APPLICATION OF GIS-BASED FUZZY LOGIC AND ANALYTICAL HIERARCHY PROCESS (AHP) TO SNOW AVALANCHE SUSCEPTIBILITY MAPPING, NORTH SAN JUAN, COLORADO

By

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B.A., Karadeniz Technical University, 2010

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirement for the degree of

Masters of Arts

Department of Geography

2016
This thesis entitled:
Application of GIS-based fuzzy logic and analytical hierarchy process (AHP) to snow avalanche susceptibility mapping, North San Juan, Colorado

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Application of GIS-based fuzzy logic and analytical hierarchy process (AHP) to snow avalanche susceptibility mapping, North San Juan, Colorado

Snow avalanches in mountainous terrain are a significant natural disaster that affect roads, structures, and threaten human lives. Mapping of snow avalanche susceptibility has the potential to decrease these risks by modeling, mapping, and visualizing susceptible terrain using Geographic Information Systems (GIS) and remote sensing imagery. The North San Juan area in Colorado, U.S. is an ideal location for studying snow avalanches, with well documented avalanche paths that effect the area around Highway 550, Red Mountain Pass and the town of Silverton. The main goal is this study is produce avalanche susceptibility maps for starting zones or release areas of an avalanche-prone area in North San Juan, Colorado by using both fuzzy logic and analytical hierarchy process (AHP) models. In the first step, avalanche locations are identified by aerial imagery and field surveys, and a total of 70 avalanche locations are mapped from various sources. Then, the avalanche inventory is randomly split into a training dataset \( \approx 70\% \) (50 avalanches) for training the models and the remaining \( \approx 30\% \) (20 avalanches) is used for validation purpose. Six data layers, as the avalanche conditioning factors, are exploited to detect the most susceptible areas for starting zones. These terrain factors are elevation, slope, aspect, plan curvature, profile curvature, and vegetation density. Subsequently avalanche susceptibility maps are produced using fuzzy logic and AHP models. For verification, I developed, receiver operating characteristics curve (ROC). The verification results showed that the fuzzy logic model (89.8\%) performed better than AHP (66.9\%) model for the study area. These avalanche susceptibility maps would be useful for hazard mitigation purpose and regional
planning in remote areas of the world where there is limited field data and with access it GIS and remote sensing imagery,
ACKNOWLEDGEMENTS

I would like to gratefully acknowledge Dr. Mark Williams for his contributions, insight and support throughout the process of completing this master thesis. I would like to thank the other members of my research committee, Dr. Richard Armstrong and Dr. Noah Molotch for their time and comments in this thesis.

This research would not have been possible without the support and funds of the Republic of Turkey Ministry of National Education. I would like to thank them for giving this opportunity to complete my master thesis in the U.S.

I would like to acknowledge and thank the department of Geography of the University of Colorado at Boulder for contributing to my educational background and professionalism.

I would like to acknowledge the support and encouragement of my parent, Musa and Hacer Yilmaz, as well as my brother, sister and friends who encouraged me to pursue my master’s degree in the U.S.

Finally, I would like to thank to my wife Briseida Gomez-Yilmaz for her support and being my partner for the rest of our life.
# TABLE OF CONTENTS

## 1 INTRODUCTION

1.1 SNOW AVALANCHES ........................................................................................................... 1

1.2 DESCRIPTION AND CLASSIFICATION .............................................................................. 2

1.3 UNDERSTANDING SUSCEPTIBILITY, RISK AND HAZARD IN AVALANCHE TERRAIN MAPPING ......................................................................................................................... 5

1.3.1 RISK AND HAZARD ........................................................................................................ 5

1.3.2 SUSCEPTIBILITY ............................................................................................................. 6

1.4 GLOBAL INFORMATION SYSTEMS [GIS] AND AVALANCHE ........................................ 6

1.5 LOCATION AND GENERAL DESCRIPTION OF THE STUDY AREA .......................... 8

1.5.1 DATASETS AND AVALANCHE DATABASE OF THE STUDY AREA ......................... 9

1.6 STATEMENT OF GOALS AND OBJECTIVES .................................................................. 10

## 2 BACKGROUND

2.1 GIS AND SNOW AVALANCHE MAPPING STUDIES .......................................................... 13

2.2 AVALANCHE TERRAIN FACTORS ..................................................................................... 14

2.2.1 ELEVATION .................................................................................................................. 15

2.2.2 SLOPE ........................................................................................................................ 15

2.2.3 ASPECT ....................................................................................................................... 16

2.2.4 PROFILE AND PLAN CURVATURE .............................................................................. 17
5.1 SUMMARY OF RESEARCH ................................................................. 72
5.2 CONTRIBUTION OF RESEARCH .................................................. 73
5.3 FUTURE WORK ........................................................................... 74

6 REFERENCES .................................................................................. 77
LIST OF TABLES

Table 1: Spatial relationship each avalanche conditioning factor and avalanche and fuzzy membership values ................................................................. 36

Table 2: If-the rules used in the study area ............................................................ 50

Table 3: Scale of preference between two parameters in AHP [Saaty et al., 2000] ............... 53

Table 4: The pair-wise comparison matrix, factor weights, and consistency ratio of data layers 55

Table 5: The weight of each avalanche conditioning factors by analytical hierarchy process [AHP] ........................................................................................................ 57

Table 6: Index of relative avalanche density [degree of fit] for different susceptibility class by fuzzy logic ........................................................................................................ 63

Table 7: Index of relative avalanche density [degree of fit] for different susceptibility class by analytical hierarchy process [AHP] ................................................................. 64
LIST OF FIGURES

Figure 1: Fatalities by state 2005-2006 to 2014-2015 in the U.S. [Colorado avalanche information center- CAIC, 2016]......................................................................................................................... 1

Figure 2: The avalanche triangle. ................................................................................................................................. 2

Figure 3: Classification of avalanches [Avalanche weather forecasting, 2016]................................. 3

Figure 4: Slab and loose snow avalanches [Delparte et al., 2008]................................................................. 4

Figure 5: Study Area-North San Juan County- ................................................................................................. 9

Figure 6: Profile curvature on the surface [ET spatial techniques, 2013] ................................. 17

Figure 7: Plan curvature on the surface [ET Spatial techniques, 2013] ................................................. 18

Figure 8: Avalanche inventory map............................................................................................................................ 26

Figure 9: Elevation of the study area. ....................................................................................................................... 27

Figure 10: Slope of the study area. ......................................................................................................................... 28

Figure 11: Aspect of the study area. .......................................................................................................................... 29

Figure 12: Profile [left] and plan [right] curvature of the study area. ...................................................... 30

Figure 13: Flowchart for NAIP 1 meter imagery based vegetation density processing. ............. 31

Figure 14: Example of vegetation density classification in an area 10 km² of the study area.... 32

Figure 15: Vegetation density of the study area. ............................................................................................... 33

Figure 16: Membership function of elevation for the study area. ............................................................. 37

Figure 17: The elevation susceptibility map of the study area using fuzzy logic method........... 38

Figure 18: Membership function of the slope for the study area............................................................. 39

Figure 19: The slope degree susceptibility map of the study area using fuzzy logic method. .... 40

Figure 20: Membership function of the aspect for the study area. ......................................................... 41

Figure 21: Membership function of the aspect for the study area. ......................................................... 42
Figure 22: Membership function of the plan curvature for the study area. ........................................ 43

Figure 23: Membership function of the profile curvature for the study area. .......................... 43

Figure 24: The plan curvature susceptibility map of the study area using fuzzy logic method. ................................................................. 44

Figure 25: The profile curvature susceptibility map of the study area using fuzzy logic method. 45

Figure 26: Member function of the vegetation density for the study area. ........................... 46

Figure 27: The vegetation density susceptibility map of the study area using fuzzy logic method. 47

Figure 28: Avalanche susceptibility map based on fuzzy logic model ........................................ 51

Figure 29: Avalanche susceptibility map based on AHP model. .............................................. 59

Figure 30: The distribution % of the training data [50 avalanche locations] in each susceptibility classes. .................................................................................................................................. 60

Figure 31: The distribution % of the validation data [20 avalanche locations] in each susceptibility classes. .................................................................................................................................. 61

Figure 32: Areas % of susceptibility classes according to R-index for validation data. ............. 62

Figure 33: Categorized cell values for fuzzy logic and AHP models........................................ 66

Figure 34: Success rate curves for the susceptibility maps produced in this study. .................. 67

Figure 35: Prediction rate curves for the susceptibility maps produced in this study. ............ 68
1 INTRODUCTION

1.1 SNOW AVALANCHES

Snow avalanches are a significant natural hazard that impact roads, structures and threaten human lives in mountainous area. Large avalanches can reach speeds in excess of 200 kilometers per hour, run out hundreds of meters on valley bottoms, and destroy forests and, reinforced concrete structures [Jamieson and Stethem, 2002]. Annually, snow avalanches in North America average 22 fatalities. Most deaths in North America are from activities related to backcountry travel-skies, snowboarders, snowmobilers, and mountaineers. According to the statistics for 2005-2015 years, a total of 241 people have been killed by avalanches in the U.S., as shown in Figure 1. Most of these disasters took place in the western and northwestern parts of the U.S. [Ayalews et al., 2013].

![Figure 1: Fatalities by state 2005-2006 to 2014-2015 in the U.S. [Colorado avalanche information center- CAIC, 2016].](image-url)
In order to understand avalanche phenomena, a review of avalanche fundamentals is necessary, particularly with regards to describing and classifying avalanches [Delparte et al., 2008]. This discussion will help in outlining the objectives of this thesis. Avalanche researchers and experts have developed a rich background of knowledge from which to further avalanche study. This background information contributes to understanding of the complexities in avalanche activity and helps to describe avalanches phenomena.

1.2 DESCRIPTION AND CLASSIFICATION

A snow avalanche is a mass of snow moving down a slope which can be so small as to be harmless to people or large enough to destroy entire forest and villages [Maggioni et al., 2004]. Snow avalanches occur from the interaction of the snowpack with, terrain and weather; these factors are often displayed as an avalanche triangle, as shown Figure 2 [Fredson and Fesler, 1994]. To create conditions for avalanche occurrence, the terrain must have the characteristics necessary for the avalanche to initiate, the weather conditions must be proper to create snowpack instability, and a trigger to initiate avalanche areas.

Figure 2: The avalanche triangle.
There are different types of snow avalanches in accordance with the many features that describe them, such as dimensions, the manner of triggering and the form of movement.

Categorization of avalanches is still under discussion and development. An overview of snow avalanches classifications is given in McClung & Schaerer [1993] and Barbolini [1999]. Currently, the most commonly used reference system is The Avalanche Atlas, published by the International Commission on Snow and Ice [UNESCO, 1981]. The categorization is performed on the basis of the characteristics of three zones identified within the avalanche path, as shown Figure 3:

1. The starting zones is the area where the snow becomes unstable and initiates movement.
2. The track is the slope which divides the starting zone from the deposition zone. Here, the avalanche is fully developed and reaches its maximum velocity.
3. The runout zone is the area where the avalanche decelerates rapidly, deposits mass, and stops. [Maggioni et al., 2004].

Figure 3: Components of an avalanche path [Avalanche weather forecasting, 2016].
The two main general types of snow avalanches are loose snow avalanches and slab avalanches. These avalanches are shown in Figure 4.

