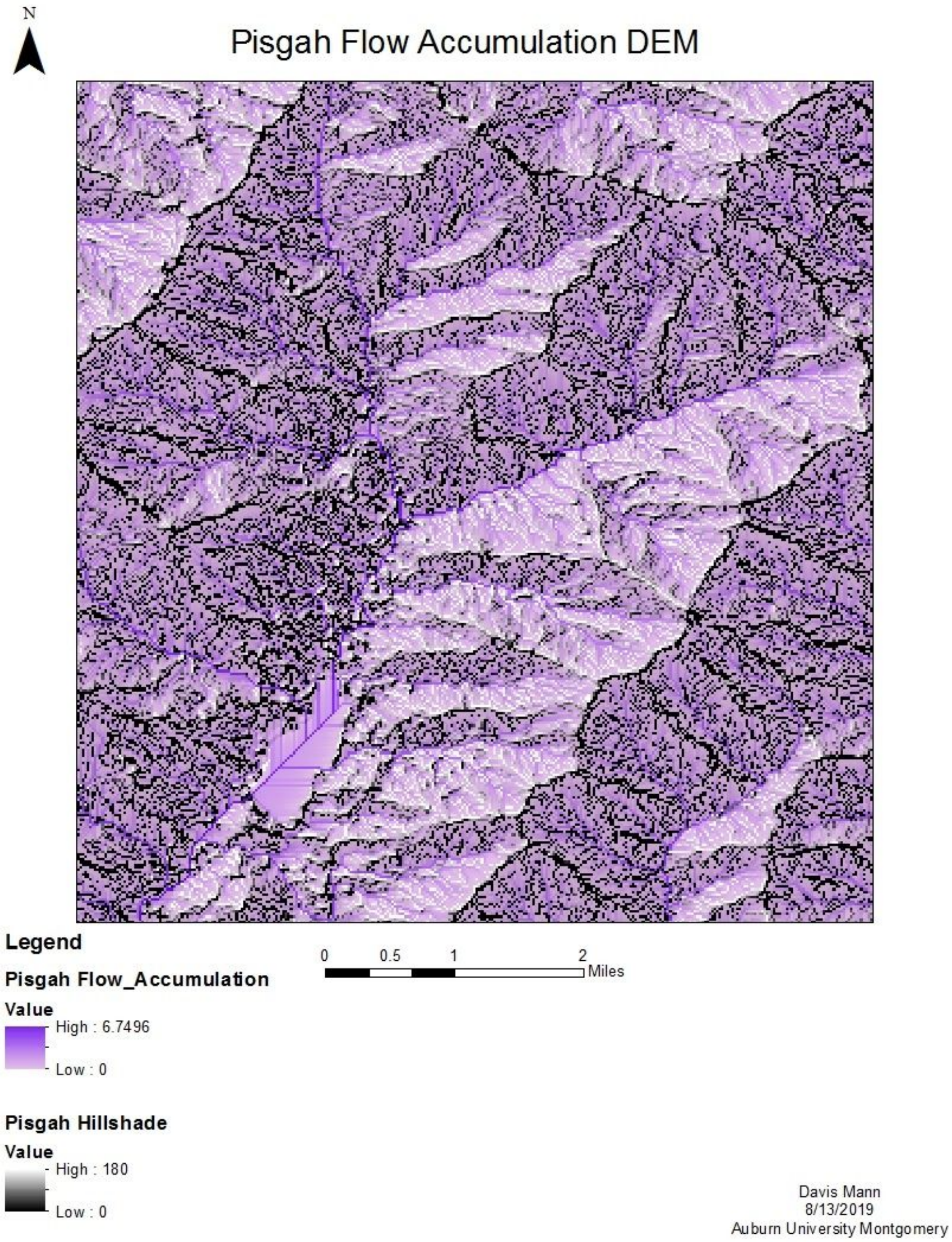

Figure 2-6: An example of a drainage network raster developed from the USGS DEMs. These layers describe the hydrological flow in the study area. They were reclassified and used as weighted rasters in the model.

