LANDSLIDE HAZARD MODELING IN VENTURA AND SANTA BARBARA

COUNTIES, CALIFORNIA USING MULTI-TIERED GEOSPATIAL

DATA ANALYSIS

by

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DEDICATION

To my mother Lainjo Nsai Joan Mary, father Gwaya Henry Lila, brothers Derick Ajumni, Blaise Jr. my sister's Glory, Irene, Edna and finally my girl Marie Killa, you all gave me the courage to start this and the strength to finish it. I couldn’t have done this without you. You all lived every moment of this journey with me, and during the high and low times, you all remained supportive.

Thank you.

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LIST OF ABBREVIATIONS

Abbreviation **Description**

GIS - Geographic Information Systems

PBH - Proximity-Based Hazards

PBHEM - Proximity-Based Hazard Exposure Model

MCPDF - Multi-criteria Probability Distribution Function

FM - Fuzzy Measures

EKB - Expert Knowledge Base

FMCPD - Fuzzy Multicriteria Probability Distribution

MCDA - Multi-criteria Decision Analysis

MCA - Multi-criteria Analysis

PDF - Probability Distribution Function

NAIP - National Agriculture Imagery Program

USDA - United States Department of Agricultural

LOF - Landslide Occurrence Frequency

ROC - Receiver Operator Curve

AUC - Area Under the Curve

LSMM - Landslide Susceptibility Mapping Models

FMM - Fuzzy Membership Measures

SVM - Support Vector Machine

USDA - United States Department of Agricultural

USGS - United States Geological Survey

MCA - Multi-criteria Analysis

NAD 1985 - North American Datum

UTM - Universal Transverse Mercator

PBEM - Proximity- Based Hazard Exposure Model

PBHEA - Proximity- Based Hazard Exposure Analysis

QPA - Quantitative Probabilistic Approach

ABSTRACT

Population growth and sprawling urbanization have resulted in higher perturbations of susceptible landscapes and more people and infrastructure exposed to hazardous landslides in southern California. This, in turn, has resulted in an increase in both frequency and magnitude of landslide disasters in the region. Landslides impact thousands of people and damage billions of dollars of infrastructure each year. Mitigation and response to these disasters can be difficult and expensive especially when reliable, high-resolution risk and hazard exposure maps are rarely available to local planners and managers at scales that can be efficiently utilized for local decision-making. Several methods for assessing landslide hazards have been proposed and implemented over the years. However, a portable, high-resolution method of assessing and visualizing landslide risk and hazard exposure remains elusive. This research provides a two-step method, enabled by geographic information systems (GIS) and multi-criteria quantitative analysis, to produce a high-resolution spatial analysis of both geophysical landslide risk and landslide hazard exposure for the built environment. Phase I of this study develops and deploys a GIS-based method for landslide risk assessment using selected geophysical attributes, including past landslide and wildfire experience, to model landslide risk within the study area of Ventura County and Santa Barbara County, California. Phase II leverages the high-resolution quantitative risk results from Phase I to develop a landslide hazard exposure model that illustrates the likelihood of landslides interacting with features of the built environment within the study area. The resulting hazard exposure

model provides a reliable, efficient ranking of potential landslide hazard exposure for each building parcel within the study area based on the integrated geophysical risk model, the geomorphological attributes of the study area and the spatial density of the built environment. This research demonstrates that, by leveraging a multi-tiered modeling process that involved both primary and secondary data, Geoscientists and hazards managers can develop high-resolution landslide risk and hazard assessments suitable for land-use and settlement planning at the local scale. In applying this approach, hazard exposure mapping can play a renewed role in assessing areas with high landslide hazards and helping mitigate the associated risks.

I. INTRODUCTION

Landslides and other forms of mass movements have become more problematic for urban planners and property owners as population growth and sprawling urbanization push land development into more geomorphologically dynamic environments. In the US alone, landslides and other forms of mass movement cause damages of more than US$ 1-2 billion and 25-50 deaths annually (National Research Council 2004, Ahuja 2011 and Iwamoto 2018). More recently, changing climatic conditions, including extreme rates of precipitation, greater propensity for drought, and rampant wildfires have acted as triggering mechanisms producing a spike in the frequency of landslide incidents, especially in southern California. For instance, the Tuesday, January 9th, 2018 mudslide in Walloped Montecito, Santa Barbara resulted in the death of 20 people, destroyed 65 homes, and damaged over 460 other residence (Santa Barbara County's emergency management report, 2018). To address these trends, urban and city planners must be able to select suitable locations for future development projects such as housing, hotel resorts, and roads.

Complex landslide susceptibility mapping models (LSMM) have emerged over the years to assess landslide susceptibility for different regions of the world. However, these assessments are often conducted at broad spatial scales making their application difficult at local scales for neighborhood planning. To help address this problem, this research selects an urbanized, landslide-prone study area, specifically Ventura and Santa Barbara counties along the southern California coastline (Figure 1) and develops a two-tiered method for generating quantitatively robust, neighborhood-scale landslide hazard assessments that meet the needs of local planners and land managers responsible for managing land parcels in landslide susceptible and hazardous environments. This research is informed by and extends current scholarship in GIScience-based landslide modeling and contributes to an improved understanding of landslide hazards from a human-environment perspective.