![Figure 4: Slab and loose snow avalanches](Delparte et al., 2008)

Loose snow avalanches start from an initial point on or near the surface and collect mass as they move down the slope. They are also known as point release avalanches. They have usually small dimensions and can be dry or wet. A slope angle that is sufficient to induce motion is required, typically greater than 40° [McClung and Schaerer, 2006]. Loose snow avalanches generally appear naturally due to factors such as snowfall or rain [precipitation] and solar radiation. More dangerous are slab avalanches, which initiate simultaneously over a large area and involve one or more layers of cohesive snow. The release area of a slab avalanche is defined as the area delimited by the crown, the flanks, and the stauchwall. Dry slab avalanches are a greater threat to backcountry users and human triggered slab avalanches result mainly from recreational activities in mountainous terrain. Thus, in this thesis, an emphasis is placed on the assessment of terrain factors necessary for the formation of dry slab avalanches.
1.3 UNDERSTANDING SUSCEPTIBILITY, RISK AND HAZARD IN AVALANCHE TERRAIN MAPPING

1.3.1 RISK AND HAZARD

Any backcountry and outdoor activities create some level of risk. These activities cause the individual to the change that they may lose something that is of values to them. Risk is a measure of the probability and severity of an adverse effect that can include a potential injury including death, loss of money or loss of possessions [CSA, 1997]. It must be recognized that risk also affords an opportunity for the individual to experience something that they highly value [Delparte et al., 2008]. Thus, risk contributes an opportunity for gain with consequence of a potential for loss.

Hazard describes the source of potential harm, danger or adverse effects, whereas risk is the likelihood or change that potential harm occurs [CSA, 1997]. Avalanche hazard is the probability of occurrence of avalanches of a particular type and magnitude in a given location within a reference period of time. Specific to the avalanche environment, a working group in Canada [Statham et al., 2006] is working towards creating expressions to identify both avalanche risk \([R_A]\) and avalanche hazard \([H_A]\). In equation 1., \([R_A]\) is determined by the physical exposure \([E_A]\) of a person or thing to \([H_A]\). Equation 2 displays that \([H_A]\) is a function of the probability of avalanches \([P_A]\) and the severity of the avalanche \([S_A]\). A significant difference between the two definitions is that risk contains exposure, whereas hazard presumes the potential to effect people but does not clearly intend physical exposure.

\[
R_A = f[H_A, E_A] \tag{1}
\]

\[
H_A = f[P_A, S_A] \tag{2}
\]
1.3.2 SUSCEPTIBILITY

Avalanche susceptibility refers to the propensity of an area to avalanche occurrence. In short, it is defined as the probability of occurrence of avalanches of a particular type in a given location. Susceptibility thus refers to the spatial likelihood or probability [given in either qualitative or quantitative terms] for an avalanche to occur in the future. Avalanche susceptibility assessment can be considered as the initial step towards an avalanche hazard and risk assessment. The susceptibility maps can be converted into avalanche hazard maps by including information of spatial, temporal, and magnitude probabilities of avalanches.

Most non-deterministic approaches to susceptibility mapping rely on the principle of precedence, that is, avalanche will occur where the geo-environmental conditions that led to avalanches in the past will again occur in the future. Hence the association of past avalanche occurrence (mainly from inventory maps) with the spatial [and, if possible temporal] distribution of conditioning factors is usually a major driving element of the method or model. In some cases, however, the conditions that dominated on the past may have changed because of factors such as climate change, construction works, land use, and also by avalanche events themselves. This then changes the susceptibility of the terrain to future avalanches, and reinforces the need to estimate the influence of all parameters when devising an avalanche susceptibility. In this thesis, avalanche susceptibility mapping will be created using global information systems [GIS].

1.4 GLOBAL INFORMATION SYSTEMS [GIS] AND AVALANCHE

Geographic Information Systems (GIS) have a vital role to model, analyze, predict, map and visualize avalanche terrain to build and improve upon avalanche terrain recognition and education for backcountry users. GIS of technological advancements are allowing for more accurate quantitative analysis, enhancing susceptibility visualization abilities, and increasing
accessibility to data. Avalanche research relies on terrain, and a key component of many uses of GIS includes detailed terrain models that can be manipulated in a variety of ways. In addition, GIS is a great way to create colorful, detailed maps that can help the public better understand many complex processes.

Making the best decision in the event of a snow avalanche encounters problems because of the lack of information and knowledge on natural phenomena and the heterogeneity and reliability of the information sources available [historical data, field measurements, and expert assessments]. Today, a major target should be to aid decision making by improving the quality, quantity, and reliability of the available information [Malczewski et al., 2006]. Snow avalanche susceptibility mapping has the potential to reduce avalanche risk by mapping, and visualizing hazardous and susceptible terrain using geographical information system [GIS] and provides useful knowledge for the evaluation of avalanche risk, and planning the future direction of city growth and avalanche protection facilities. In regards to this, the use of a geographic information system [GIS] is essential within avalanche research and for the production of avalanche susceptibility maps, because it utilizes the capability of analyzing topographic terrain information and manages the large amounts of data involved in analysis.

In avalanche studies, there are two primary uses for GIS. The first is that GIS can be used to effectively map avalanche terrain this typically involves mapping starting zones by looking at slope angles and vegetation cover or mapping the whole avalanche path considering more terrain factors [elevation, slope, aspect, curvature, land cover]. More complicated models use various techniques to move the snow from the starting zone downhill, thereby mapping out avalanche tracks and runouts. The second common suggestions for GIS is to use it for avalanche forecasting. Some propose the creation of a complicated model that attempts to map factors like
snowfall, wind loading, energy balance, and changes in weak layer strength to come up with a
detailed map of potential problem areas [McCollister and Birkeland et al., 2004]. In this thesis
use GIS and high quality digital terrain data to scientifically create avalanche susceptible terrain
and visualize the results. The need has been established for better analysis, communication, and
visualization of avalanche susceptible terrain to aid decision-making.

1.5 LOCATION AND GENERAL DESCRIPTION OF THE STUDY AREA

The study area is located in the North San Juan Mountains in the southern Rocky
Mountains, in the heart of the San Juan Mountains of Colorado, with numerous peaks above
14,000 feet [4267 m] in height as shown Figure 5. It has the highest mean elevation of any
county in the United States, at 11,240 feet [3,426 m]. It regularly stays open during the snowy
winter season. In the study area, mountainous land covers approximately ≈80% of the region.
San Juan County is more mountainous towards the western and southwest parts, with the highest
mountains and hills. San Juan Province has 387 square miles of land area and 0.87 square miles
of water area. Climate in the San Juan Mountains is typical of alpine and subalpine
microclimates in the Southern Rocky Mountains and is also strongly influenced by the North
Precipitation in the area also originates from mid-continental troughs and the subtropical jet
stream. A nearby SNOTEL station [Red Mountain Pass, 713] at roughly the mean elevation of
the field area (although not in the field area) indicates annual temperature is ~ 1 °C while
average annual precipitation is ~ 75 cm [2/3 of which is winter; 60 cm of snow cover through
winter months is typical]. Maximum river discharge occurs in the late spring [May and June] as
temperatures warm and snowpack melts. Since these climate data are recorded at an elevation
similar to the middle of the field area, the actual conditions are probably slightly cooler and
wetter throughout the upper portion of the valley and warmer and drier throughout the lower portion of the field area. Vegetation varies with altitude but is typically coniferous forest \textit{(Picea engelmannii and Abies lasiocarpa)} in the lower field area and alpine tundra in the upper field area \cite{Johnson et al., 2013}.

Figure 5: Study Area-North San Juan County.

1.5.1 DATASETS AND AVALANCHE DATABASE OF THE STUDY AREA

This study utilized both digital data and avalanche records from a database collected in North San Juan County over a 50-years period \cite{Colorado Avalanche Information Center, 2015}. The digital data consisted of base map information, digital elevation data [DEM] and aerial imagery. The DEM is a digital cartographic and geographic dataset of elevations in xyz
coordinates. Most digital elevation data are derived from stereo photogrammetry capture which is based on the interpretation of aerial photographs using either manual or automated means that allows the representation of geometric properties of the earth’s surface [Wilson and Gallant, 2000]. Many DEMs are composed of regularly spaced grid points; a TIN [triangulated irregular network], further, represents an irregular network of digital elevation points representing surfaces such as ridges, breaks, peaks in slope that are represented with triangular facets. In this thesis, the Advanced Space-borne Thermal Emission and Reflection Radiometer [ASTER] digital elevation model [DEM] having vertical accuracies generally approximately 10 meters [9.4m] resolution is used as a raster product and obtained elevation, slope, aspect, profile and plan curvature layers from this DEM.

Imagery from the National agriculture imagery program [NAIP] [1-meter, 3 bands of imagery] was used to classify, vegetation density and decide avalanche the locations of the study area. NAIP imagery is acquired at a one-meter ground sample distance with a horizontal accuracy that matches within six meters of photo–identifiable ground control points, which are used during image inspection. It uses spectral resolution in natural colors [Red, Green, Blue, or RGB]; some states have four bands of data: RGB and Near Infrared in the U.S. In this study, NAIP imagery is used to create high resolution vegetation density layer and for avalanche locations. Avalanche locations is identified by using aerial photographs/NAIP imagery, field survey and avalanches inventory maps. Total 70 avalanche locations was found and decided to use in this research.

1.6 STATEMENT OF GOALS AND OBJECTIVES

The overarching goal of this thesis is to develop techniques for designing avalanche susceptibility maps for areas of the world where there is limited and often no field measurements
of avalanche paths and climate information. While GIS is useful for cartographic reproductions and visualizations, this study aims to focus on the use of GIS for modeling snow avalanche susceptible terrain for starting areas using both fuzzy logic and analytical hierarchy process [AHP] approaches. The fuzzy logic is an approach to computing based on degrees of truth rather than the usual true or false [1 or 0] Boolean logic, often called crisp values, on which the modern computer is based. The Analytic Hierarchy Process [AHP] is a theory of measurement through pairwise comparisons and relies on the judgements of experts or decision makers to derive priority scales [Saaty, 2008]. In short, AHP is a multi-criteria decision-making approach. These models are exploited to predict where avalanches may occur in future. Avalanche locations are identified by aerial photographs and field surveys, and a total of 70 avalanches are mapped from various sources. Then, the avalanche inventory is randomly split into a training dataset \( \approx 70\% \) [50 avalanches] for training the models and remaining \( \approx 30 \% \) [20 avalanches] is used for validation purpose. Six data layers, as the avalanche conditioning factors, are exploited to detect the most susceptible areas. These factors are elevation, slope degree, aspect, profile curvature, plan curvature, and vegetation density. Subsequently, snow avalanche susceptibility maps are produced using fuzzy logic and AHP models for starting or release areas of avalanches. For verification, the relative density index [R-index] and receiver operating characteristics [ROC] curve, it also called the area under the curve [UAC], are used.

The four main objectives of this research are:

1) Build a detailed digital snow avalanche susceptibility map for starting zones using fuzzy logic method for the North San Juan, Colorado. This involves historical avalanche events (training data) to accurately digitize the avalanche susceptible areas.
2) Build a detailed digital snow avalanche susceptibility map for starting zones using the AHP method for the North San Juan, Colorado. This involves incorporating expert and decision maker’s knowledge to accurately digitize the avalanche susceptible areas.

3) Identify snow avalanche susceptible terrain according to a GIS based on fuzzy logic and AHP approaches. A GIS compatible framework will be devised to maps very high, high, moderate, and low avalanche terrains based upon topographic factors and vegetation density.

4) Validation and comparison of fuzzy logic model with AHP model.
2 BACKGROUND

2.1 GIS AND SNOW AVALANCHE MAPPING STUDIES

GIS has become increasingly helpful and useful in snow avalanche research. All around the world, GIS is been used to monitor and document avalanche occurrences and, locations of snow profiles for many years. In the past most avalanche and snow profile data observations have been recorded as hard copies with no digital spatial component. Recent technology advances make it possible to carry observations and data into a GIS for modeling and sharing. Nowadays, in some research, historical hand-drawn avalanche area and path data is converted to digital GIS data, then loaded into a database that can be linked to the original hard-copy occurrence, snow profile, and weather data.