With the Log10_FlowAccumulation layer created, the final step in preparing the hydrological data for use as a weighted layer was to reclassify. Like the slope layer, the

Reclassify tool was used to weight the levels of flow accumulation in each cell by order of its susceptibility to debris flow landslides. In this case, the higher the flow accumulation in the network, the higher it would be weighted in reclassification on a 0-9 scale. This process of Fill > Flow Direction > Flow Accumulation > Log10 calculation > Reclassify was used for all five DEMs covering the study area.

2.2.3 Developing Rainfall Data

The rainfall data obtained and used for this study covers the entirety of North Carolina and is a raster layer that gives value to cells based on the average annual rainfall in inches. This data was acquired over thirty years from 1970 to 2000, giving more confidence that this data was an accurate representation of annual rainfall in the Appalachian mountains. However, two issues had to be resolved with this data before it could be applied in the susceptibility model. First, because the rainfall data covers the whole state of North Carolina, the data would have to be made to fit with the data. Resolving this first issue could be done by defining the processing extent of the dataview. By changing the processing extent to match that of a specified DEM layer, this defined that DEM as the area extent within which new data could be created. Beyond ensuring that data could be created within a desired DEMs area, by defining the processing extent it was also ensured that new data created within this extent would not be inaccurate when performing the processes for resolving the second issue with the rainfall data.

The second issue is that the rainfall data is presented in a lower resolution than the rest of the raster data which is presented in 30m spatial resolution. This required finding a process which could change the resolution of the data without altering the values or the extent of the raster. By resampling the data, the resolution could be made to match with the rest of the data in the dataview. The resample tool is located within the Raster Processes of the ArcToolbox and was used in resampling the rainfall data. Before resampling the data; however, the processing extent of the dataview needed to be defined based on the DEM of interest so that the resampled raster layer only extends to that DEM, ensuring the accuracy of the data when used later. After inputting the annual rainfall raster layer in the resample tool, the user has the option to define the X and Y values manually or match it to another raster in the dataview. Since matching the spatial resolution to the other data was desired, the base DEM was chosen as the output cell size. After running the Resample tool the output would produce a new resampled annual rainfall raster with a 30m spatial resolution, matching the other data.

Now that the annual rainfall data had been resampled and made congruent with all of the other data in the project, it could now be reclassified using the same method of reclassification as the other raster layers. By using the reclassify tool in ArcToolbox, it was possible to specify the weight levels of the annual rainfall layer. Like in the Bathrellos et al (2017) study, the higher the amount of annual rainfall an area receives, the higher its susceptibility ranking will be. This ranking was done on a one to ten scale of equal intervals. This process of resampling and reclassifying the annual rainfall data was repeated for all 5 DEM areas in the project.

2.2.4 Developing Land Cover Data

Using the NLCD data provided the project with a favorable starting point in regards to reclassifying land use data. Due to the NLCD classifying all land in the United States based on the primary land use, this meant that all types of land cover classifications could be reclassified and weighted in one raster.

Similar to the annual rainfall data, the area covered by the NLCD layer is much larger than that of the individual DEMs that make up the study area. In this case, the NLCD layer covers the whole of the continental United States. This issue was rectified in the same way during the reclassification process by defining the processing extent to be the same as the DEMs that covered the study area. Unlike the annual rainfall data, the NLCD layer has a spatial resolution of 30m, making resampling the data unnecessary.

The reclassification of the land use data followed a different process than the reclassification of the slope, drainage and rainfall data. While the other data could have their impact on landslide susceptibility weighted based on an incremental increase, the land use data needed to have the weight ratings be assigned based on how each specific land cover type contributes to landslide susceptibility. Each value was reclassified based on a ranking of one through eight. How each value was ranked in the reclassification was based on research pertaining to how land cover influences landslide susceptibility as described in the literature review.

The mechanical effects of each value were of particular interest here. In regards to vegetation the mechanical effects relate to how each NLCD value contributes to overall cohesion of soil. Research has shown that soil cohesion is strengthened by root systems but that the strength of root induced cohesion can vary based on key factors. These being the soil penetration and density of the roots (Kuriakose 2006). In vegetation with larger root systems the matrix formed by the roots and soil have a more positive effect on slope stability than vegetation with smaller root systems. Furthermore, this root induced cohesion will only be significant if there is a strong root presence in the top 60cm of soil (Kuriakose 2006). This research informed the rankings of the vegetation values in the NLCD classification system. Vegetation values that were more likely to have dense, more penetrative root systems such as deciduous and evergreen forest were ranked as having a lower impact on landslide susceptibility than those that were likely to have weaker and less penetrative root systems like shrubs, pasture and croplands.