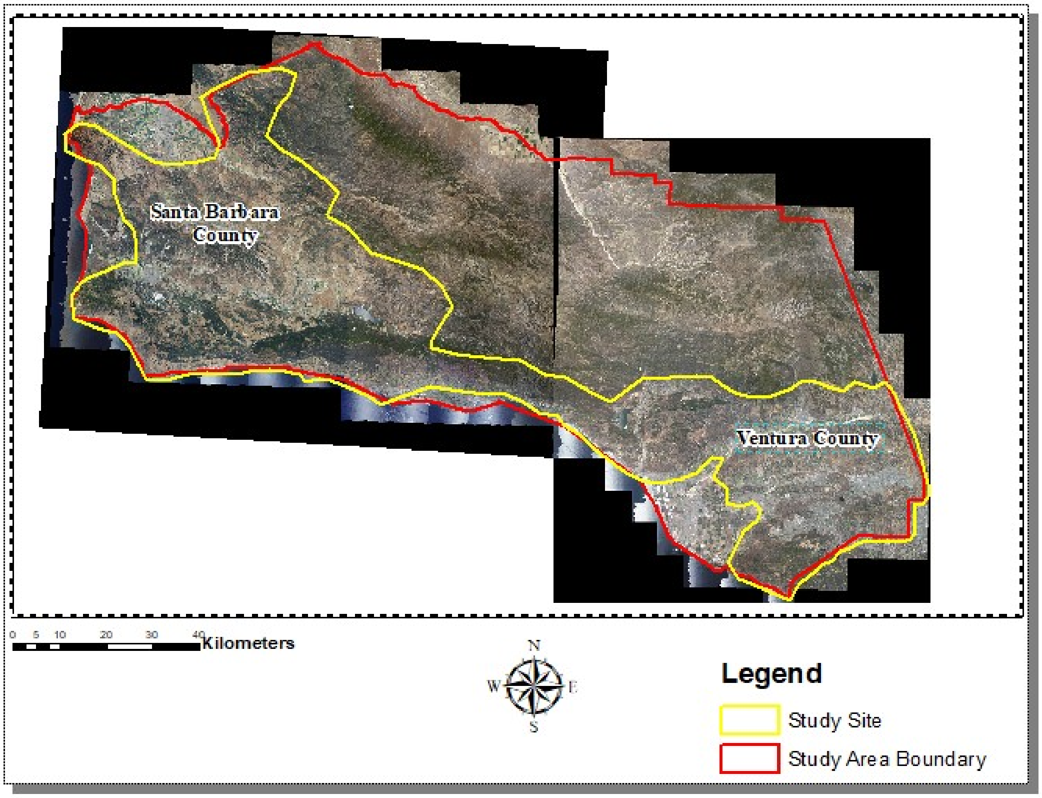

Figure 1. Illustrates the Map of Study Site.

Overall, the objective of this study is to put forward a GIScience-based method for developing neighborhood-scale assessments of environmental landslide hazards in landslide-prone regions. However, like most other areas of the United States, there is a lack of high-resolution, geophysical landslide risk data that is necessary to conduct human-environment hazards analysis for this region. In particular, there are no spatially and temporally robust datasets available that would enable a high-resolution assessment appropriate for hazard analysis at the scale of building parcels, individual structures, and small neighborhoods. Therefore, the first phase of this research develops, validates and operationalizes a GIScience-based methodology for generating high-resolution spatial landslide susceptibility models using multiple environmental causative factors, as shown by current geophysical landslide literature. The second phase of this research illustrates the utility of the landslide susceptibility model in developing hazard exposure models at a building parcel level or neighborhood-scale.

1.1. PHASE ONE: COMPLEX LANDSLIDE SUSCEPTIBILITY MODELING

A successful realization of landslide susceptibility and hazard exposure modeling requires a data-driven model of landslide frequency, and a knowledge base model (KBM) of fuzzy operators to be integrated or combined. The underlying principles of this approach is a combination of fuzzy set theory and fuzzy logic. Fuzzy set theory employs a membership function (MF) that expresses the degree of membership of a value concerning a specific attribute of interest. The attribute of interest is measured at discrete intervals usually between 1 and 0. Fuzzy membership functions (MF) can be expressed as a table relating map classifications to membership values (Pradhan 2010; 2011, and Feizizadeh et al. 2014). Fuzzy logic, on the other hand, is straightforward and easy to implement. This approach can be successfully integrated with GIS – multi-criteria analysis (MCA) and used to model imprecise objectives such as landslide susceptibility (Akgun et al. 2012). The fuzzy logic technique is ideal because it leads to a flexible combination of weighted criteria that can subsequently be implemented through a GIS-MCA, to further improve the accuracy of model results (Pradhan 2010; Pourghasemi et al., 2012). Fuzzy logic permits the input of vague, imprecise, and ambiguous information (Balezentiene et al. 2013). It is commonly used in spatial planning to treat spatial objects within a study area on a map as either member of a set or not; for example, an object can either belong to the set (1) or the set (0). This approach is unique in that it uses the location of known landslides to estimate weightings or coefficients for the GIS-MCA.

A sample of 599 landslide locations within the study area was identified through visual interpretation of aerial imagery from National Agriculture Imagery Program (NAIP) and digitized. From the sum of 599 digitized landslide locations, a sample of 150 landslide locations are randomly selected and extracted using a geographic information system software (GIS) randomization tool. The sampled landslide datasets are subsequently used as validation data, while the remaining 499 landslide locations data used as training data.

Eleven landslide criteria factors were extracted from each landslide location including; slope, aspect, curvature, elevation, precipitation, soils, proximity to fault lines, proximity to roads, land use/land cover, fire experience, and terrain roughness. The landslide occurrence frequency for each class of criteria factors were computed. The fuzzy membership values were calculated for each criteria factor using the landslide occurrence frequency for the respective classes of all eleven criteria factors. Index maps of landslide susceptibility were created for each criteria factor and included in the GIS. Fuzzy membership classes for the conditioning factors of landslide hazards were integrated, resulting in a landslide susceptibility map classified from very low to very high. The 499 training and 150 cross-validations landslide locations mentioned earlier were used to train and validate the model quantitatively. Once the model was validated, the landslide susceptibility GIS layer was generated, illustrating the overall geophysical risk of landslides in the study area. This new, high-resolution GIS layer was then used below in Phase (II) to derive a proximity-based exposure model, illustrating the hazardousness of the built environment within the study area.

1.2. PHASE TWO: PROXIMITY-BASED LANDSLIDE HAZARD MODELING

The second phase of this study develops and deploys a proximity-based exposure, or hazard model by analyzing the intersection between the high-resolution susceptibility model developed in Phase (I) with the spatial features of the human-built environmental systems. Phase (II) is a four-step process in which the hazard exposure of the building parcels within the study area are quantified and ranked from low – high risk based on landslide proximity and landslide impact likelihood respectively. Step 1 calculated the Euclidean proximity distance of exposed building parcels to classified zones of landslide susceptibility (Thrust distance). Step 2 calculated potential debris flow impacts to buildings, taking into consideration the horizontal, vertical and linear characteristics of possible debris flow. Step 3 computed building exposure patterns using weighted proximity measures against landslide susceptibility zones. Step 4 integrated the landslide susceptibility model achieved in Phase (I) with the proximity-based hazard exposure model from steps 1-3 above to illustrate the spatially diverse patterns of landslide hazard within the study site.