In this section, I have researched and explored articles relating to the topics of avalanche mapping in a number of reports and scientific journals, as they are all of central significance to understanding, and modeling avalanches. Some of the earliest geospatial areas used for snow avalanche research includes the creation of the avalanche hazard maps and avalanche atlases for cities and transportation corridors in Norway, Switzerland, and Colorado [Armstrong et al., 1976; Borrel et al., 1992; Frutiger et al., 1980; Hestnes and Lied, 1980; Ives and Plam, 1980; Miller et al., 1976]. Meanwhile hazard maps and atlases were created using terrain factors, such as slope, aspect, elevation, alpha angles, and curvature of avalanche paths, for creating runout models and risk to structures and people [Bakkehoi et al., 1983; Bovis and Mears, 1976; Frutiger et al., 1990; Hestnes and Lied, 1980; Lied and Bakkehoi, 1980; McClung and Lied, 1987]. Some studies have used DEMs to model runout distance in combination with known, potential, locations of avalanche paths using GIS in order to map risk and potential hazard areas.
Terrain characteristics and DEM have a typical grid resolution ranging between 5m and 100m to determine potential avalanche hazard areas. Models and databases can be used in combination with meteorological data to simulate avalanche activity and weather or snowpack properties at daily to seasonal scales. Avalanche atlases and hazard maps combined with computer-literate practitioners has enabled the establishment of easily manageable and updateable databases.

2.2 AVALANCHE TERRAIN FACTORS

The assessment of avalanche susceptibility is difficult because there are many factors affecting an avalanche. These factors; topographic characteristics, weather conditions, snowpack structure, natural triggers, and human activity contribute to avalanche susceptibility assessment. The meteorological components consist of snowfall magnitude and rate, wind, precipitation, and temperature. As well, the meteorological component, snow structure springs from successive snowfalls. The stability of the resulting layer structure depends a great deal on the bonds between layers and their cohesion. The meteorological components and snowpack structure rely on weather conditions and change continuously, whereas the topography is a constant factor for avalanche assessment. Thus, in this thesis, I only consider the topographic factors and vegetation density to avalanches assessments. In order to model the starting zones in a GIS requires a DEM and a digital land cover layer, usually depicting vegetation density. Terrain factors such as elevation, slope, aspect, profile curvature, and plan curvature, are derived...
from the DEM. In addition to that, vegetation density is derived from NAIP imagery and DEM using some processes on them. The details of each factor are explained in the following subsections.

2.2.1 ELEVATION

Elevation has an important influence on snow avalanche initiation because snowfall, wind, and temperature vary with altitude. Usually, the wind speed at high altitudes increases with height due to the characteristics of global wind belts. The amount of wind-transported snow generally increases with height on mountains. There is more snow loading due to wind by the process of windward slopes being scoured and deposition occurring over ridges onto lee slopes. Also, snow that falls on lower elevations often melts in the warmer air below and therefore changes to rain by the time it reaches the ground. The frequency of snow avalanches at low altitudes [below 1000 m] is likely to be reduced due to this change in precipitation type. In addition to elevation effects, upper slopes have different snowpack conditions, exposure to wind and sun, and ground cover than lower slopes. This produces avalanches on upper slopes when conditions on lower slopes are stable [McClung and Schaerer, 2006].

2.2.2 SLOPE

Slope is the most significant terrain factor in the assessment of potential snow avalanches. Most avalanche events happened in an area where the slope angle is greater than 30°. The starting zone is typically an area between 30 and 45 degrees in steepness [Butler and Walsh, 1990; LaChapelle et al., 1985]. Perla [1977] found that the mean slope angle for 194 slab avalanches was 38 degrees with a standard deviation of 5 degrees. Bjornsson [1980] found that the most common starting zones in Iceland occurred in gullies and slopes beneath rock walls between 30 and 40 degrees in slope angle. Armstrong [1974] found that starting zones occurred
on all types of slopes including open, unconfined slopes and gullies. Salm et al. [1990] suggested considering as release area, for dense avalanche calculations, regions with a slope angle between 30° [eventually 28°] and 50°. Schweizer & Jamieson [2001] analyzed 809 skier-triggered avalanches and found a mean slope angle of 38.8°.

On occasional events, avalanches start on gentle slopes of less than 25° [e.g., slush flow involving wet snow with high water content], but generally the shear stress induced by gravity on gentle slopes is not large enough to initiate an avalanche [Ancey et al., 2009]. Because the amounts of snow deposition on steep slopes are limited by high amounts of shear stress, avalanches are very frequent and of small dimension for inclinations in excess of 45° to 50°.

2.2.3 ASPECT

Aspect is a predominant parameter in evaluating potential snow susceptible areas, especially high risk areas. It is influenced directly by the radiation heat or solar radiation and exposure to wind. The orientation of slopes with respect to the sun has a significant effect on the stability of the snowpack structure, especially snowpack temperature and temperature gradient. Austrian and Swiss statistics reported that 50% of all avalanches occur in the northern sector [NW–N–NE] of the aspect [Benedikt et al., 2002]. In the northern hemisphere, in general, northern facing slopes are characterized by strong temperature gradients and thus are more prone to the presence of weak layers [depth hoar, surface hoar, and facets]. But, rapid warming in the spring can generate avalanche releases on sunny southern facing slopes [Schweizer et al., 2003].

Aspect with respect to exposure to wind is one of the most significant terrain parameters contributing to the initiation of avalanches. Wind deposits add shear stress to the snowpack. As exposed starting zones on lee slopes are subject to loading of wind transported snow that is transported from windward slopes [McClung and Schaerer, 2006]. Higher density and cohesive
snow deposits from wind action provide an opportunity for the formation of slab avalanches when overlaying a snowpack that contains a weak layer [Delparte et al., 2008]. Wind deposits add shear stress to the snowpack. Feick et al. [2007] observed that wind was the most crucial factor for predicting surface hoar formation and destruction and its resulting impact on spatial variation of snow stability. Schweizer et al. [2006], make the observation that topography and meteorological conditions of wind and solar radiation are the most important factors in the spatial variability of snow stability and that wind causes random spatial variation above tree line. These considerations shows the impacts of wind is a very difficult process to model, especially mountainous terrain where topography can change wind direction at a micro-climate level.

2.2.4 PROFILE AND PLAN CURVATURE

Profile curvature is parallel to the direction of the maximum slope. It affects the acceleration and deceleration of flow across the surface. In GIS, curvature is computed in a way that it is separated into two orthogonal components where the effects of gravitational process are either maximized [profile curvature] or minimized [plan curvature]. A negative profile curvature value indicates that the surface is upwardly convex. A positive value indicates that the surface is upwardly concave as shown Figure 6.

Figure 6: Profile curvature on the surface [ET spatial techniques, 2013]
Plan curvature is perpendicular to the direction of the maximum slope. It relates to the convergence and divergence of flow across a surface. A positive values indicates the surface is sideardly convex. A negative plan indicates the surface is sidewardly concave as shown Figure 7.

![Plan curvature on the surface](image)

**Figure 7: Plan curvature on the surface [ET Spatial techniques, 2013]**

Profile convex surfaces cause an unstable situation in the snow mantle, allowing the appearance of the fractures due to stress, while profile concave surfaces incline the snow accumulation and its stabilization [Ignacio C et al., 2002]. Thus, concave surfaces have more shear stress due to cumulative and increasing snow mass and gravity. The profile curvature help understanding that defines clearly the existence of stress forces in the truly interesting direction, that is, hillside direction [in which the main involved force acts: the one of gravity]. In the fact, the vertical- the one of the potential avalanche advance- is the truly significant direction concerning the snow mantle unstabilization, offering a breakage section in the most harmful direction, the one perpendicular to the avalanche movement. Avalanche paths that have a concave plan curvature, such as a bowl or a cirque, are able to trap blowing snow from several directions in relation to the wind direction [Armstrong and Williams, 1986], while on those paths that have convex plan curvature the snow is often blown away resulting in a thinner snow-pack. Maggioni and Gruber [2002] used the plan curvature to separate concave areas from convex areas while they were looking for the influence of topographic parameters on avalanche release
dimension and frequency. They differentiated convex areas from concave areas based on the following rule: concave areas are profile curvature is smaller than -0.2, convex areas are profile curvature is bigger than +0.2, and flat areas are profile curvature is between -0.2 and +0.2 values. They found that profile concave areas have more avalanche risk and hazard. Sukhishvilli and Megrelidze [2011] used the plan curvature to assess snow avalanche risk in Georgia. Plan curvature was represented by values smaller than –0.2 is concave areas, values between +0.2 and -0.2 is flat areas, and values bigger than +0.2 is convex areas in their study. They found that plan concave areas have more risk at the initiation of avalanches. Snehmani et al [2013] used the plan curvature to demarcate the potential snow avalanche sites using remote sensing and ground observations. Profile curvature is represented by values smaller than 0 is convex, equal to 0 is flat and bigger than 0 is concave areas in his research. Vontobel, Harvey, and Purves [2013] used a curvature classification scheme to analyze the terrain characteristics of human triggered avalanches and their starting zones. They analyzed both profile and plan curvature on 146 avalanche starting zones. They found that avalanches were more frequent in starting zones with concave plan curvature and concave profile curvature. Gleason [1195] and McClung [2001] found that avalanches happened often in starting zones with concave plan curvature.

2.2.5 VEGETATION DENSITY

One of the main functions of forests in mountainous region is to protect people, buildings, and infrastructure against natural hazards, such as avalanches and rock fall [Brang et al., 2006]. Avalanche activity is heavily influenced by forest over. Dense vegetation coverage provides the best defense against snow avalanches [Ciolli et al., 1998]. Density and tree characteristics are key factors influencing vegetation protection ability. Dense vegetation interrupts and prevents snow transport by wind, and they influence radiation transfer and so it
influences the character of the snow cover. Tree crowns and trunks have a significant impact on avalanches. Tree crowns intercept the snowfall, allowing 50% to 90% of falling snow to reach the ground and so snow is released gradually as lumps and meltwater to produce an irregular snowpack structure. Tree trunks might support the snowpack, preventing slab avalanches if the density of tree is great enough. Heavy and moderate timber cover provides an anchor for snowpack that prohibits avalanche formation [McClung and Schaerer, 2006]. Thin timber does not really inhibit avalanche formation and in some cases can actually promote avalanche activity by a fracture line connecting the small areas of weakness around the base of each tree. Rocks have the same behavior like thin timber for promoting avalanche activity by a fracture line. Shrubs have a complex interaction with avalanches. Shrubs in the surface of a shallow snowpack can hinder avalanches, but they can also inhibit snow settlement, creating a loose, weak base for future snowfalls. Bare ground is always an obvious concern for snow avalanches.