When ranking the various classifications of urban build-up in the NLCD classification system, the landslide inventory data also provided information about where initiation points and deposits of debris flow landslides were likely to occur in the Blue Ridge Mountains. The more developed urban areas experienced less landslide activity than less developed areas. Specifically analyzing initiation points showed that many landslides in the area start on or near mountain roads that traverse along ridges with steep slopes. Roads cut through mountainous regions are known to induce landslide activity by weakening support and reducing resisting forces (Meinhardt 2015).

These roads are classified as Developed, Open Space in the NLCD and have the highest landslide susceptibility ranking in the reclassification. The susceptibility ranking is lowered per each level of Urban development.

2.2.5 Constructing the Susceptibility Model

The reclassified raster layers needed to be put through a raster calculation in order to create a suitability layer that classified landslide susceptibility across the study area. Using this method, the calculation will create a raster layer that essentially ranks the overall landslide susceptibility of all points in the area of a DEM. Points that exhibit high susceptibility rankings within each category of data will rank higher in overall susceptibility than those that do not. The resulting raster layer is called the susceptibility raster, an example of one of the susceptibility rasters can be seen in the Results section.

With the successful creation of a landslide susceptibility raster, the methods and processes that led to its creation could now be compiled into a model that runs all of these processes in one action. This model, when run, will output a landslide susceptibility raster after prompting the user to enter a few parameter layers that the model will need to create it. These parameters layers are as follows: a DEM of the area of interest, a rainfall raster layer that covers annual or seasonal data and an NLCD raster layer. The processes in the model follow along with what is detailed above in how each reclassified layer was created. The DEM is used in the model to create the reclassified Slope layer. It is also used to create the reclassified drainage network layer, following the Fill > Flow Direction > Flow Accumulation > Log10 process ending with the reclassifying of the Log10_FlowAccumulation layer. The rainfall raster layer is used in the model to create a reclassified rainfall layer. It follows the same flow of processes as described in the last section. After defining the processing extent the rainfall raster is first resampled. In the model the resampling process uses the base DEM for its resampling layer in order to make the rainfall layer congruent with the other data. After this, the rainfall layer is reclassified. Finally, the land cover data is used by the model to create a reclassified land cover raster by following the exact same process as described in the above section. This model in its default state is made to work specifically with NLCD data; if other land cover data is to be used then the reclassification tool in the land use "tree" will need to be customized to rank values based on the alternative land cover data values. Figure 2-7 shows a representation of the debris flow susceptibility model.

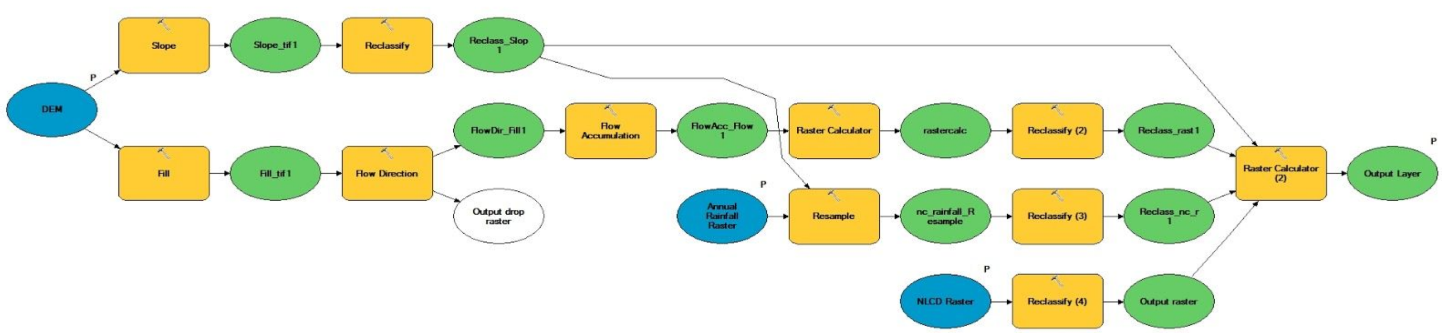

Figure 2-7: A representation of the Debris Flow susceptibility model. Each of the processes that need to be performed on the data are shown here. This automated process creates a susceptibility raster when the parameter layers are entered.