1.3. DISSERTATION OUTLINE

This study produces high-resolution landslide risk and hazards exposure maps that can serve as guides to urban planners and decision makers, ensuring effective and efficient use of space for urbanization while reducing potential hazard exposure and cost effects associated with landslide hazards. Chapter (I), introduces the general concept(s) of landslides and hazards. It summarizes the principles of landslides and the instability of the slopes of Southern California as well as presents the two main phases of the analysis, phase (I) and phase (II), highlighting the general issues associated with both. Chapter (II), begins with a general overview of the study area background. It states the research objectives of the study with some intended questions to be answered. It describes the site and situation of the study area and provides general information on the type and abundance of landslides, including the geomorphology, lithology, structure, climate, and other physiographic characteristics. Furthermore, this chapter provides information on the nature and extent of the damage caused by landslides in this area. Chapter (III), describes the processes associated with phase (I) – landslide susceptibility model in detail and discusses the literature review. The literature review involves a study of the principal methods of assessment (old, new and hybrid), from the process of choosing a mapping scale to determining the relationship between a preferred mapping scale and the suitable method for modeling. This chapter also addresses concepts and definitions useful for landslide susceptibility modeling, including literature guided discussions on the differences between probabilistic (quantitative) and heuristic (qualitative) approaches. I weigh the strengths and weaknesses of each of the approaches proposed in the literature and the problems associated with their application and the limitations of the results obtained. I review the various applications of fuzzy logic and multi-criteria, their strengths, weaknesses and how to overcome some of its non-linearity issues. Here, I also discuss the conceptual and theoretical framework for the geophysical risk model, providing a rationale for the criteria employed in this analysis process. I also briefly outline the criteria used to recognize and map landslides from stereoscopic aerial photographs and the assumptions made in this analysis as well as present descriptions and explanations for the topographic, environmental and thematic datasets used to perform the susceptibility analysis. Further, I elaborate on the data and methodology applied to phase (I) of this study, I explain the procedure of data collection, data preparation, data analysis, model validation and the subsequent development, and implementation of the landslide susceptibility model on a neighborhood scale. Chapter (IV), describes the processes associated with phase (II) – Proximity-based hazard exposure model in detail and discusses the problem statement and literature review. The literature review process involves a detailed analysis of the various research methods and advancements that have been made in the vast body of knowledge in the field of hazards and recent efforts at hazard quantification and risk calculation. This chapter, also discusses the conceptual framework for phase (II), the data preparations, methodology and the final hazard exposure results. Chapter (V), presents the limitations encountered in-phase (I) and phase (II) of this study, elaborating on their applicability and suggested recommendations. The chapter concludes with some general discussions in hazards literature and outlines the various literatures cited.

II. GEOGRAPHIC SETTING

2.1. BACKGROUND

A landslide can be defined as the movement of a mass of rock, debris, or soil down a slope, under the influence of gravity (Nemčok et al. 1972; Varnes 1978; Hutchinson 1988; Cruden 1991; Cruden and Varnes 1996). Landslides are triggered by a variety of geomorphic, environmental, climatic and anthropogenic phenomena including intense or prolonged rainfall, earthquakes, rapid snow melting, and a variety of human activities. Landslide processes can occur in the following forms; flows, slides, falling movements, and many landslides exhibit a combination of two or more types of movements (Varnes 1978; Crozier 1986; Hutchinson 1988; Cruden and Varnes 1996; Dikau et al. 1996). Landslides occur when the destabilizing forces acting on a hillside are more significant than the counter stabilizing forces (See Figure 2) below.

Figure 2. La Conchita Landslide, 2005 California. - Courtesy of Mark Reid, USGS

The ratio referred to as the safety factor, indicates slope instability in the sense that when the ratio is less than 1.0, the slope is unstable and will likely fail if triggering factors exceed thresholds that have caused similar slopes to fail in the past (Randall et al. 2005). Landslides are assessed by the magnitude of their respective triggering factors; depth of the area of impact, the volume of rock and soil material involved in the slide process, the frequency of occurrence, the speed and the triggering factors such as earthquakes, tremors, anthropogenic activities, as well as precipitation. Rising damages to human environmental systems from landslides and other forms of mass movements resulted in increasing human activity on landslide susceptible landscapes around the world such as in Maierato in Southern Italy, Santa Barbara and Ventura, Southern California (Brenning et al. 2015).

Worldwide, landslides are responsible for billions of dollars in damages and thousands of deaths and injuries each year (Smith et al. 2009). Due to limited funding and the scarcity of high-resolution data for modeling, most landslide risks analysis are conducted at large, regional and medium geographic scales (Ward et al. 1981; Wilson and Keefer 1983; Terlien et al. 1995; Jibson et al. 1998; Jibson 2001; Collins and Znidarcic 2004; He and Beighley 2008). Landslide risk models of large and medium scale (1:10,000-1: 50,000) are usually problematic for urban development and hazard mitigation agencies because of the lack of homogeneity in landslide inventory datasets, terrain morphology, and composition (Van Westen et al. 2006).There are ongoing efforts to develop two and three-dimensional models of landslide risk and hazard exposure maps, as land development patterns in many remote communities push infrastructure and people further into landslide-prone environments (Wieczorek 1984; Gritzner 2001; Ayalew 2004; Booth 2009). So far, the modeling efforts have not delivered the high-resolution modeling techniques and maps that can be easily replicated and implemented by local development planners. When high-resolution building parcel level, and or neighborhood, landslide susceptibility and hazard exposure maps are too expensive for local planners or unavailable to the public, hazard mitigation can be difficult and costly.

Over the past 116 years, the coastal population of Southern California has increased from approximately 794,817 in 1910 to 22,422,614 in 2015 (US Census Bureau, 2016). The rate of anthropogenic activities (construction of roads and other hillside utilities) under the banner of development has followed population growth, resulting in the emergence of numerous residential settlements at the base of, or on, unstable slopes along the Southern California Coastline (Zell and Lurie 2002). These trends have pushed infrastructure further into landslide-prone environments and placed a growing number of people into evermore precarious locations (see Figure 3). Some sites are more susceptible to landslides than others. Settlement areas at greater risk are those closer to steep slopes, road cuts and or excavations, areas of historical or existing landslides, and areas where human development has altered slopes. In the Californian Southern Coastline, residents often settled in areas known as debris cones, where steep mountain streams debouched onto the valley floor (Rice 1985). These areas are attractive because of the abundant water supply, but pose a grave risk of landslides, particularly as expanding development perturbs these landscapes.

The ability to identify areas prone to landslides, and the relative probability of landslide occurrence at resolutions that can be leveraged by local planners and homeowners, is a critical step in gaining control over landslide hazard. Previous research has identified the need for high-resolution landslide mapping as indicated below:

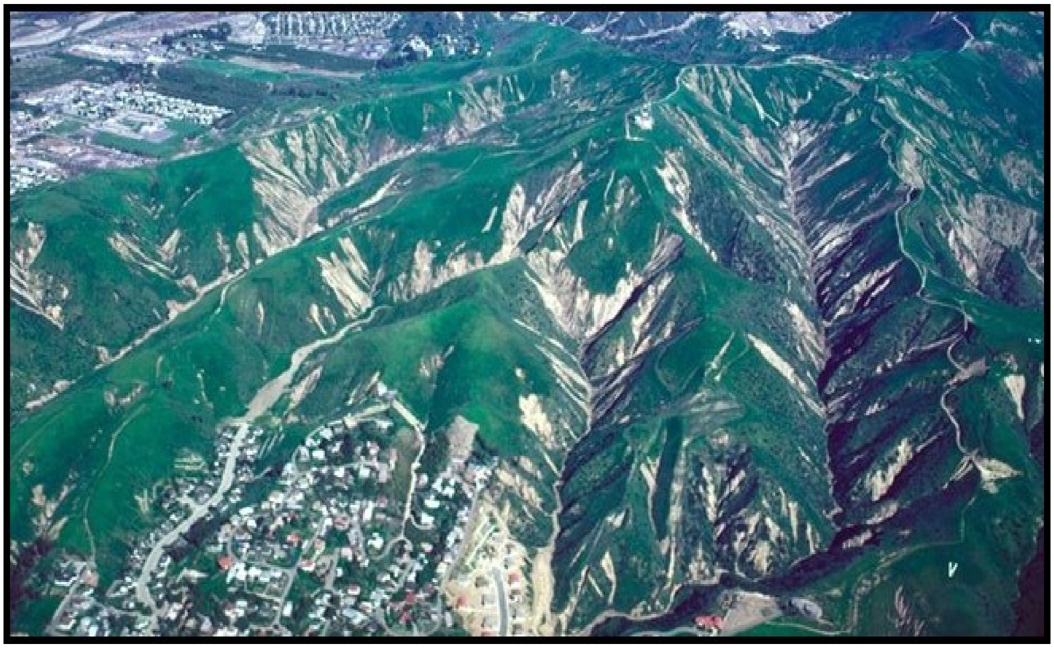

Figure 3. Landslide & Debris Flow Scars, San Gabriel Mountains - Courtesy of USGS

> (…) Land sliding is a worldwide problem that probably results in thousands of deaths and tens of billions of dollars of damage each year. Much of this loss would be avoidable if the problems were recognized early, but less than one percent of the world has landslide inventory maps that show where landslides have been a problem in the past, and even smaller areas have landslide susceptibility maps that show the severity of landslide problems in terms decision makers understand. Landslides are more manageable and predictable than earthquakes, volcanic eruptions, and some storms, but only a few countries have taken advantage of this knowledge to reduce landslide hazards. Land sliding is likely to become more important to decision makers in the future as more people move into urban areas in mountain environments and as the interaction between deforestation, soil erosion, stream-habitat destruction, and land sliding become more apparent. (…) (Brabb 1991, p.60).

State environmental agencies such as the United State Geological Survey (USGS) have led the way in landslide and hazard mitigation through assessments and publication of landslide information (Olshansky 2006). Nonetheless, their efforts have been limited because of insufficient funding and budgetary cuts in recent years. The Californian legislature approved the "Landslide Hazard Identification Program," which was instrumental in producing several maps that helped local planners with landslide hazard planning (Olshansky and Rogers 1986).

Unfortunately, the program was replaced in the 1990s by the Seismic Hazard Mapping Act, which has failed to provide sufficient detail for quality planning because it produces low-resolution hazard maps for large regions which turn to be unhelpful to local planners at a building parcel level. While the USGS now believes it has established a new means of identifying landslide hazard zones with greater detail than ever before, the necessary funding for a comprehensive program has yet to be approved (Olshansky and Rogers 1987).

The purpose of this research is to generate high-resolution, site-specific hazard exposure maps of building parcels that can be used to illustrate geospatially-diverse hazard risk at a scale that can be used by local planners and emergency managers.

2.2. RESEARCH OBJECTIVES

Hazards scholars and researchers, including geomorphologists and environmental engineers, have yet to reach a consensus on some of the crucial concepts in landslide and hazard research. Some of the concepts above include; the scale of analysis for visualization, suitable methods for collecting data, model training and model validation as well as appropriate inventory estimates. For example, the term “landslide” is often used to describe a different aspect of the mass wasting phenomena namely; the process, the movement, and the deposit of debris (Guzzetti et al. 1999).

This research builds on recent efforts by hazards scholars to advance current modeling methods and develop new approaches to more precisely assess, model, and visualize environmental risks and hazards. This study, aims at promoting a unique approach to mapping landslide susceptibility and hazard exposure using a combination of deterministic and probabilistic approaches in association with an array of environmental and infrastructural datasets that can be leveraged by hazards researchers, emergency response teams, urban developers and local planners to assess risk and hazard patterns at a very high resolution and geospatial scale.

The objectives of this study are two-fold: 1) develop a fuzzy-based geophysical, high-resolution predictive landslide susceptibility model for use by local planners and urban developers in prioritizing U.S. hazard emergency and mitigation response, road management activities and settlement planning. This objective employs a hybrid combination of qualitative and quantitative approaches to model shallow and deep-seated landslides using high-resolution (local/neighborhood) datasets for Ventura and Santa Barbara counties in Southern California. 2) Develop a high resolution, efficient, Cost effective and replicable proximity-based hazard exposure model (PBHEM) for use in prioritizing settlement and developments along the Southern Californian Coastline.

The research objectives and related geoprocessing questions outlined above was achieved in two Phases. The first Phase (I), focuses on generating high-resolution geophysical landslide susceptibility models of the study area. In phase (I), a geophysical landslide susceptibility model is developed, applied and evaluated within the context of the tumultuous geomorphology of the southern Californian coastline region. The geophysical risk model in this study was created by constructing a database containing various geospatial, topographical, environmental and geomorphological terrain parameters contributing to past landslide occurrence. Terrain attributes at mapped landslide locations are assessed through a variety of GIS techniques and used in combination with likelihood ratio and fuzzy logic systems to evaluate relative likelihood of landslide occurrence within the study area. The final geophysical risk model's output performance is then evaluated for accuracy using the area under the curve statistical technique (AUC).

Phase (II), focuses on the integration of the geophysical landslide susceptibility model created in Phase (I) with selected and weighted infrastructural (developed land parcels) and topographical attributes (surface cover, slope angle and debris flow direction and cost) to assess and quantify hazard exposure of the human-built environmental systems within the study site based on the respective proximities of building parcels to the landslide zones.

2.3. STUDY AREA

2.3.1. Mapping Unit Site and Situation

The study covers an area 15,532.16 sq. Km. (5,997.00 sq. mi.) and is comprised of Ventura and Santa Barbara counties illustrated in (Figure 4) below.

As of 1990, Southern California hosts approximately 28% urban land, 66% undeveloped areas and 6% agricultural land (Yiping and Beighley 2008). From 1980 to 2000, the population of Southern California exploded to about 55% almost 18.7 million people according to the 1980 - 2000 censuses (Yiping and Beighley 2008). Towns like Ventura, Orange, San Diego Santa Barbara and Los Angeles counties experienced the most significant population growths. With the population growth juxtaposed with the highly hazardous nature of the geophysical landscape, “The question is not if, but when the next landslide will impact the community” (Gurrola 2005).