2.3 FUZZY LOGIC

Natural process can seldom be described or modelled as a result of sharply defined criteria or variables. Expert decision making thus contains important degrees of uncertainty or vagueness owing to the complex nature of the process and the factors involved. Current algorithms usually do not incorporate this uncertainty of the input factors as they integrate binary classification schemes where the results in a very serious way rely on the definition of thresholds. Eventually, such algorithms can only distinguish between areas where avalanche susceptible areas are possible and where they are not. Therefore, existing release areas algorithms mostly cause worst case scenarios, including all possible area that can potential release. While this may be appropriate for an extreme situation, it is not suited to depict smaller release areas, where only parts of the potential area releases. These kind of issues cannot be
solved through a classical logic method; thus, with this in mind. Zadeh [1965] introduced and developed the fuzzy logic approach in an effort to handle such imprecise data. This method deals with the concept of sharp [so-called crisp] borders by introduction the membership function. Every factor, as opposed to belonging [or not] to a class, is attributed a degree of membership belonging to that class [referred to as a set in fuzzy set theory]. A fuzzy set is characterized as a set of membership functions and is defined mathematically as follows in equation 3 [Burrough and McDonnell, 1998]:

If Z is a collection of objects denoted generally by z, then the fuzzy set A in Z is a set of ordered pairs.

\[
A = (Z, MF(z)) \text{ for all } z \in Z
\]  

[3]

Where the membership function MF is known as the “grade of membership of z in A”. Usually, the membership function MF (z) is defined in the internal [0, 1] with 1 representing full membership of the set and 0 representing non-membership. This method is very attractive for natural hazards applications because it allow the integration of human reasoning capabilities into knowledge –based expect systems. Furthermore, it has already been successfully used and applied to landslide susceptibility mapping [Schernthanner et al, 2007, Ercanoglu and Gokceoglu 2004, Nefeslioglu, Sezer, Duman, and Bozkir, 2010]. There are many landslide susceptibility mapping studies using fuzzy logic around the world. There are some avalanche studies using fuzzy set and logic method but there is not any comprehensive avalanche susceptibility mapping using fuzzy logic approach for starting zone of avalanches. Risk modeling of wet snow avalanches [Zischg et al., 2005]; avalanche release area estimation [Ghinoi and Chung, 2005]; fuzzy rule-based systems for prediction of direct action avalanches [Pant and Ganju, 2004]; fuzzy factorial analysis of snow avalanches [Jaccard et al., 1989];
fuzzy modeling of powder snow avalanches [Barpi et al., 2004]. In this thesis, avalanche susceptibility areas are determined using fuzzy logic approach and a fuzzy if-then rule is created. Such a method would be in particular useful and helpful for the definition of more frequent avalanches, where a differentiation between areas of different likelihood to release is necessary.

2.4 MULTI CRITERIA DECISION ANALYSIS [MCDA] AND ANALYTICAL HIERARCHY PROCESS [AHP]

Multi criteria decision analysis [MCDA] provides a rich collection of techniques for complex decision problems and designing, evaluating, and prioritizing alternative decisions [Malczewski et al., 2006]. As for MCDA can be defined “a collection of formal approaches which seek to take explicit account of [key factors] in helping individuals or groups explore decisions that matter” [Belton and Stewart, 2002]. For approximately 20 years, MCDA methods have been used for spatial problems by coupling them with GIS [Carver et al., 1991; Malczewski et al., 2006]. Accordingly, many spatial decision problems give rise to the GIS based multi criteria decision analysis [MCDA]. These two distinctive areas of research, GIS and MCDA, can benefit from each other [Laaribi et al., 1996; Malczewski et al., 1999; Thill et al., 1999; Chakhar and Martel, 2003]. Overall, GIS techniques and procedures have an important role to play in analysis decision problems.

The analytical hierarchy process [AHP] is a multi-criteria decision making approach that has been successfully applied to a wide variety of decision making situations and was introduced and developed by Saaty [1977and 1980]. The AHP is also a decision support tool which can be used to solve complex decision problems. It is a methodology that synthesizes a decision maker’s preference judgments for each of the decision alternatives, under each criterion within a
decision hierarchy, to create a quantitative measure of the decision maker’s relative preference for each decision alternative. The AHP approach involves the following steps:

1) Break a decision problem into a decision hierarchy, including all criteria, sub-criteria and decision alternatives.

2) Organize pairwise comparisons of all decision alternatives under each criterion, based on Saaty’s 9-point preference importance scale.

3) Produce the local priority weights using the eigenvector approach.

4) Synthesize the local priority weights to create the overall preference weights for each decision alternative.

5) Check the inconsistency level of the decision maker’s pairwise comparisons. [If level of inconsistency is unacceptable, then the decision maker should go back to the pairwise comparisons described in step 2 because the decision marker is less consistent and untrustworthy.]

The use of GIS and AHP has proven successful in natural hazard analysis such as snow avalanches, landslides, floods, and [Ayalew et al., 2004; Gamper et al. 2006; Fernandes and Luts 2010] and other geo-environmental studies [Dai et al. 2001; Joerin et al. 2001; Kolat et al. 2006]. The use of a GIS is essential within avalanche research and for the production of avalanche hazard and susceptibility models, because it utilizes the capability of analyzing topographic terrain information and manages the large amounts of data involved in AHP.

2.5 VALIDATION AND EVALUATION OF MAPPING RESULTS

Model validation purposes at comparing the modeling results with real world situation in order to assess the accuracy, and it also makes possible the comparison among different models. The acceptance of a model needs to perform criteria in some aspects: Adequacy in describing the
system behavior robustness to small changes of the input data, and its accuracy in predicting the observed data [Frattini, Crosta, and Carrara, 2010]. Receiver operating characteristic (ROC) plot approach is the most popular method for accuracy assessment. Relative density index (R-index) is a traditional validation approach. ROC analysis originated in the early 1950's with electronic signal detection theory [Swets et al., 1988]. ROC method were used in many natural disaster mapping validation and evaluation [Chung and Fabbri, 1999; Pourghasemi, Gokceoglu and Pradhan, 2012; Pradhan and Kim, 2014]. The ROC method may help to determine how well the resulting avalanche susceptibility maps have classified the areas of existing avalanches and how well the model predictor variable predicts the avalanche. R-index is also called degree of fit. Baeza and Corominas [2001] developed an index of relative landslide density [i.e., degree of fit] and this method was used to assess the association between landslide inventory and the landslide susceptibility map in many studies [Pradhan and Kim, 2014; Shahabi and Hasbim, 2014]. In this thesis, ROC and R-index analyzes are used to evaluate the correlation between the avalanche susceptibility maps and avalanche inventory locations [70 avalanche locations].
3 METHODS AND RESULTS

3.1 DATA ACQUISITION AND PREPROCESSING

3.1.1 AVALANCHE INVENTORY MAP

Avalanche inventor is essential and a key starting point for studying the relationship among avalanches and terrain conditioning factors. In order to produce a detailed and reliable avalanche inventory map, extensive field surveys and observations are performed in the study area. 1-meter resolution aerial imagery were used to determine avalanche locations with well supported field survey. The location of each avalanche was recorded by a point extracted from the crown and the center line of the debris path. Some avalanche locations were taken from the Colorado Avalanche Information Center [CAIC]. I identified a total number of 70 avalanches in study area since 1965 in a time series. There are more avalanche locations but I chose large and significant avalanches at random. Of the 70 avalanches identified, randomly 50 [≈70%] locations were chosen for the avalanche susceptibility identified, while remaining 20 [≈30%] cases were used for the model validation, as shown in Figure 8.
3.1.2 TERRAIN CONDITIONING FACTORS

3.1.2.1 Elevation

Elevation in the starting zone is a significant factor with respect to avalanche frequency [Smith and McClung, 1997]. Elevation data is obtained from the ASTER digital elevation model [DEM] in a resolution of 10m. From this DEM, thematic data layers including slope, aspect, plan and profile curvature was derived. In this thesis, elevation ranged from 2816 to 4080 m. Elevation values were divided into six categories using 200-m intervals, as shown in Figure 9.
3.1.2.2 Slope

Slope is the most important terrain factor in avalanche formation. Systematic identification of starting areas considers slope angle with values between 30°-45° [Perla et al., 1997]. In this study, slope varies from 0° to more than 74°. The entire slope is analyzed using GIS techniques and is divided into four categories as follows: 0°-25°, 25°-30°, 30°-45°, >45°, which are divisions most widely used in previous studies and literature review. These four categories is shown in Figure 10.
Figure 10: Slope of the study area.

3.1.2.3 Aspect

Aspect has two different impact on avalanche formation, with respect to solar radiation and exposure to wind. Aspect influences the radiation balance which then impacts the snow pack temperature and temperature gradient [Delparte et al., 2008]. It also affects the exposure to wind. Wind deposits make an extra shear stress to the snowpack. In starting zones, lee slopes are exposed to loading of wind transformed snow. In this study, aspect of the terrain surface is divided into eight categories, as shown Figure 11. For this study area, wind data were taken
from the Center for Snow and Avalanche Studies Center, Silverton and data shows that prevailing winds are southeastern-south, south, southwestern-west, west and west-northwestern prevailing winds in North San Juan County.

Figure 11: Aspect of the study area.

3.1.2.4 Profile and Plan Curvature

Profile and plan curvature are determining factors for the acceleration/ deceleration and convergence/divergence of near-surface flows [Gallant and Wilson, 2000; Mosley et al., 1976]. The shape of the slope influences deposition and depth of snow [Luckman et al, 1978]. For an avalanche starting zone, wind can deposit snow in plan curvature areas and deplete snow from
convex areas [Gleason et al, 1994]. In this research, Plan and profile curvature was divided two into two categories; convex and concave areas, as shown Figure 12.

![Figure 12: Profile (left) and plan (right) curvature of the study area.](image)

3.1.2.5 Vegetation Density Extraction

Initiation of avalanche is heavily influenced by vegetation density and cover. In general, avalanches can initiate on any slope with a certain inclination unless dense forest is available to prevent avalanche initiation [Munter et al., 1997; SLF et al., 2000; Gubler and Rychetnik, 1991]. Forests of sufficient size and density inhibit avalanche formation by anchoring the snow to the ground in the starting zone [Mears et al., 1992]. The use of the forests as active avalanche protection is well known and much research has been done to identify the characteristics that make forest good avalanche protection [Frey et al., 1987; Schneebeli and Meyer-Grass, 1993]. In this thesis, the objective of the vegetation density extraction is to create a vegetation density
layer using existing data sets. An approach is used to create high resolution GIS vegetation density layer integrating NAIP 1-meter [three bands] images with 10 meter aspect and slope raster data. This approach uses NAIP 1-meter [three bands] images covering the project area. Representative areas are selected and polygons manually created for five types of ground cover [Heavy forest, Moderate Forest, Light forest, Rock, Open ground] from a visual inspection of the NAIP and slope angle layer. NAIP images convert to the sample resolution with slope and aspect using the resample tool in ArcGIS. A signature profile is created as the input feature class. A maximum likelihood classification [method: maximum likelihood, accuracy :91%] of the entire area will be then processed using the signature profile along with the NAIP 1 meter, aspect, and slope layers. Flowchart of this method shown in Figure 13 and an example of the result is shown Figure 14. Finally, vegetation density (types of the ground cover) of the study area shown in Figure 15.

Figure 13: Flowchart for NAIP 1 meter imagery based vegetation density processing.

In this study, we use the maximum likelihood classification which is one of the most common classification techniques used with remote sensing image data to classify to our study area since pixels are assigned to the class of highest probability and the maximum likelihood
classifier is considered to give more accurate estimates. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability [that is, the maximum likelihood]. If the highest probability is smaller than a threshold you specify, the pixel remains unclassified [Richards et al., 2013]. As the last step, the results of this operation was processed with the boundary clean tool to reduce anomalies.

Figure 14: Example of vegetation density classification in an area 10 km² of the study area.
Figure 15: Vegetation density of the study area.

3.2 AVALANCHE SUSCEPTIBILITY MAPPING

3.2.1 APPLICATION OF FUZZY LOGIC

The fuzzy set theory was introduced by Zadeh [1965]. It is one of the most significant tools to handle complex environmental problems. Thus, the fuzzy set theory has been commonly used for many scientific studies in different disciplines. The suggestion of fuzzy logic is to consider the spatial objects on a map as the members of a set. In the classical set theory, an object is a member of a set if it has a membership value of 1 or is not a member if it has a
membership value of 0 [Hines et al., 1997]. In the fuzzy set theory, membership can take on any value between 0 and 1, reflecting the degree of certainty of membership [Zadeh et al., 1965]. The fuzzy set theory uses the idea of a membership function that states the degree of membership in relation to some attribute of interest. With maps, commonly, the attribute of interest is measured over discrete intervals, and the membership values [Pradhan et al., 2010b, 2010a, b]. Fuzzy logic is useful and helpful because it is straightforward to understand and implement. The fuzzy logic method allows more flexible combinations of weighted maps and could be readily implemented with a GIS modeling language [Pradhan et al., 2010b]. This is different from data-driven methods such as weights of evidence or logistic regression, which use the locations of known objects such as avalanches to estimate weights.