Once all of the "trees" have been run in the model and the reclassified slope, drainage network, rainfall, and land cover data have been created, the model runs all of these reclassified layers through a raster calculation. The method for calculating the susceptibility raster utilizes the Weighted Linear Combination method, represented by this operator:

$$LI = \sum_{i=1}^{n} R_i W_i$$

Where *LI* is Landslide Susceptibility index, *n* is the number of parameters, *Ri* is the rating of factor *i and Wi* is the overall weight of factor *i* (Bathrellos 2017)*.* The Weighted Linear Combination multiplies the weight assigned to each attribute of the reclassified parameter layer by the scaled value given for that attribute. It then sums the results of each factor together to create a total score (Drobne 2009). The susceptibility raster is outputted which classifies cells in the area of the raster based on their overall weighted susceptibility ranking. A final reclassify operation is done on the output layer which will rank the values of the suitability analysis on a 1-6 scale using standard deviations (Bathrellos 2017). After repeated successful run throughs of the model had been achieved, this model was used to create susceptibility rasters for the entire study area in and around the Blue Ridge Mountains of North Carolina, Creating five susceptibility rasters in total. With the model complete and susceptibility rasters successfully produced, an analysis of the results of the model could now be completed.

For verification, identifying which raster value each landslide initiation point was located on was the primary method used (Bathrellos 2017). The amount of landslide points located in each susceptibility ranking could be found using the Extract values from Points operation. Using one of the Susceptibility rasters and a selection of the Landslide initiation points located within that raster's area as input data, this operation creates a new attribute field for the point data that identifies the value from the input raster they are overlaid on. The results of the verification method are seen in the Results section. The Asheville and West Jefferson susceptibility rasters were verified.

III: Results

The output results of the susceptibility model is a raster layer that ranks the cells in the study area based on their level of susceptibility to debris flow landslides as defined by the parameters of the model. Using standard deviations on the susceptibility raster data, the areas with the highest susceptibility in relation to the rest of the raster's area can be identified. It should be noted that each of the five individual susceptibility rasters is analyzing a different section of the study area by itself rather than comparing to the whole of the Blue Ridge Mountains and surrounding areas. This means that the max value for landslide susceptibility in each section is different.

Examining the areas that were ranked highest in susceptibility consistently showed a pattern in regards to the features of these areas. Given the parameters and how the reclassified data is weighted, the highest ranked areas will likely be those that are on the steepest slopes, on or near a high flow accumulation area, receive moderate to high amounts of rainfall annually and have very little vegetation and minimal urban buildup. A consistent finding of the rasters was that areas that met these conditions were along steep mountain ridges as well as along mountain roads, which are classified as developed, open space by the NLCD. These areas had the most potential to be ranked as high susceptibility per the parameters set by the model. However, in order to assess whether areas that match these criteria are a plausible source of landslide activity in the Blue Ridge Mountains, a comparison would need to be made against existing landslide activity data.

For comparison, the NC DEQ landslide inventory maps were used. These maps show where past landslide deposits have formed for a select number of counties that are within the study area. Georeferencing these maps to the county they represent in the dataview provided a better look at where deposit areas existed in relation to the high susceptibility areas identified by the model rasters. Using the georeferenced map to see where the deposits are can help in confirming whether the model has located the high susceptibility areas or not. Figures 3-1 and 3-2 show a map of a high susceptibility area in Buncombe county and that same area from the landslide deposit map, respectively. This area matches the description above of areas that would likely be identified by the model as having high susceptibility. The high susceptibility areas marked in red appear along the steepest slopes in the area where there is minimal vegetation in relation to the surrounding area. Near the top of these slopes lie mountain roads as well which have been found according to researchers to contribute heavily to landslide susceptibility (Meinhardt 2015). Closer inspection of the map data will show that where the highly susceptible areas appear on slopes the identified areas roughly follow the drainage pattern seen in the drainage network data.