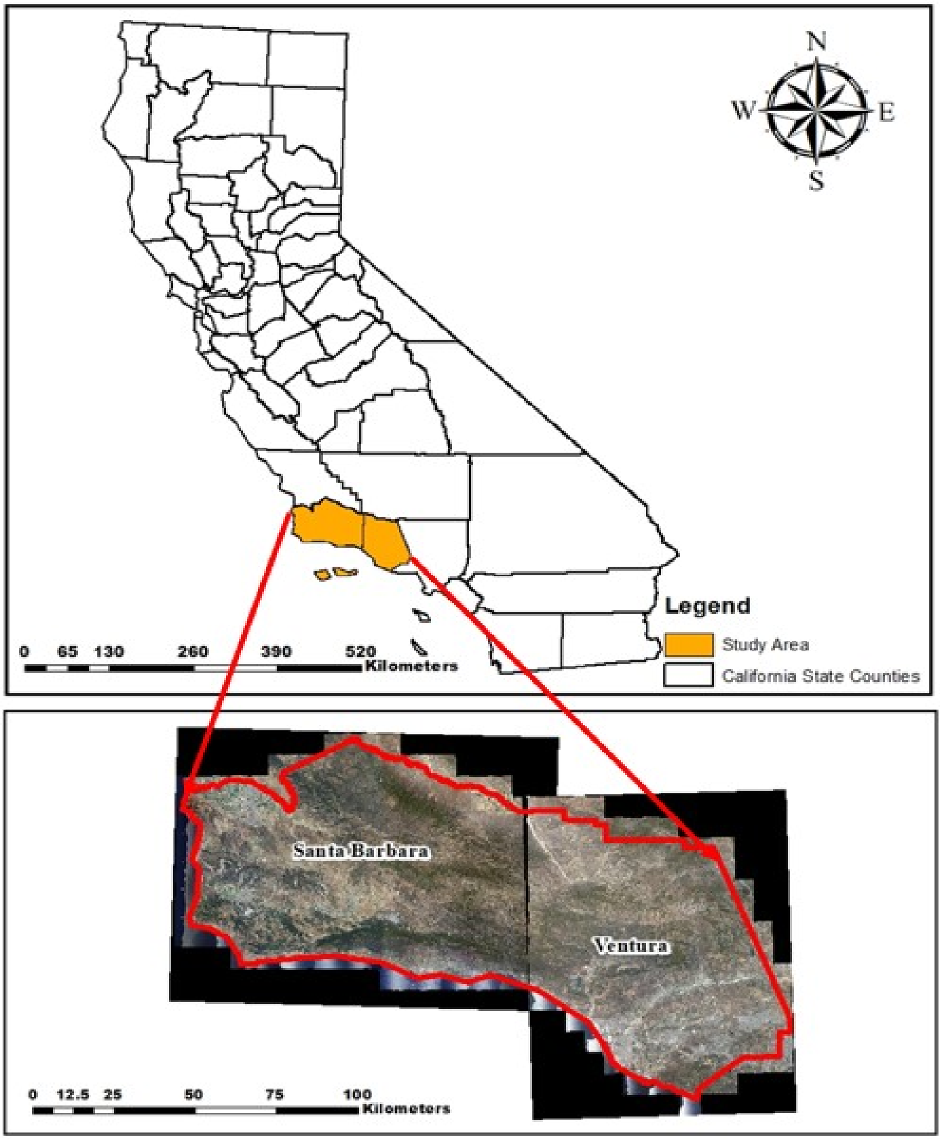

Figure 4. Study Area Mapping Unit

Landslides within this region are also triggered by heavy rains fueled by the Mediterranean climate, which usually causes abundant precipitation in specific regions resulting in rapid superficial mudflows. A combination of triggers such as seismic activity, tectonic uplifting within rocks of weak density and local underground springs, create an immensely precarious landslide sensitive area. Most of the soils and rocks in this region have been weakened by natural or human causes such as previous earthquakes and urban development of hillsides. Southern California lies astride a significant tectonic plate boundary defined by the San Andreas Fault and other structurally related faults that are spread across a broad region. This dynamic tectonic environment has created a spectacular landscape of rugged mountains and steep-walled valleys that compose much of the region's scenic beauty. Unfortunately, this extraordinary landscape also presents serious geologic hazards. Just as tectonic forces are steadily pushing the landscape upward, gravity is relentlessly tugging it downward. When gravity prevails, landslides do occur (USGS Factsheet 2005).

2.3.2. Physical Landscape

The study area illustrated in Figure 4 above is bounded by the Mojave Desert to the east and the Pacific Ocean to the west. This area has diverse geomorphology and complex geology form due to the subduction of the Pacific and North American tectonic plates. Interactions between these two plates can create earthquakes of varying intensities that can trigger mass movements, such as landslides. Earthquake-induced landslides have been documented from as early as 372 BC and are responsible for thousands of deaths and billions of dollars of damages (Keefer 1984). The coastal mountain ranges and coastal settlements along the San Andreas Fault are some of the most hazardous geomorphic regions in the entire country due to their geographic setting. Most of the landslides occurring in Southern California are a small portion of a much larger complex landslide region (USGS Factsheet, 2004). The mean elevation is about 615.67m (2,019.92 ft) above sea level. Approximately half of the area has ground slope higher than 50% (27°), and a third has a slope higher than 70% (35°) (Yiping and Beighley 2008). The ocean and continental air masses (maritime tropical and humid subtropical respectively) interact with the regional topography and display a broad diversity of weather and climate. Mean annual precipitation is 432mm (17in), ranging from as low as 229mm (9in) to 1295mm (51in).

Slope failure in this region is from the Holocene Paleo sea cliff which is the seaward edge of an ancient landslide that has produced slumps, debris, and mudflows. Two examples of such landslides are the 1995 and 2005 La Conchita landslides. The rock formations on the cliff include marine sediments from the Monterey and Pico formation (Jibson 2005). In the top sections of the slopes, the rocks consist of siliceous shale, siltstone and sandstone of the Middle to Upper Miocene Monterey formation, while the lower parts of the slope consist of siltstone, sand, and mudstone of the Pliocene Pico formation which covers the entire cliff face. Studies show that most landslides in the Southern Coast of California began a few thousand years ago but are younger than the subsurface coastal marine-terrace (Goldberg 2006).

2.3.3. Human Landscape

The earliest occupants of Coastal Southern California were American Indians (Keeley 2002). However, on September 28, 1542, Juan Rodriguez Cabrillo and his crew, the first Europeans to visit California entered the San Diego Bay and named it Alta California. In 1821, Mexico gained independence from Spain, and Alta California became a Mexican province rather than a Spanish colony (Hoover 1992). Twenty-seven years later, in 1848 gold was discovered at Sutter's Mill, catalyzing a period that was referred to as the “Gold Rush” (Johnson 2001), this event dramatically altered the course of California's history as miners rushed into the area and California earned its statehood on September 9, 1850 (McCurdy et al. 1976). The Gold Rush brought thousands of immigrants, both foreign and domestic, to southern California (Mei 1984; Rohrbough

1997; Holliday and Lamar 2015). This mass migration into the coastal regions, combined with the state's natural riches, assured California's success as it developed its diversified agriculture, fisheries, forestry, mining, aircraft plants, shipyards, tourism, and recreation industries (Nash 1998; Rawls and Smith 1999).