The idea of using fuzzy approach in avalanche susceptibility mapping is to consider the pixels on any causal factor layer as susceptible to avalanches for starting zones or release areas. Pixels can be numeric and range from 0 [i.e., not susceptible] to 1 [i.e., susceptible]. Pixel values must be in the range of 0 to 1, but there is no practical restraint on the choice of values. Values are chosen to show the degree of membership of a set, based upon subjective judgment as shown by Bonham [1994] for mineral exploration, or they can be derived by various functions representing the reality such as J-shape, sigmoidal, and linear functions [Eastmen et al., 2004]. These values can be user or decision defined, or can be derived from a frequency ratio [Lee et al., 2007; Pradhan et al., 2009], or through analytical hierarchy process [Saaty et al., 1977], this analytical hierarch process is one of most used tools for snow avalanche studies. In this thesis, fuzzy membership values have been assigned based on a frequency ratio model [Table 1]. In this part, 50 avalanche locations obtained from the avalanche inventory map was used for the frequency model. The frequency ratio, a ratio between the occurrence and non-occurrence of
avalanches in each pixel, was calculated for each factor’s type or range that has been identified as significant with respect to the initiation of avalanches. An area ratio for each factor’s type or range to the total area was determined. Finally, frequency ratios for each factor’s type or range were calculated by dividing the avalanche occurrence ratio by the area ratio as:

\[
Fr = \frac{\text{Avalanche occurrence ratio}}{\text{area ratio}} \quad [4]
\]

Then, the frequency ratio was normalized between 0 and 1 to describe the fuzzy membership functions. For inference in a rule-based fuzzy model, the fuzzy idea need to be represented by an implication function. The implication is called a fuzzy if-then rule or a fuzzy conditional statement [Alvarez et al., 2000]. A fuzzy set is a collection of paired members, which consist of members and degree of support or confidence for these members. In a discrete form, the fuzzy set about 7 might be expressed as [0.1/5, 0.7/6, 0.7/8, and 0.1/9]. In a fuzzy set notation, the members after the slash [/] are the members of the set [or appropriate numerical grades in each case], and the values before the slash are the degrees of confidence or membership of these numbers. The use of fuzzy sets to represent linguistic terms enables one to represent more accurately and consistently something which is fuzzy [Juang et al., 1992]. A linguistic variable whose values are words, phases, or sentences are labels of fuzzy sets [Zadeh et al., 1973]. In this study, the following fuzzy sets are used to express the input parameters in linguistic forms:

1) Very low = [1/1, 0.75/2, 0.5/3, 0.25/4, 0/5]
2) Low = [0/1, 0.25/2, 0.75/3, 1/4, 0/5]
3) Moderate = [0/1, 0.5/2, 1/3, 0.5/4, 0/5]
4) High = [0/1, 1/2, 0.75/3, 0.25/4, 0/5]
5) Very high = [0/1, 0.25/2, 0.5/3, 0.75/4, 1/5].
Table 1: Spatial relationship each avalanche conditioning factor and avalanche and fuzzy membership values

<table>
<thead>
<tr>
<th>Factor</th>
<th>Class</th>
<th>No. of pixels in domain</th>
<th>Percentage of domain</th>
<th>No. of avalanche</th>
<th>Percentage of avalanche</th>
<th>Frequency ratio</th>
<th>Fuzzy membership</th>
</tr>
</thead>
<tbody>
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<td>97.8</td>
<td>11.86</td>
<td>1</td>
<td>2</td>
<td>0.17</td>
<td>0.03</td>
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<tr>
<td></td>
<td>3000-3200</td>
<td>195.3</td>
<td>73.68</td>
<td>2</td>
<td>4</td>
<td>0.17</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>3200-3400</td>
<td>211.9</td>
<td>25.70</td>
<td>5</td>
<td>10</td>
<td>0.39</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>3400-3600</td>
<td>198.3</td>
<td>24.05</td>
<td>21</td>
<td>42</td>
<td>1.75</td>
<td>0.32</td>
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<tr>
<td></td>
<td>3600-3800</td>
<td>106.3</td>
<td>12.90</td>
<td>16</td>
<td>32</td>
<td>2.48</td>
<td>0.45</td>
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<td>&gt;3800</td>
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<td>1.82</td>
<td>5</td>
<td>10</td>
<td>5.49</td>
<td>1</td>
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<td>10</td>
<td>0.54</td>
<td>0.25</td>
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<td>40.89</td>
<td>44</td>
<td>88</td>
<td>2.15</td>
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<tr>
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<td>28.2</td>
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<td>2</td>
<td>0.58</td>
<td>0.27</td>
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<td>11.26</td>
<td>13</td>
<td>26</td>
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<td>9</td>
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<td></td>
<td>E</td>
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<td>14.09</td>
<td>11</td>
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<td>1.11</td>
<td>0.48</td>
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<td>Plan curvature</td>
<td>Concave &lt;0</td>
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<td>43.72</td>
<td>44</td>
<td>88</td>
<td>20.13</td>
<td>1</td>
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<tr>
<td></td>
<td>Convex &gt;0</td>
<td>464.0</td>
<td>56.28</td>
<td>6</td>
<td>12</td>
<td>2.13</td>
<td>0.10</td>
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<td>Profile curvature</td>
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<td>49.11</td>
<td>8</td>
<td>16</td>
<td>3.26</td>
<td>0.20</td>
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<tr>
<td></td>
<td>Convex &gt;0</td>
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<td>50.89</td>
<td>42</td>
<td>84</td>
<td>16.51</td>
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<td>37.71</td>
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<td>0</td>
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<td></td>
<td>Open ground</td>
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<td>11.93</td>
<td>29</td>
<td>58</td>
<td>4.86</td>
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</tr>
<tr>
<td></td>
<td>Rock</td>
<td>52.4</td>
<td>63.5</td>
<td>11</td>
<td>22</td>
<td>3.46</td>
<td>0.74</td>
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</tbody>
</table>

Domain: pixels in study area, domain (%): (domain/total pixels in study area)*100, avalanche: number of avalanche occurrences, avalanche (%): (avalanche /total number of avalanche occurrence)*100 and frequency ratio: avalanche (%) / domain (%)
In addition to input sets, the outputs of each factor are also classified into groups in terms of avalanche susceptibility. The degree of memberships in the fuzzy set representations for the outputs are formed and obtained from the normalized results of frequency ratios. The main purpose of the utilization of membership degrees is to express all numbers between 0 and 1. This closed interval [0, 1] contributes a standardization for each factor. The membership function of each terrain factor is calculated and given following equations. In equation, the value 1 refers the most susceptible, while the values 0 represents the non-susceptible areas.

Elevation ranges from 2816m to 4080m and according to the inventory map in the study area, the lowest elevation occurred 2962m [Figure 17]. To produce an index map representing the elevation, I used equation 5. This equation is a regression equation and it is obtained using frequency ratios of each criteria of elevation factor.

\[
\mu(E) = \begin{cases} 
0, & \text{if } E < 2962 \\
y = (-2.8176) + (0.0009 \times x), & \text{if } 2962 \leq E < 3800 \\
1, & \text{if } E \geq 3800 
\end{cases} 
\] 

[5]
Where $\mu_E$ is the membership value for the elevation. Index map of elevation factor is produced after above processing and index map of elevation shown in Figure 16.

Figure 17: The elevation susceptibility map of the study area using fuzzy logic method.

Slope ranged from $0^\circ$ to $74^\circ$ in the study area, as shown in Figure 19. According to the avalanche inventory map, there was not any avalanche event on slope angles less than $25^\circ$. To simulate the natural conditions of the area, the triangular membership function is selected for the slope degree in equation 6.
Figure 18: Membership function of the slope for the study area.

\[
\mu(S) = \begin{cases} 
0, & \text{if } S < 25 \\
\frac{S - 25}{38 - 25}, & \text{if } 25 \leq S < 38 \\
1, & \text{if } S = 38 \\
\frac{45 - S}{45 - 38}, & \text{if } 38 \leq S < 45 \\
0.27, & \text{if } S \geq 45
\end{cases}
\]  

where \( \mu(S) \) is the membership value for the slope. Using equation 6 and the slope map of the study area, the slope degree susceptibility map of the study area is produced, as shown Figure 19.
Figure 19: The slope degree susceptibility map of the study area using fuzzy logic method.

According to the inventory map, most of the avalanche incidents have occurred on northwestern, north, and northeastern facing slopes due to prevailing wind and solar radiation, as shown Figure 20. A triangular membership function is also selected in equation 7 to produce the aspect susceptibility map. The aspect susceptibility map is shown in Figure 21.
Figure 20: Membership function of the aspect for the study area.

\[
\mu(A) = \begin{cases} 
1, & \text{if } A = 0 \text{ and } A = 360 \\
\frac{A - 135}{0 - 135}, & \text{if } 0 < A < 135 \\
0, & \text{if } A = 135 \\
\frac{A - 135}{360 - 135}, & \text{if } 135 < A < 360
\end{cases}
\]  

[7]

Where \( \mu(A) \) is the membership value for the aspect.
Figure 21: Membership function of the aspect for the study area using fuzzy logic method.

The avalanche inventory map shows that most of the avalanche accidents occurred in concave areas for plan and profile curvature, as shown Figures 22 and 23. A linear membership function was applied using equations 8 and 9 to create plan and profile curvature susceptibility maps for the study area. Plan curvature susceptibility map is shown in Figure 24 and the profile curvature susceptibility map is shown in Figure 25.
Figure 22: Membership function of the plan curvature for the study area.

\[ \mu(PL) = \begin{cases} 
1, & \text{if } PL < -8.1 \\
\frac{4.9 - PL}{4.9 - (-8.1)}, & \text{if } -8.1 \leq PL \leq 4.9 \\
0.11, & \text{if } PL > 4.9
\end{cases} \]  [8]

Figure 23: Membership function of the profile curvature for the study area.
\[ \mu(PF) = \begin{cases} 
0.20, & \text{if } PF \leq -2.8 \\
\frac{PF - (-2.8)}{5.2 - (-2.8)}, & \text{if } -2.8 < PF < 5.2 \\
1, & \text{if } PF \geq 5.2 
\end{cases} \] [9]

Where \( \mu_{PL} \) is the membership value for the plan curvature and \( \mu_{PF} \) is the membership value for the profile curvature.

Figure 24: The plan curvature susceptibility map of the study area using fuzzy logic method
Figure 25: The profile curvature susceptibility map of the study area using fuzzy logic method.

As shown in Figure 26, most of the avalanche incidents occurred on open ground. A regression equation is obtained from Figure 26 and this equation, as shown in equation 10, is used to produce the vegetation density susceptibility map. This susceptibility map shown in Figure 27. In equation 10, 1 represents heavy forest, 2 represents moderate forest, 3 represent light forest, 4 represents rock and 5 represents open ground.
Figure 26: Membership function of the vegetation density for the study area.

\[
\mu(VD) = \begin{cases} 
0, & \text{if } VD \leq 1 \\
(-0.77) + (0.39 \times VD), & \text{if } 2 \leq VD < 5 \\
1, & \text{if } VD = 5 
\end{cases}
\]  

[10]

Where \( \muVD \) is the membership value for the vegetation density.
Figure 27: The vegetation density susceptibility map of the study area using fuzzy logic method.

After all these processing above, the fuzzy set representations of the conditioning parameters of the avalanches for each terrain factor are obtained from these equations as follows:

1) \( \mu \) Elevation = [0/1, 0/2, 0.15/3, 0.33/4, 0.51/5, 1/6].