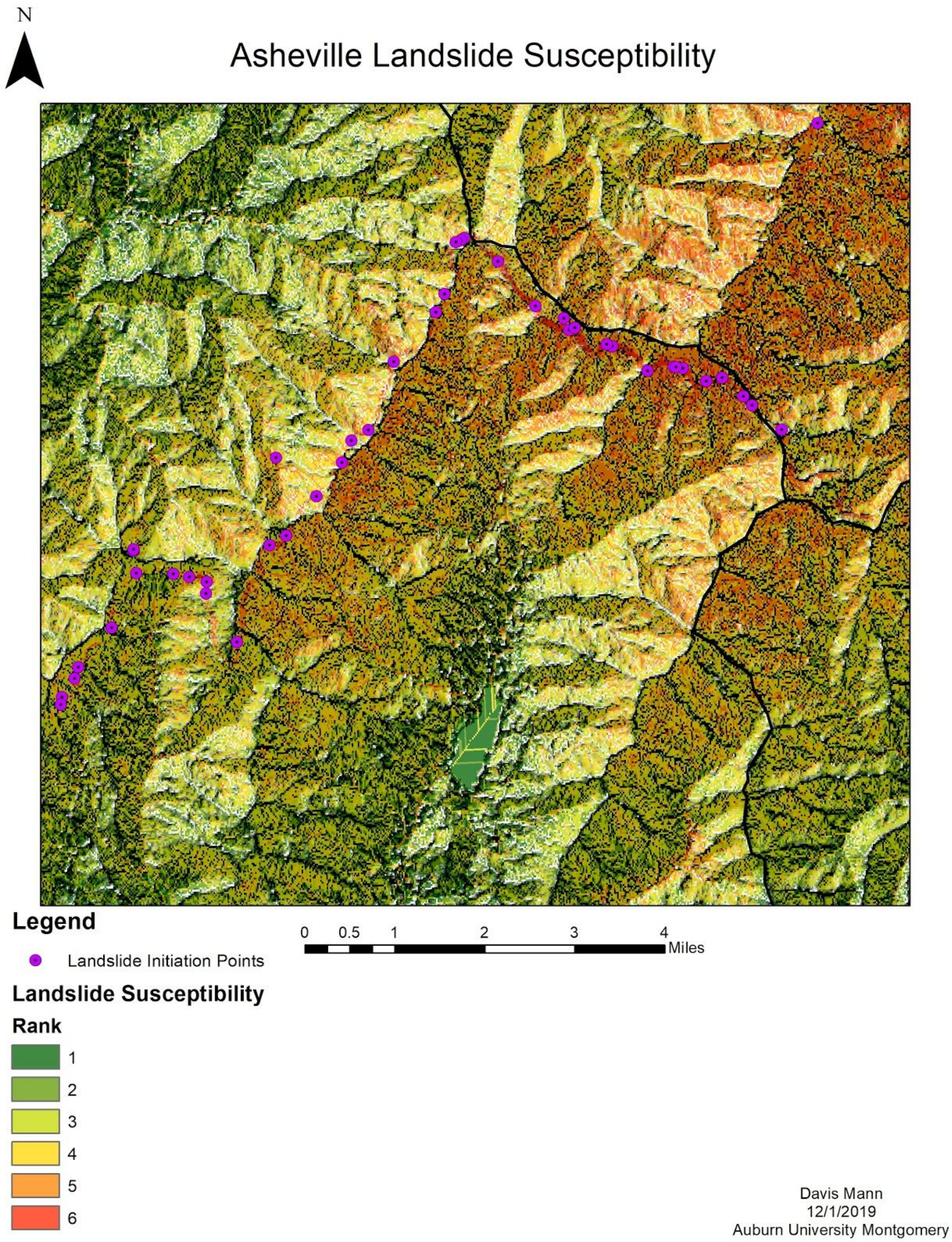

Figure 3-1: This is a map showing a close up of the results of the susceptibility model's output raster. This is an area in the Asheville DEM that has many of the characteristics of high susceptibility areas as identified by the raster. Steep slopes, mountain roads, heavy rain and high flow accumulation are all present here. The past landslide points also support the findings that this is a highly susceptible area for debris flows.