The increase in the population of southern California was almost invariably associated with intensive and locally excessive exploitation of the land, including gold mining, urban sprawl and construction of roads and railways. These activities resulted in rapid growth of the built environment, including dense metropolitan and residential zones (Parker 1937). In many areas along the southern Californian coastline including counties such as Orange, Buenaventura, and Santa Barbara, due to its local physiographical setting, new settlements and infrastructure expand into dangerous or potentially hazardous areas, such as those damaged in La Conchita (Jibson 2005; Murphy and Stover 2008).

Based on 1990s land use/land cover data, the southern region of California is comprised of approximately 28% urban lands, 66% undeveloped areas and 6% agricultural lands. In recent decades, Southern California has experienced substantial population growth. Based on census data from 1980 and 2000, 18.7 million people (55% of California's total population) reside in this region. From 1980 to 2000, the population increased at a rate of 41%, including, Riverside at 113%, San Diego at 51%, Orange at 47%, Ventura at 42%, Santa Barbara at 34% and Los Angeles Counties at 21. Population growth, urbanization, expansion of settlements, and life-lines over hazardous areas, have caused an increase in landslide activities and other forms of mass wasting (Selby 2000). The tables (Tables 1-4) and bar graphs (Figures 5-8) below illustrate changes in total population and annual population change from 1870 to 2016 for the state of California, City of Los Angeles, Ventura County, and Santa Barbara County.

Table 1. California State Population Change from 1870-2016.
Source: California Quick Facts - US Census Bureau.

State	Census Year	Population	Population Change %
California	1870	560,247	47.70%
	1880	864,694	54.30%
	1890	1,213,398	40.30%
	1900	1,485,053	22.40%
	1910	2,377,549	60.10%
	1920	3,426,861	44.10%
	1930	5,677,251	65.70%
	1940	6,907,387	21.70%
	1950	10,586,223	53.30%
	1960	15,717,204	48.50%
	1970	19,953,134	27.00%
	1980	23,667,902	18.60%
	1990	29,760,021	25.70%
	2000	33,871,648	13.80%
	2010	37,253,956	10.00%
	2016	39,250,017	5.40%

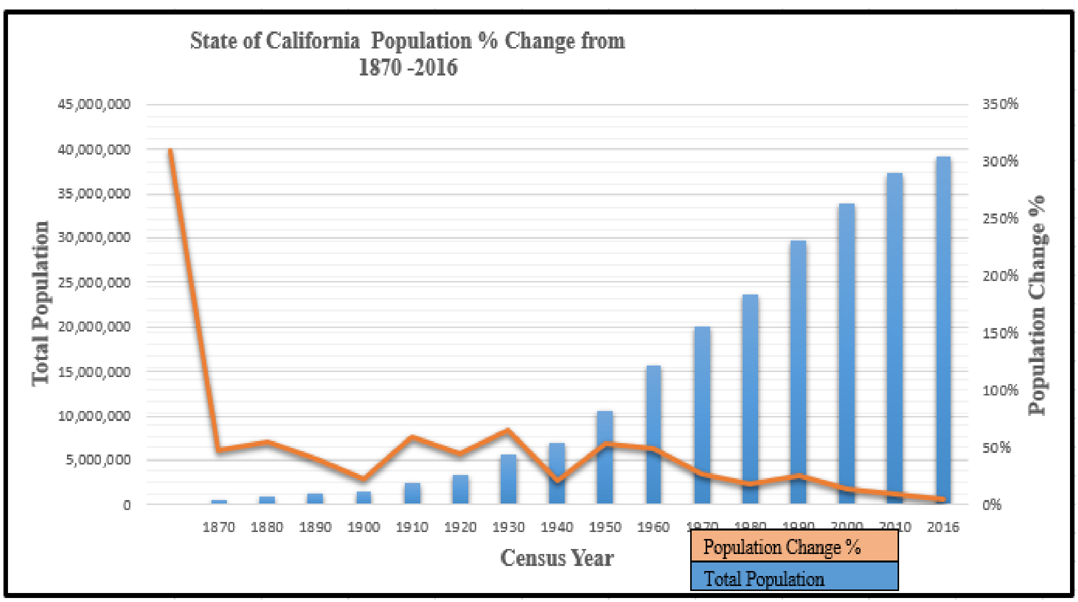

Figure 5. Bar Graph Illustrating Population and Population Change % of California from 1870-2016. Source: California Quick Facts - US Census Bureau.

Table 2. Los Angeles, California Population Change from 1870-2015.
Source: Census of Population and Housing - Census.gov.

State	Census Year	Population	Population Change %
Los Angeles, CA	1870	5,725	30.60%
	1880	11,183	95.20%
	1890	50,395	350.60%
	1900	102,479	103.40%
	1910	319,198	211.50%
	1920	576,673	80.70%
	1930	1,238,048	114.70%
	1940	1,504,277	21.50%
	1950	1,970,358	31%
	1960	2,479,015	25.80%
	1970	2,811,801	13.40%
	1980	2,968,528	5.60%
	1990	3,485,398	17.40%
	2000	3,694,820	6%
	2010	3,792,621	2.60%
	2015	3,971,883	4.70%

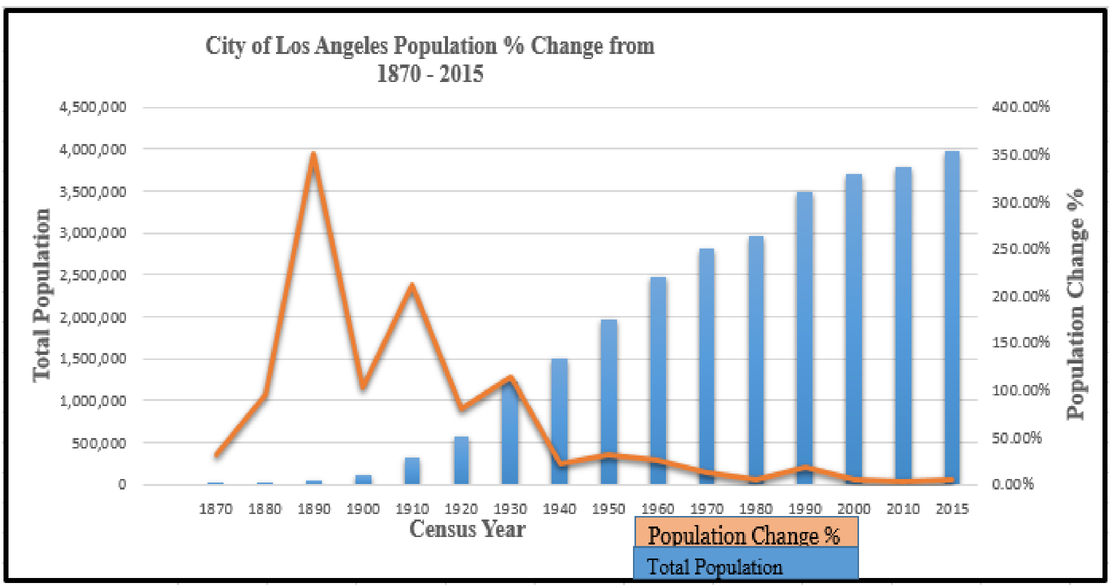

Figure 6. Bar Graph Illustrating Population and Population Change % for Los Angeles, California from 1870-2015. **Source: Census of Population and Housing - Census.gov.**

Table 3. Ventura County, California Population Change from 1900-2015.
Source: Census of Population and Housing - Census.gov.