2) \( \mu \) Slope = [0/1, 0.5/2, 1/3, 0.27/4].

3) \( \mu \) Aspect = [1/1, 0.67/2, 0.33/3, 0/4, 0.20/5, 0.40/6, 0.60/7, 0.80/8].

4) \( \mu \) Plan curvature = [0.11/1, 1/2].

5) \( \mu \) Profile curvature = [0.20/1, 1/2].
6) \( \mu \) Vegetation Density = [0/1, 0.01/2, 0.4/3, 0.79/4, 1/5].

In the next part, the fuzzy logic representing the inputs and outputs as expressed is extracted using the fuzzy rules in Table 2. Considering the fuzzy if-then rules, the fuzzy index maps representing elevation, slope, aspect, plan curvature, profile curvature, and vegetation density, as shown in Figure 17, 19, 21, 24, 25 and 27, were produced using the previously produced maps in Figure 9, 10, 11, 12, and 15. When producing the fuzzy index maps for terrain factors, python scripts were written in ArcGIS to compute fuzzy sets for each terrain parameter using the equations above. Finally, all the fuzzy index maps were combined by overlaying based on the minimum operator in fuzzy mathematics, as shown in equation 11. Thus, the avalanche susceptibility map was created using the fuzzy approach in Figure 28.

\[
\mu_{\text{combination}} = \min(\mu_A, \mu_B, \mu_C, \ldots) \tag{11}
\]

Minimum values will be calculated for each parameter combination and will be assigned to represent the avalanche susceptibility. The main reason for taking the minimum value at each pixel to finding the most susceptible areas that meet all criteria [Alharbi et al., 2013]. Then, the avalanche susceptibility map will be classified into 4 classes (low, moderate, high, very high) based on natural break classification scheme [Falaschi et al., 2009; Bednarik et al., 2010; Constantin et al., 2010; Erner et al., 2010; Ram Mohan et al., 2011; Xu et al., 2012].

The frequency ratio displays the spatial relationship between the avalanche and avalanche conditioning factor [Table 1]. For elevation >3800m, the ratio is 5.49, which indicates a high probability of avalanche occurrence [Table 1]. For elevation 2816m-300m and 3000m-3200m, the frequency ratio is 0.17, which indicates a very low probability of avalanche occurrence [Table 1].
In the case of the slope [Table 1] between 30 and 45°, the ratio is 2.15, which shows a high probability of avalanche occurrence [Table 1]. For slope degrees between 0 and 25, the frequency ratio is 0, which shows there is not any probability of avalanche occurrence [Table 1]. However, for slope degrees between 25 and 30°, the ratio is 0.54, which means a very low probability of avalanche occurrence [Table 1].

In case of aspect [Table 1], avalanches are most abundant on north-facing, northeastern and east-facing slopes. The frequency of avalanches is lowest on south-facing and southwestern slopes. The frequency ratio is 0 on southeastern slope, which means there is not avalanche occurrence in this slope based on the avalanche inventory data.

In case of plan and profile curvature, most of the avalanches activity occurs in concave areas. Frequency ratios are 2.13 and 3.26, which indicates a very low probability of avalanche occurrence on convex areas [Table 1].

In case of vegetation density [Table 1], the avalanche occurrence values are higher in open grounds and lower in moderate forest areas, which means a very low probability of avalanche occurrence in moderate forest areas and highest probability in open grounds. In heavy forest areas, there is not any avalanche occurrence.
Table 2 If-the rules used in the study area

<table>
<thead>
<tr>
<th>Rule no.</th>
<th>Antecedent part</th>
<th>Consequent part</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>If elevation is very low</td>
<td>Then avalanche susceptibility is non-susceptible</td>
</tr>
<tr>
<td>2</td>
<td>If elevation is low</td>
<td>Then avalanche susceptibility is very low</td>
</tr>
<tr>
<td>3</td>
<td>If elevation is moderate</td>
<td>Then avalanche susceptibility is low</td>
</tr>
<tr>
<td>4</td>
<td>If elevation is high</td>
<td>Then avalanche susceptibility is moderate</td>
</tr>
<tr>
<td>5</td>
<td>If elevation is very high</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>6</td>
<td>If slope is very low</td>
<td>Then avalanche susceptibility is non-susceptible</td>
</tr>
<tr>
<td>7</td>
<td>If slope is low</td>
<td>Then avalanche susceptibility is moderate</td>
</tr>
<tr>
<td>8</td>
<td>If slope is moderate</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>9</td>
<td>If slope is high and very high</td>
<td>Then avalanche susceptibility is low</td>
</tr>
<tr>
<td>10</td>
<td>If aspect is N</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>11</td>
<td>If aspect is NW</td>
<td>Then avalanche susceptibility is high</td>
</tr>
<tr>
<td>12</td>
<td>If aspect NE or W</td>
<td>Then avalanche susceptibility is moderate</td>
</tr>
<tr>
<td>13</td>
<td>If aspect E or SW</td>
<td>Then avalanche susceptibility is low</td>
</tr>
<tr>
<td>14</td>
<td>If aspect is S</td>
<td>Then avalanche susceptibility is very low</td>
</tr>
<tr>
<td>15</td>
<td>If aspect is SE</td>
<td>Then avalanche susceptibility is non-susceptible</td>
</tr>
<tr>
<td>16</td>
<td>If plan curvature is convex</td>
<td>Then avalanche susceptibility is very low</td>
</tr>
<tr>
<td>17</td>
<td>If plan curvature is concave</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>18</td>
<td>If profile curvature is convex</td>
<td>Then avalanche susceptibility is very low</td>
</tr>
<tr>
<td>19</td>
<td>If profile curvature is concave</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>20</td>
<td>If vegetation density is heavy</td>
<td>Then avalanche susceptibility non-susceptible</td>
</tr>
<tr>
<td>21</td>
<td>If vegetation density is moderate</td>
<td>Then avalanche susceptibility is very low</td>
</tr>
<tr>
<td>22</td>
<td>If vegetation density is light forest</td>
<td>Then avalanche susceptibility is low</td>
</tr>
<tr>
<td>23</td>
<td>If vegetation density is open ground</td>
<td>Then avalanche susceptibility is very high</td>
</tr>
<tr>
<td>24</td>
<td>If vegetation density rock</td>
<td>Then avalanche susceptibility is high</td>
</tr>
</tbody>
</table>
Figure 28: Avalanche susceptibility map based on fuzzy logic model.

3.2.2 APPLICATION OF ANALYTICAL HIERARCHY PROCESS

The analytical hierarchy process [AHP] is a semi-qualitative approach, which involves a matrix-based pair-wise compression of the contribution of different factors for avalanches. AHP is a multi-criteria decision making approach, which enables the user to reach at a scale preference drawn from a set of alternatives [Saaty et al., 1980]. This helps decision makers find
what the best suits their goals and their understanding of the problem. This mathematical
approach is widely used in natural disaster susceptibility analysis-avalanche hazard and
susceptibility analysis, site selection, suitability analysis, regional planning, etc [Pourghasemi
and Pradhan, 2012]. AHP includes several steps:

1) Break a complex unstructured problem down into its component factors which the
parameters are chosen in this study.

2) Arrange these factors in a hierarchic order.

3) Assign numerical values according to their subjective relevance to determine the relative
importance of each factor.

4) Synthesize the rating to determine the priorities to be assigned to these factors [Saaty and
Vargas, 2001].

When organizing the factors in a hierarchical order, there should be a relative importance of one
factor over another forming a pair-wise comparison matrix, with scores given in Table 3. In the
construction of a pair-wise comparison matrix, each factor is rated against every other factor by
assigning a relative dominant value between 1 and 9 to the intersecting cell in Table 4. In this
thesis, the susceptibility weight values for terrain factors and their criterion were determined by
pairwise comparisons in the context of the AHP. Weight values of criteria are completely based
on upon real data; however, the assignment of weights for terrain factors and criterion of factors
is very subjective because it is dependent on the judgments of the author. In order to avoid this
subjectivity, the susceptibility of weights values for each terrain factor and criterion of factor is
evaluated by avalanche judgments of several experts as shown in Table 4 and Table 5.
Table 3 Scale of preference between two parameters in AHP [Saaty et al., 2000]

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
<th>Definition</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>Two activities contribute equally to the objective</td>
</tr>
<tr>
<td>2</td>
<td>Weak or slight</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
<td>Experience and judgment slightly or moderately favor one activity over another</td>
</tr>
<tr>
<td>4</td>
<td>Moderate plus</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
<td>Experience and judgment strongly favor one activity over another</td>
</tr>
<tr>
<td>6</td>
<td>Strong plus</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Very strong</td>
<td>An activity is strongly favored and its dominance demonstrated in practice</td>
</tr>
<tr>
<td>8</td>
<td>Very, very strong</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Extreme strong</td>
<td>The evidence favoring one activity over another is of the highest possible order of affirmation</td>
</tr>
</tbody>
</table>

Reciprocals of above if activity i has one of the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i.

When the factor on the vertical axis is more important that the factor on the horizontal axis, this value changes between 1 and 9. Contrary, the value changes between the reciprocals 1/2 and 1/9. In these approaches, the effects of each parameter to the susceptibility of avalanches relative to each other are determined by dual evaluation in determining the preferences in the effects of the parameters to the avalanche susceptibility map. The determination of the values of the parameters related to each other is a situation that relies on the judgment of expert and decision maker. The avalanche susceptibility map [ASM] using AHP model is constructed using the following equation 12 in ArcGIS:
ASMahp = [(elevation × Wahp) × (slope × Wahp) × (aspect × Wahp)]

\[ \times (\text{plan curvature} \times \text{Wahp}) \times (\text{profile curvature} \times \text{Wahp}) \times (\text{vegetation density} \times \text{Wahp}) \]

Where \( W_{AHP} \) is the weightage for each avalanche conditioning factor. The pixel values obtained are then classified into 4 classes [low, moderate, high, and very high] based on natural break to determine the class intervals in the avalanche susceptibility map, as shown Figure 28.

For the AHP model, the final result includes the weights of the derived factors class weights, and a calculated consistency ratio [CR], as presented see in the Table 4.

\[
\text{Consistency Ratio}[CR] = \frac{\text{CI}}{\text{RI}}
\]

[13]

Where CI is the consistency index, which measures the deviation from consistency; RI is a consistency index of randomly generated matrices and depends on the number of elements being compared.

\[
\text{CI} = \frac{\gamma_{\text{max}} - n}{(n - 1)}
\]

[14]
Table 4 The pair-wise comparison matrix, factor weights, and consistency ratio of data layers

<table>
<thead>
<tr>
<th>Factors and classes</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation</td>
<td></td>
</tr>
<tr>
<td>2816-3000</td>
<td>1</td>
</tr>
<tr>
<td>3000-3200</td>
<td>2</td>
</tr>
<tr>
<td>3200-3400</td>
<td>3</td>
</tr>
<tr>
<td>3400-3600</td>
<td>4</td>
</tr>
<tr>
<td>3600-3800</td>
<td>5</td>
</tr>
<tr>
<td>&gt;3800</td>
<td>6</td>
</tr>
<tr>
<td>CR</td>
<td>0.0199</td>
</tr>
<tr>
<td>Slope</td>
<td>0-25</td>
</tr>
<tr>
<td>0-25</td>
<td>1</td>
</tr>
<tr>
<td>25-30</td>
<td>2</td>
</tr>
<tr>
<td>30-45</td>
<td>7</td>
</tr>
<tr>
<td>&gt;45</td>
<td>3</td>
</tr>
<tr>
<td>CR</td>
<td>0.0299</td>
</tr>
<tr>
<td>Aspect</td>
<td>N</td>
</tr>
<tr>
<td>N</td>
<td>1</td>
</tr>
<tr>
<td>NE</td>
<td>1/2</td>
</tr>
<tr>
<td>E</td>
<td>1/3</td>
</tr>
<tr>
<td>SE</td>
<td>1/4</td>
</tr>
<tr>
<td>S</td>
<td>1/8</td>
</tr>
<tr>
<td>SW</td>
<td>1/7</td>
</tr>
<tr>
<td>W</td>
<td>1/6</td>
</tr>
<tr>
<td>NW</td>
<td>1/5</td>
</tr>
<tr>
<td>CR</td>
<td>0.023</td>
</tr>
</tbody>
</table>
### Table 4 continued