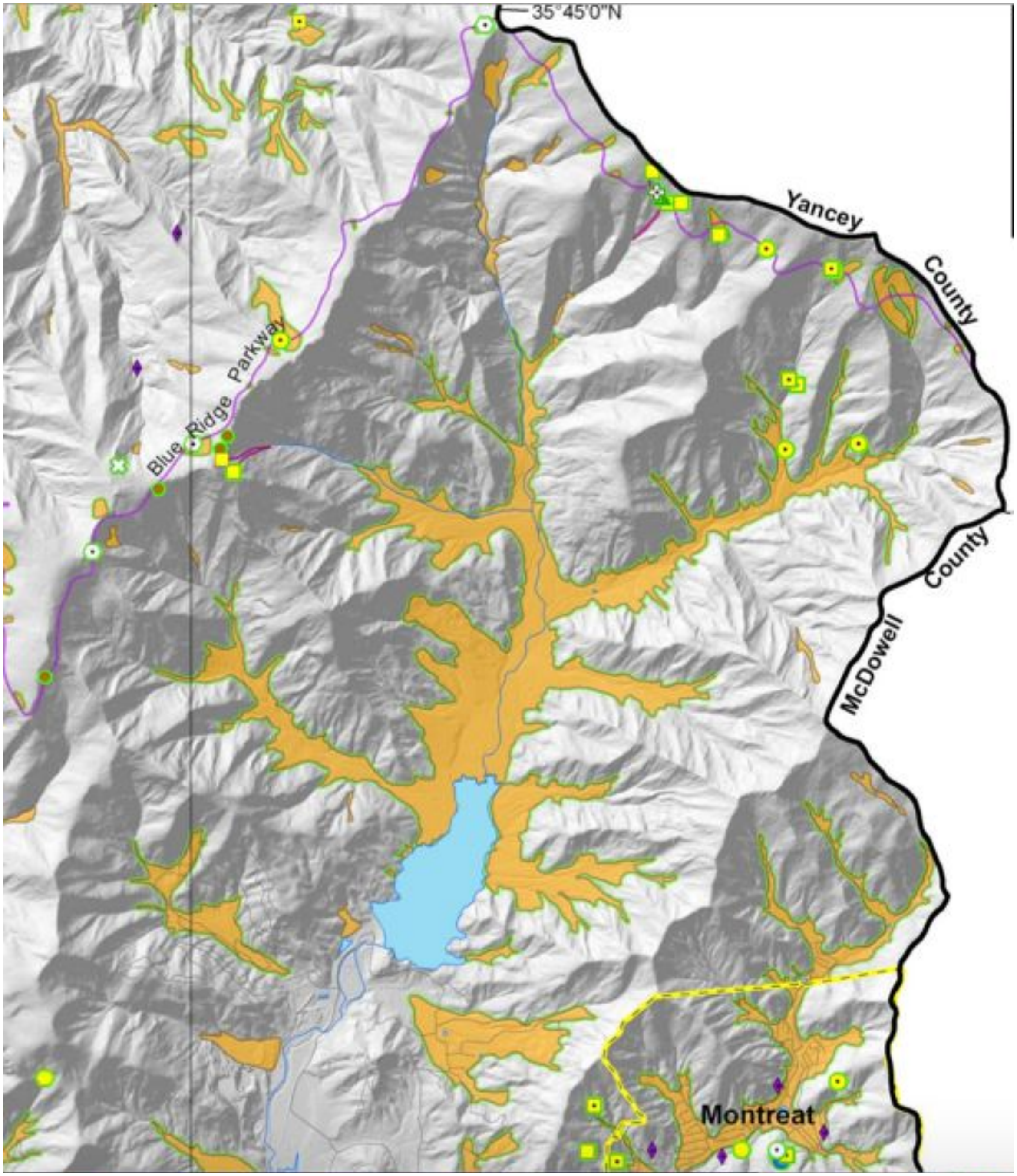

Figure 3-2: This portion of the deposit map shows the same area as Figure 3-1. Note that the deposits shown here are in areas where the drainage network of the high susceptibility areas in the previous figure would bring them.