State	Census Year	Population	Population Change %
Ventura County, CA	1900	2,370	6.50%
	1910	2,901	17.40%
	1920	4,156	43.30%
	1930	11,603	179.20%
	1940	13,264	14.30%
	1950	16,534	24.70%
	1960	29,114	76.10%
	1970	57,964	99.10%
	1980	73,774	27.30%
	1990	92,576	25.50%
	2000	100,916	9.00%
	2010	809,080	5.50%
	2015	840,833	3.3%

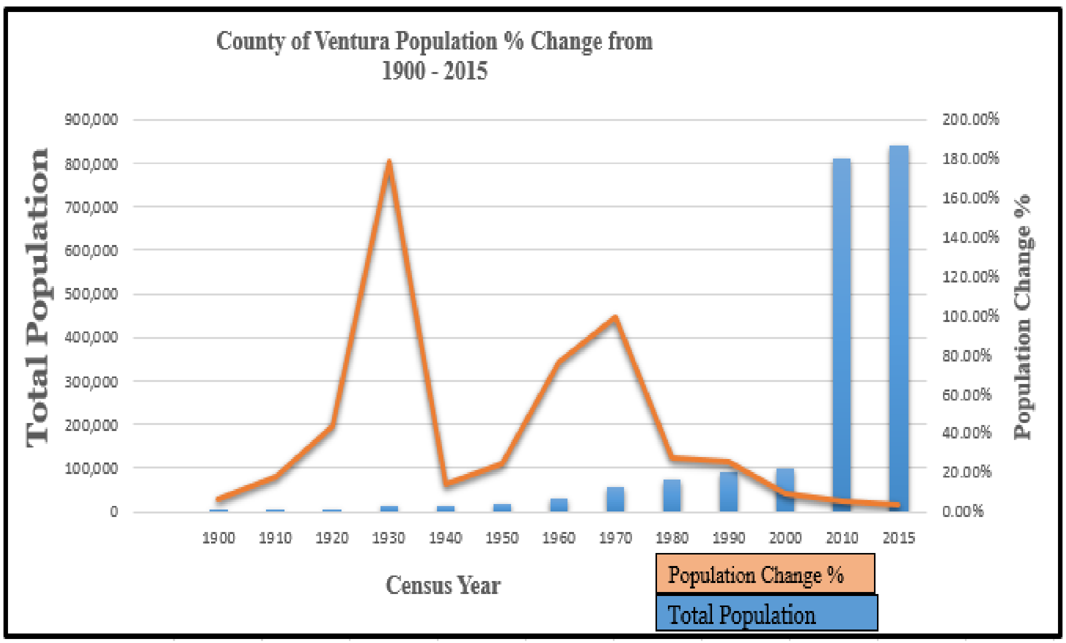

Figure 7. Bar Graph Illustrating Population and Population Change % for Ventura County, California from 1900 – 2015.
Source: Census of Population and Housing - Census.gov.

Table 4. Santa Barbara County, California Population Change from 1870-2015.
Source: Census of Population and Housing - Census.gov.

State	Census Year	Population	Population Change %
Santa Barbara County	1870	7,784	199.70%
	1880	9,513	22.20%
	1890	15,754	65.60%
	1900	18,934	20.20%
	1910	27,738	46.60%
	1920	41,097	48.20%
	1930	65,167	58.60%
	1940	70,555	8.30%
	1950	98,220	39.20%
	1960	168,962	72%
	1970	264,324	56.40%
	1980	298,694	13%
	1990	369,608	23.70%
	2000	399,347	8%
	2010	423,895	6.10%
	2015	444,789	4.90%

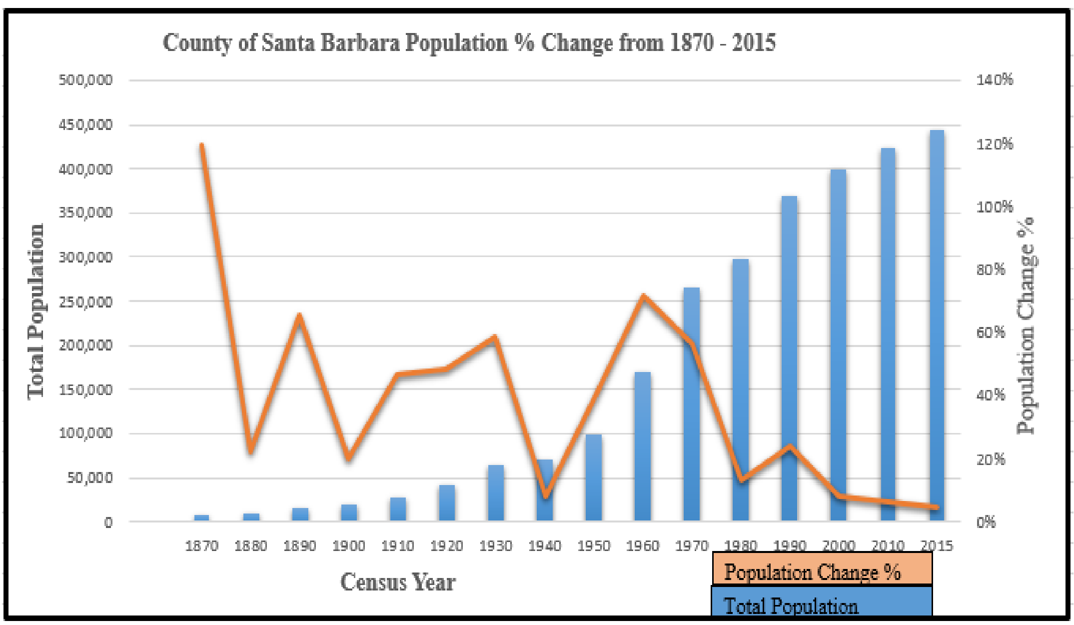

Figure 8. Bar Graph Illustrating Population and Population Change % for Santa Barbara County, California from 1870 – 2015.
Source: Census of Population and Housing - Census.gov.