Factors and classes

<table>
<thead>
<tr>
<th>Plan curvature</th>
<th>&gt;0 convex</th>
<th>&lt;0 concave</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;0 convex</td>
<td>1</td>
<td>1/3</td>
<td>0.33</td>
</tr>
<tr>
<td>&lt;0 concave</td>
<td>3</td>
<td>1</td>
<td>0.67</td>
</tr>
<tr>
<td>CR</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Profile curvature</th>
<th>&lt;0 convex</th>
<th>&gt;0 concave</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0 convex</td>
<td>1</td>
<td>1/7</td>
<td>0.13</td>
</tr>
<tr>
<td>&gt;0 concave</td>
<td>7</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>CR</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Vegetation density</th>
<th>Heavy forest</th>
<th>Moderate forest</th>
<th>Light forest</th>
<th>Rock</th>
<th>Open ground</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy forest</td>
<td>1</td>
<td>1/2</td>
<td>1/4</td>
<td>1/9</td>
<td>1/9</td>
<td>0.04</td>
</tr>
<tr>
<td>Moderate forest</td>
<td>2</td>
<td>1</td>
<td>1/2</td>
<td>1/6</td>
<td>1/6</td>
<td>0.07</td>
</tr>
<tr>
<td>Light forest</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>1/4</td>
<td>1/4</td>
<td>0.12</td>
</tr>
<tr>
<td>Rock</td>
<td>9</td>
<td>6</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0.39</td>
</tr>
<tr>
<td>Open ground</td>
<td>9</td>
<td>6</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0.38</td>
</tr>
<tr>
<td>CR</td>
<td>0.0089</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5 The weight of each avalanche conditioning factors by analytical hierarchy process [AHP]

<table>
<thead>
<tr>
<th>Terrain Factors</th>
<th>Elevation</th>
<th>Slope</th>
<th>Aspect</th>
<th>Profile curvature</th>
<th>Plan curvature</th>
<th>Vegetation density</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation</td>
<td>1</td>
<td>1/7</td>
<td>2</td>
<td>3</td>
<td>1/2</td>
<td>1/5</td>
<td>0.08</td>
</tr>
<tr>
<td>Slope</td>
<td>7</td>
<td>1</td>
<td>8</td>
<td>9</td>
<td>5</td>
<td>3</td>
<td>0.47</td>
</tr>
<tr>
<td>Aspect</td>
<td>1/2</td>
<td>1/8</td>
<td>1</td>
<td>2</td>
<td>1/4</td>
<td>1/7</td>
<td>0.05</td>
</tr>
<tr>
<td>Profile curvature</td>
<td>1/3</td>
<td>1/9</td>
<td>1/2</td>
<td>1</td>
<td>1/5</td>
<td>1/7</td>
<td>0.03</td>
</tr>
<tr>
<td>Plan curvature</td>
<td>2</td>
<td>1/5</td>
<td>4</td>
<td>1/3</td>
<td>1</td>
<td>1/3</td>
<td>0.10</td>
</tr>
<tr>
<td>Vegetation density</td>
<td>5</td>
<td>1/3</td>
<td>7</td>
<td>7</td>
<td>3</td>
<td>1</td>
<td>0.27</td>
</tr>
<tr>
<td>CR</td>
<td>0.009</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
In terms of numbers, the largest eigenvalue $\gamma_{\text{max}}$ is always greater than or equal to the number of elements $[n]$. If a pairwise comparison does not include any inconsistencies, $\gamma_{\text{max}}$ is equal to the number of elements $[n]$. The more inconsistent the comparisons are, the further value of computed $\gamma_{\text{max}}$ is from $n$. In addition to inconsistencies of pairwise comparisons, a CR with a value higher than 0.10 requires re-evaluation of the judgments in the original matrix of pairwise comparisons, because the decision marker is less consistent and untrustworthy, they are too close for comfort to randomness.

With the AHP method, the values of spatial factors weights are defined. Using a weighted linear sum procedure [Voogd et al., 1983], the obtained weights are used to calculate the avalanche susceptibility. In this study, the CR is 0.009, as shown Table 5; the ratio indicates a reasonable level of consistency in the pair-wise that is good enough to recognize the factor weights. As a result, the weight corresponding to slope is large, whereas profile curvature is lowest in table 5. For all classes of the acquired class weights, the CRs are less than 0.1 in table 4, the ratio indicates a reasonable level of consistency in the pair-wise comparison that is good enough to recognize the class weights. For avalanche susceptibility mapping by the AHP model, as shown Figure 29, I used the following equation 15 in ArcGIS:

$$ASM = [(\text{elevation} \times 0.08) \times (\text{slope} \times 0.47) \times (\text{aspect} \times 0.05) \times (\text{plan curvature} \times 0.10) \times (\text{profile curvature} \times 0.03) \times (\text{vegetation density} \times 0.27)]$$
3.3 VALIDATION OF THE AVALANCHE SUSCEPTIBILITY MAPS

3.3.1 TRADITIONAL VALIDATION METHOD [R-INDEX]

The avalanche susceptibility validation model used the degree of fit to assess the association between the avalanche inventory and the avalanche susceptibility map. This validation approach is generally used for natural disaster susceptibility models, especially for
landslides. Baeza and Corominas [2001] defined a relative landslide density index [R-index] [i.e., degree of fit]. In this thesis, I applied this method for assessment of avalanche susceptibility models. Firstly, the distribution of the actual avalanche locations [training and validation dataset] is determined according to the avalanche susceptibility zones, as shown in Figures 30 and 31.

Figure 30: The distribution % of the training data [50 avalanche locations] in each susceptibility classes.

The degree of fit \( \text{DF}_i \) as it applies to avalanche susceptibility maps was defined as follow in equation 16.

\[
\text{DF}_i = \frac{\left( \frac{n_i}{N_i} \right)}{\sum \left( \frac{n_i}{N_i} \right)} \times 100
\]

[16]

Where \( n_i \) is the area occupied by the avalanches in each susceptibility class \( i \), and \( N_i \) is the total area covered by susceptibility map. The degree of fit for each susceptibility class represents the
Figure 31: The distribution % of the validation data [20 avalanche locations] in each susceptibility classes.

percentage of area included in each susceptibility class. To evaluate the validity of the map, the predicted susceptibility map is compared with the same avalanche dataset as that used for producing the model. Tables 6 and 7 show the degree of fit of avalanche occurrences, including training and validation avalanches for both fuzzy logic and AHP models. At the first step, the training avalanches were used to check the degree of fit. Training avalanches occurrences value are mostly concentrated in the very high weight value zones for both models. Next, the degree of fit for the validation avalanches data is calculated. The results shows the avalanches are again concentrated in the very high weight value range for both models. Generally, there is a gradual increase in the frequency from low susceptibility zone to the very high susceptibility zone for the study area, as shown Figure 32. The fuzzy model [89.29%] has higher value than AHP model [67.97%] in the very high class for validation avalanches. In this study, a large number of
avalanches are clearly evident in the areas of the very high susceptibility, and the fuzzy logic model has higher value in the areas of the very high susceptibility.

There are some researches to identify and determine snow avalanche release areas using the fuzzy logic approach but they did not categorize the release areas to the susceptibility and hazard classes. This is the first study that assesses the starting or release areas using the fuzzy logic method and then categorize them to avalanche susceptibility classes.

Figure 32: Areas % of susceptibility classes according to R-index for validation data.
Table 6 Index of relative avalanche density [degree of fit] for different susceptibility class by fuzzy logic

<table>
<thead>
<tr>
<th>Class</th>
<th>Training avalanche</th>
<th>Validation avalanche</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>763178</td>
</tr>
<tr>
<td>Moderate</td>
<td>2</td>
<td>37209</td>
</tr>
<tr>
<td>High</td>
<td>15</td>
<td>15254</td>
</tr>
<tr>
<td>Very high</td>
<td>32</td>
<td>8582</td>
</tr>
</tbody>
</table>
### Table 7: Index of relative avalanche density [degree of fit] for different susceptibility class by analytical hierarchy process [AHP]

<table>
<thead>
<tr>
<th>Class</th>
<th>Training avalanche</th>
<th>Validation avalanche</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Area occupied by avalanche in each susceptibility class [n_i]</td>
<td>Area of susceptibility class [N_i]</td>
</tr>
<tr>
<td>Low</td>
<td>2</td>
<td>780317</td>
</tr>
<tr>
<td>Moderate</td>
<td>5</td>
<td>36105</td>
</tr>
<tr>
<td>High</td>
<td>17</td>
<td>4764</td>
</tr>
<tr>
<td>Very high</td>
<td>26</td>
<td>3039</td>
</tr>
</tbody>
</table>
3.3.2. **RECEIVER OPERATING CHARACTERISTICS (ROC)**

A significant evaluation of prediction models is the task of validating the predicted results. For the purpose of verification, 20 randomly selected avalanche locations (≈30%) were used. In this thesis, the training dataset is almost twice as big as the testing/validation dataset. Such a relationship between the model development and testing sets enables presentative analytical results [Ayalew et al., 2004]. Then, the pixel values obtained were classified into low, moderate, high, very high susceptibility classes to decide the class intervals in the avalanche susceptibility maps, as shown in Figures 27 and 28. For this purpose, a natural breaks classifier has been selected because this classification scheme is widely used in the literature [Falaschi et al., 2009; Bednarik et al., 2010; Constantin et al., 2010; Erner et al., 2010; Ram Mohan et al., 2011; Xu et al., 2012]. The produced maps were compared with the existing avalanche locations. For validation, we used both success and prediction rate curves by comparing the existing avalanche locations with two avalanche susceptibility maps. To obtain the success and prediction rate curves for the avalanche susceptibility map, the calculated avalanche susceptibility values of all cells was sorted in descending order. Then the order cell values were categorized into 100 classes using “quantile” method in ArcGIS, with 1% cumulative intervals, and classified avalanche susceptibility maps are also prepared with the slicing operation in ArcGIS, as shown in Figure 33. This map was then crossed with the avalanche training and testing-validation datasets respectively. Then, these cross table values are inputted and later evaluated in Statistical Package for the Social Sciences [SPSS] program and thus the success rate curve and the predictive accuracy curve were created.

The success rate curves represent the percentage of correctly classified objects [i.e., terrain units] on the y axis and the percentage of area classified as positive [i.e., unstable] on the
x axis [Vazquez-Selem and Zinck, 1994; Zinck et al., 2001; Chung and Fabbri, 2003]. One success rate curve is better than another if it is closer to the upper left corner of the distribution.

![Figure 33: Categorized cell values for fuzzy logic and AHP models.](image)

The success rate results are obtained by using the training dataset ≈70% [50 avalanche locations]. The success rate curve is obtained by plotting the cumulative percentage of observed avalanche occurrence against the area cumulative in decreasing total weight values. Figure 34 shows the success rate curve for the fuzzy and AHP models. The area under the curve [AUC] can be used to qualitatively assess the prediction accuracy. The model with fuzzy logic has the highest area under curve with a value 0.845, whereas AHP has 0.675. That means the overall success rate of the avalanche susceptibility map is 84.5% by fuzzy model and 67.5% by AHP model. Since the success rate method used the training avalanche pixels that have already been used for building the avalanche models, the success rate is not a suitable method for evaluation.
the prediction capability of the models. However, the success rate method can help to determine how well the resulting avalanche susceptibility maps have classified the areas of existing avalanches.