3.1: Results of Verification

Verification was first performed on the Asheville susceptibility raster using the extract value to points operation. The area of the Asheville DEM contains 342 landslide points from the landslide inventory. The table below (Figure 3-3) show the results of the verification.

Asheville_Susceptibility Raster Verification Results		
Susceptibility Ranking (raster values)	# of Landslide initiation points	% of Landslide initiation points
1	11	3.2%
2	23	6.7%
3	77	22.5%
4	62	18.1%
5	57	16.7%
6	27	7.9%
No Value	85	24.9%

Figure 3-3: The results of the verification of the Asheville susceptibility raster using landslide initiation points. 75.1% of the points were found within susceptible areas. 40.64% of the points were located within medium ranked susceptibility areas.

According to the results of this verification method, 75.4% of the past landslide initiation points within the area of the Asheville DEM were located within areas the Susceptibility model found to be susceptible. Among these the majority were found to be located in medium susceptibility areas (those with a ranking of 3 or 4). The same study was conducted in the area of the West Jefferson DEM (WJEFF). This area had the most landslide activity of all the study areas. There are 527 landslide points located within the WJEFF DEMs area. The results are seen below in Figure 3-4.

WJEFF_Susceptibility Raster Verification Results		
Susceptibility Ranking (raster values)	# of Landslide initiation points	% of Landslide initiation points
1	25	4.7%
2	90	17.0%
3	95	18.0%
4	98	18.6%
5	31	5.9%
6	10	1.9%
No Value	178	33.8%

Figure 3-4: The results of the verification of the West Jefferson susceptibility raster using landslide initiation points. 66.1% of the points were found within susceptible areas. 33.8% of the points were located within no value areas.

The results of the extract values from points operation on the West Jefferson final susceptibility raster show that again, the majority of landslide points (66.2%) were located in areas identified as susceptible. The majority of those that were detected were also in the medium susceptibility range. However, here the amount detected in low susceptibility areas is higher than those in the high areas. Also, the amount of areas located in no value areas is higher, slightly over one-third were not found to be in areas of susceptibility. Upon analysis of the points located in no value areas in both susceptibility rasters, these points tend to be located near other areas of various susceptibility levels.

IV: Discussion and Conclusion

The debris flow landslide susceptibility model produces a raster layer identifying high susceptibility landslide areas based on the factors and weights supplied by the user. Upon comparison to historical records, these identified areas were found to be around areas with high amounts of landslide debris at the base of or around the mountain ridge they were located on. Verification of the model found most of the landslide points to be located in susceptible, the majority of these being within areas of medium susceptibility. The results of the verification of the model support the hypothesis that the methods used in this study can be used to create a model in GIS that locates susceptible areas. This method being a suitability model that weights various factors according to their influence on debris flow landslide susceptibility.

The quality of the suitability analysis is improved with the use of multivariate principles to predict the probability of landslide data, like in the research of Nandi and Shakoor (2009). By utilizing the suitability analysis approach each individual factor could be weighted by overall contribution toward susceptibility (Pradhan 2010), the significance of the factors could then be reflected in the data producing a more accurate map (Nandi 2009). Multivariate approaches treat the factors of landslide susceptibility as part of a whole, rather than entirely individual forces. Each factor interacts and thus contributes to susceptibility but not equally (Nandi 2009). The suitability analysis approach improved the model by accurately identifying high susceptibility areas based on how highly influential factors interacted as well as narrowing the risk of areas with disproportionate factors skewing the results. It also helped curb the risk of bias that may have resulted in using a point based approach (Attaway 2016).