![ROC Curve](image)

**Figure 34**: Success rate curves for the susceptibility maps produced in this study. Cumulative frequency diagrams showing percentage of study area classified as susceptible (x-axis) in cumulative percent of avalanche occurrence (y-axis). [SE: standard errors and AUC: under the area curve].

The prediction rate shows how well the model and predictor variable predicts the avalanche. This method is already widely used as a measure of performance of a predictive rule [Yesilnacar and Topal, 2005; Van Den Eeckaut et al., 2006; Pradhan et al., 2010; Pourghasemi et al., 2012]. The receiver operating characteristics curve (ROC) plots the different accuracy values acquired against the whole range of possible threshold values of the functions, and the ROC servers as a global accuracy statistic for the model, without regard to of a specific discriminate threshold. This curve was obtained by plotting all combinations of sensitivities and proportions of false negatives (1-specific), which can be obtained by varying the decision threshold. ROC curve area has a range of values between 0.5 and 1 for a good fit, while values
below 0.5 shows a random fit [Swets et al., 1988]. The results of the prediction curve are shown in Figure 35, it is clear that the susceptibility map using fuzzy logic model, the AUC is 0.898, which corresponds to the prediction accuracy of 89.8%, whereas susceptibility map using AHP model, the AUC is 0.669 and its prediction accuracy is 66.9%.

Figure 35: Prediction rate curves for the susceptibility maps produced in this study. Cumulative frequency diagrams showing percentage of study area classified as susceptible (x-axis) in cumulative percent of avalanche occurrence (y-axis). [SE: standard errors and AUC: under the area curve].
4 DISCUSSION

4.1 MODEL EVALUATION AND SELECTION FOR AVALANCHE SUSCEPTIBILITY ANALYSIS

AHP model is commonly based on a rating system provided by expert opinion or decision maker. In fact, expert opinion is very helpful in solving complex problems like avalanches. However, to some scope, opinion can change for every individual expert and therefore can be subjected to cognitive limitations with uncertainty and subjectivity. Another part of the situation is that data-driven methods are also powerful in avalanche susceptibility mapping and involve less subjectivity. Thus, it is significant to analyze the spatial relationship between the avalanche conditioning factors and avalanche locations. Fuzzy logic model lets users order parametric importance before the avalanche susceptibility analyses application. It is based on two resemblance relation values represent parametric relationships [by parametric pair wises] on avalanche occurrences and avalanche locations individually [by each avalanche conditioning actor and avalanche locations]. The first one described the avalanche susceptibility relationships among the parameter pairs, whereas the second one expresses the relationship between the conditioning factors and avalanche locations.

The ROC validation result displayed that the fuzzy logic model has better prediction accuracy of 89.9%, which is better than the AHP model [66.9%]. Both ROC and R-index validation approaches confirm that overall fuzzy logic model has higher prediction accuracy that the AHP model. Despite the AHP method was based on expert opinion or decision maker, it is thought that the selection of the avalanche conditioning factors on avalanche occurrence alloys the subjectivity concept in this method leading to poor result. Although models used in this
research produced reasonable and logical results, however, it should be not forgotten that the reliability the results is clearly affected by the avalanche location data that is, the avalanche inventory map.

4.2 DATA FOR AVALANCE SUSCEPTIBILITY ANALYSIS

In this study, meteorological components and snowpack structure is not considered because they depend on weather conditions and change continuously. Moreover, due to inaccessibility of mountainous natural terrain and cost, snowpack structure is not consulted for starting zones. The meteorological components include wind, temperature, snowfall, and precipitation intensity. However, to some extent, wind is accounted for this study in relation to slope aspect exposure to wind because exposed starting zones on lee slopes are subject to loading of wind transported snow that is transported from windward slopes [McClung and Schaerer, 2006]. In this study, avalanche data from historical events were taken in the middle of the winter season. Due to there are not many avalanche occurrence data in southern aspects but still northern and eastern aspects are domain at avalanche occurrence due to exposure to wind.

In addition, the assumption that past avalanche frequency can be used to describe the future occurrence is not always supported in some study area. Thus, unique conditional analysis could be an effective complement as proved in Klimes [2012].

The results can be affected by spatial resolution and the quality of data. Scale factor controls the derivatives of a digital elevation model [DEM]. Slope, aspect, plan and profile curvature can be varied in different ways as scale changes. Reliable assessment depend on the quality and the scale of the available data and the selection of appropriate methodology for analysis and modeling [Choi et al., 2012]. Nowadays, rapid advances are making Earth observation techniques more successful and powerful for avalanche detection, mapping, and
monitoring and hazard analysis. Remote sensing imagery in higher spatial resolution, such as SPOT or IKONOS, could be acquired to improve the result. Current researches also show that air-borne laser scanning LIDAR or digital photogrammetry enables the generation of high quality DEM datasets with fine spatial resolution, which offers detail topographic data, can significantly improve the accuracy [Buhler et al., 2012].

The impact by data classification method on the final susceptibility result continue to be unclear. Indeed, the natural breaks [Jenks] classification method was initially tested in this study. Then, equal interval classification was tested and eventually there were not significant changes. This result is supported by Quinn [2014] who suggested that all of those potential groupings (e.g. Equal interval or natural breaks, equal area) would have minimal effect to the resulting susceptibility model and would therefore be valid means of simplifying the analysis.
CONCLUSION AND FUTURE WORK

5.1 SUMMARY OF RESEARCH

Avalanches are among the most hazardous natural disasters. The mountainous terrain and severe weather conditions make North San Juan, Colorado unique as the most vulnerable to the risk of avalanches. Based on the result and interpretation of this thesis on avalanche susceptibility mapping for starting zones in this study area, several conclusions can be made.

Avalanche susceptibility assessment contributes the most significant information for hazard assessment. In avalanche–prone mountainous areas, direct geomorphological accessing for avalanche hazard is virtually impossible. Remote sensing [air-borne or space-borne] techniques contribute robust and capable alternatives for identifying, detecting and monitoring avalanches and their related factors. This study is expected to produce a map, and also to contribute to develop appropriate strategies for avalanche susceptibility mapping by the help of GIS and remote sensing technology.

This research attempts to determine a zonation map of avalanche susceptibility for starting zones and delineate the highly susceptible area of avalanche of North San Juan, Colorado. Various methodologies have been suggested for avalanche susceptibility mappings. The locations of historical avalanches recorded in the avalanche inventory map and the selective factors [elevation, slope, aspect, plan curvature, profile curvature, and vegetation density] are assessed by fuzzy logic method and analytical hierarchy process [AHP] method. It can be concluded that the distribution of avalanche is largely governed by a combination of geo-environmental factors, such as elevation of 3500m-4080m, slope of 30° -45°, aspect of NW, N, NE, E, plan and profile curvature of the concave, vegetation density of open ground. In this
thesis, the statistically-based fuzzy logic and AHP model are demonstrated to estimate the avalanche susceptibility based on the environmental settings and historical avalanche record in North San Juan, Colorado. Figures 27 and 28 show the detail avalanche susceptibility zonation maps by fuzzy logic approach and AHP approach, respectively.

More importantly, this research attempts to suggest a new model assessment technique for avalanche susceptibility mapping. The verification result displays satisfying and well enough relationships between the susceptibility map and avalanche location data. These approaches are straightforward and cost effective and can be applied in other areas with similar topographic settings. The validation result shows that fuzzy logic model [89.9%] is superior to the AHP model [66.9%] for the study area in terms of prediction accuracy.

5.2 CONTRIBUTION OF RESEARCH

In previous studies, there was a lack of comprehensive research using fuzzy logic model for avalanche susceptibility mapping. For analytical hierarchy process [AHP] model, there are many researches for avalanche susceptibility and hazard maps but we used both models and then compared models in terms of their accuracy. In past studies, most of the models have had an accuracy of less than 90%. For example, Veitinger [2015] identified potential slab avalanche release areas from estimated winter terrain using the fuzzy logic approach. His model had an accuracy of about 60% and 80%. Chang and Chung [2003] created a statistical GIS-based model for the prediction of snow avalanche susceptibility using terrain features. The accuracy of their susceptibility maps was between 67% and 82%. In comparison to the accuracy in this model which is nearly 90%.

The significance of this study has showed that the GIS-based on fuzzy logic and analytical hierarchy process [AHP] models are two of the most valuable tools to locate and identify potential
avalanche susceptibility areas for site planning and management. The models obtained from GIS layers [terrain conditioning factors] will not prevent avalanches, but will contribute to reducing fatal avalanches, because they involve the members of confidence for paired members and a set of evaluation criteria represented as map layers. Local authorities and land use planners should use these maps but should also note that the avalanches in high and very high susceptibility areas might repeat themselves, due to heavy snowfalls. Models as a first step to conduct suitability analysis in support of decision making because the combination of high snow cover and highly sophisticated infrastructure with human interaction is playing a major role. The protection of transport routes, settlements, tourism areas and ultimately human lives is essential. Site planning, construction of supporting structures, and control programs by using GIS-based fuzzy logic and analytical hierarchy process [AHP] models in these areas will be the most significant methods for enhancement of avalanche safety.

5.3 FUTURE WORK

Determining snow avalanche runout extent is an important consideration for mapping avalanche susceptibility and hazard. Determining the potential avalanche runout distance has been an issue that transportation, resources, communities, and recreational in mountainous terrain have always dealt with. There are two main approaches to address the serious concern of avalanche runout: statistical run-out modeling and dynamic avalanche runout models. In future work, in order to estimate the avalanche runout, an alpha-beta statistical runout model will be used. An alpha-beta equation will obtained carrying out field study on about 100 avalanches or more. To determine runout an approach will be taken to first identify starting zones. High and very high classes of fuzzy logic model will be taken as staring zones. Then, the avalanche flow will model from starting areas down the valley sides. In identifying potential avalanche starting
areas, use a topographic parameter “distance to ridge” as an important variable in addition to terrain factors elevation, slope, aspect, plan and profile curvature, and vegetation density.

Distance to ridges is important due to the influence of snow transport. Snow deposition on windward side of the ridge may form cohesive slabs and scoured slopes on the lee side may result in a shallow snowpack [Delparte, Jamieson, and Waters, 2008]. To isolate the starting zone area of an avalanche path, all ridgelines within the North San Juan will be identified in GIS by using DEM data to isolate areas with no other points upstream of them. The tops of the ridges can be relatively flat and are generally considered safe terrain to travel; however, starting areas are expected on either side of the ridges depending upon climatic conditions. Spatial analyst and the hydrology toolset will be used to identify and extract ridgelines from an elevation raster [DEM]. To isolate these areas, the ridgelines will be buffered to include areas 20 m from the ridge tops. When the potential starting areas are identified, the flow paths from these areas will be modeled using the D8 flow routing algorithm as described in GIS. To find out avalanche flow paths from the top of the starting zones to valley bottoms. A least cost path analysis will then run with the potential starting areas as the input grid and DEM as the cost distance raster that will determine the cost surface from most to least cost and D8 grid as the grid to determine the path based on a cell by cell basis with the least accumulative cost. The results will be displayed by flow routing lines. This flow routing lines will be used like an avalanche path centerlines. The next step is to determine the avalanche runout location point along the length of the flow paths. The simplified alpha-beta runout equation established for North San Juan County will be employed. In GIS the point at which the flow lines intersect slopes of 10° or less will readily be identified and the β angle can be determined. The alpha angle will be computed by using the equation above. The maximum runout will be calculated and subsequently mapped the results in
GIS. These lines will indicate the expected length of the runout zone. The lateral extents [width] of these areas will be determined using air photos and field observations integrating vegetation density and slope degree.
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