The research on the effects of vegetation on landslide susceptibility provided valuable insight into the mechanics of debris flow landslides that drastically affected the weighting of the land cover features of the study area. In particular, the weighting of areas with lower levels of vegetation as being more susceptible to debris flows than areas with higher levels of vegetation (Shu 2019). Along with this, areas classified as being developed, open space, were classified as having higher susceptibility based on observation of the landslide inventory's initiation points and past literature (Meinhardt 2015). Many of the areas of high susceptibility are located near ridges or along mountain roads due to the way the data was weighted which would be supportive of the research conducted on this subject as well as being consistent with where initiation points were typically found according to the inventory data. In the Asheville susceptibility raster's area, 75% of landslide initiation points were located in areas identified as being susceptible. However, the majority were located in areas of medium susceptibility or blind spots in the data where null values were assigned. This suggests that there is still area for improvement in the model that can make the results more reflective of reality.

Though the results of the model were improved by this research and more on landslide susceptibility modeling, there are areas to improve within the data gathering process and analysis of the data that could lead to an enhancement of the models ability to detect susceptibility. One such area could be the addition of comprehensive soil and geolithic data. Research has suggested that the geological makeup of a region can have an influence on landslide activity (Kawabata 2009). Areas of mostly sedimentary type geography may be more susceptible than other areas and can thus be weighed against other types of geology in the model. Inclusion of both soil and geology data is supported by the data gathering schematic that influenced how data was gathered for this project (Westen 2008). The data could also benefit from the use of buffer zones if they were to be used in the model as a weighted feature. Buffer zones could help the results be more precise when determining how proximity to data features such as roads could impact susceptibility. Buffer zones can also be applied to the landslide inventory data on landslide initiation points for the same reason. Whether or not the buffer zones would need to be converted to raster data in order to work with the model would need to determined. Alternatively, Euclidean distance rasters could be utilized instead to avoid converting data (Bayes 2014).

One other area that is a potential limit to the model’s ability to accurately assess susceptibility is in the weighting of each factors overall effect on susceptibility in the Weighted Linear Combination. This also applies to how the land cover classifications are weighted. While each factor and land cover classification were weighted based on previous research, a more refined method of weighting would likely improve the model. Much of the previous research utilized point based statistics in order to identify factors that contributed to overall susceptibility. Utilizing suitability analysis to create the susceptibility raster is still desirable due to its elimination of point bias (Bathrellos 2017); however, point based models may still be used as a method to determine weight values of the different factors. More accurate weights could be applied in the Weighted Linear Combination if a factors overall contribution to susceptibility was previously quantified, leading to a more accurate susceptibility raster.

A significant portion of the susceptibility rasters were identified as no value which impacted the verification of the model. Many landslide inventory points could not have the susceptibility of the area they were located identified due to them having no value. Inclusion of other factors such as Geology and distance from roads could mitigate this issue. Another solution could be to perform a raster calculation that fills in no value cells based on averages of nearby cells. Conditional statements that perform this function would be ideal to use in the raster calculator. As the results of the verification show, there are too many landslide points located in no value areas to be insignificant and a solution should be found for future studies.

In conclusion, using methods and ideas derived from past research on landslide susceptibility, a method of creating a debris flow landslide susceptibility model was developed using GIS. The model successfully produced a susceptibility raster of the study area in the Blue Ridge Mountains of North Carolina and surrounding regions. The model type used is a Suitability analysis and uses raster data for its parameters representing slope, hydrology, land cover and annual rainfall in order to create reclassifications of the data that are weighted according to how each level of the data impacts susceptibility. The weighting of land cover classification was based on past research done on the effects of vegetation and urban development on debris flow susceptibility (Shu 2019). The accuracy of the results can possibly be improved further with the addition of more data parameters such as soil and geology, more precise data on proximity to roads and past landslide initiation points as well as a more accurate method of weighting factors overall influence on susceptibility. Despite this, the model is capable of producing rasters that locate areas of susceptibility to debris flow activity based on comparison to historical data on landslide points and deposits in the area.

GIS can be a powerful tool for analysis of environmental features. Using methods like the ones discussed in this study, it can accomplish even more by examining the interaction of these characteristics that cause events such as landslides to occur. In this research, the goal was to create a predictive model in the form of a suitability analysis that can provide useful information about the Blue Ridge Mountain region for any who need it. With further development, the interactions that create landslide events could be better understood and used to create an improved susceptibility map.

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