Human intervention has played a vital role in stimulating the natural antecedents of the hazards mentioned above by disturbing some of the very fragile natural equilibria of the unstable landscapes (Alexander 1992). For example, in Buenaventura, La Conchita and Santa Barbara, agrarian grapevine activities, road constructions, coastal settlement expansions, wildfire soil surface glazing, and deforestation have resulted in frequent mudflow and mudslides whenever soil saturation values exceed certain stability thresholds (Coates 1985; Chaudhary 2005). As a result, the region provides an ideal setting for studying landslides.

III. PHASE ONE:

COMPLEX LANDSLIDE SUSCEPTIBILITY MODELING

Landslides are recognized as critical geomorphologic processes due to the role they play in the development of hill slopes in mountainous regions, and to related socio-economic consequences. There are many causes of landslides, and their distribution varies with the changing conditioning factors. Slope stability depends on many causative factors, and the knowledge of these variables can help to predict the volume and types of landslides to expect in the future. In this study, past landslide activity and triggering factors were used to assess landslide susceptibility along the southern Californian coastline. The geospatial attributes of the study area were analyzed in regard to their vulnerability to landslides and the corresponding output susceptibility maps used for the for development of urban settlement plans and disaster mitigation activities. One of the most critical stages in landslide susceptibility mapping is the selection of landslide causal, conditioning and triggering factors as well as the weighting of the selected causative factors in accordance to their influence on slope stability (Mukenga et al. 2017). High-resolution aerial imageries helped with the delineation of past and present landslide activity, and a geographic information system (GIS) was used for the derivation of static factors (slope, aspect and surface curvature) and time-dependent factors (annual precipitation) that are needed to produce landslide susceptibility maps. The high susceptibility to landslides in southern California is mainly due to the complex geological setting with the contemporary crustal adjustments, varying slopes and relief, heavy snow and rainfall along with ever-increasing human interference (Nagarajan et al. 1998). To implement strategic planning and safe mitigation measures, identification of landslide-prone areas and Landslide Susceptibility Zonation (LSZ) is crucial. Determining the probability or likelihood of dynamic events such as landslides is a multifaceted process that considers a variety of factors. A comparison of the distribution of various landslide criteria factors results in the identification of areas with different landslide probabilities which is a complex task because the occurrence of the landslide is dependent on many factors (Park et al. 2013).

Due to the complex nature of landslide susceptibility models, the disconnect between the appreciation of crucial landslide information and the related landslide hazard decision-making process is made even more pronounced. To address this problem, a new approach is needed to facilitate the generation and dissemination of information about landslide potential. Consequently, this work presents a practical, efficient, cheap and readily replicable approach to the development of a high-resolution parcel scale landslide predictive model using a geographic information system (GIS). In this next chapter, I discuss the various methods and techniques used in landslide assessment over the years as recorded in multiple landslide review articles, and the new contributions that have been added to the vast literature. Then, I present a high-resolution landslide susceptibility assessment of the study area at a building parcel level that can be used by urban developers and local planners for settlement and hazard mitigation purposes.

3.1. LITERATURE REVIEW

A successful landslide susceptibility and hazard assessment involve a mixture of several quantitative and qualitative approaches (Aleotti and Chowdhury 1999). Landslide susceptibility and hazard mapping methods can be grouped into three distinct categories namely; deterministic, heuristic and statistical (Clerici et al. 2006). These main categories can be further subdivided into the following; engineering or geotechnical, new soft computing model or expert-based and probabilistic methods (Guzzetti et al. 1999). The determinist approach relies heavily on the physical laws governing slope instability (Okimura and Kawatani 1986; Montgomery and Dietrich 1994; Dietrich et al. 1995). According to Ercanoglou and Gokceoglou (2004), the deterministic approach is frequently used for relatively small homogenous areas and requires detailed geotechnical and hydrological data. In order to apply this method to regional and medium scales, the data will have to be oversimplified. In the heuristic approach, the conditioning factors (instability factors) are ranked and weighted according to their likelihood of causing slope failure. This method is sometimes criticized because it entails a considerable degree of subjectivity.

Many localized studies have been conducted evaluating the relevance of the factors affecting landslides using expert dependent systems and data-driven approaches (Suzen and Kaya 2012). Data-dependent approaches aim at assessing the statistical significance of each landslide conditioning factor based on the existing landslide inventory data or available historical landslide inventory data. These data-driven approaches of bivariate statistical analysis including methods such as weights of evidence (Neuhauser and Terhorst 2007; Dahal et al. 2007; Van et al. 2009 and Martha et al. 2013), landslide index, and multivariate statistical analysis methods such as discriminant analysis (Carrara et al. 1991; Guzzetti et al. 2005), factor analysis (Maharaj 1993; Ercanoglu et al. 2004) and logistic regression (Ohlmacher and Davis 2003; Ayalew and Yamagishi 2004; Suzen and Kaya 2011; Gorsevski et al. 2006) have emerged as reliable statistical modeling approaches. So far, statistical methods are the most appropriate for landslide susceptibility assessments at the regional and medium scale levels (Gunther et al. 2013). These approaches are highly favored because of their objectivity and efficiency in creating landslide predictive models. One core principle and guiding theory surrounding landslide mapping using the above methods is the assumption that future landslide occurrence stands in relation to the present ones (Carrara et al. 1994). This means that slope failure in the future will be more likely to occur under the same conditions that led to the past and present instability (Clerici et al. 2006). Hence, a statistical combination of parameters or factors that led to slope failure and landslides in the past can lead to quantitative predictions of landslides in areas currently free of landslides (Gunther et al. 2013).

Generally, landslide criteria factors are known and can be categorized into the following major groups: geological, topographical, geotechnical and environmental (Suzen and Kaya 2011). In most cases, some of these factors are statistically significant in the model while others are not. A causal factor can be relevant to a multivariate susceptibility analysis in one location and not in another adjacent area. This variance can be due to the differences in scale and spatial resolution of datasets between the two sites. Spatial resolutions are more readily confronted than are temporal resolutions for examining issues germane to geomorphology (Walsh and Butler 1998). Over large areas, the spatial resolution of data is usually lower than over smaller areas. The differences in scale and spatial resolution of datasets is significant in landslide and hazard modeling (Bayr and Dommenget 2014). Small-scale analyses are most useful when they produce high spatial resolution models, but the datasets are rarely available if they are available at all, their formats are sometimes inconsistent across all necessary landscape attributes.

This inconsistency in dataset formats introduces unwanted errors to the modeling process.

The influence of each variable on the occurrence of a landslide is evaluated independently and variables combined into an equation (Guzzetti et al. 1999; Suzen and Doyuran 2004; Aterberg and Cheng 2002; Thiart et al. 2003 and Conoscenti et al. 2008). Among the multivariate statistical methods, logistic regression has the advantage of less rigorous data distribution requirements and can handle a variety of datasets such as continuous, categorical and binary (Lee and Min 2001; Lulseged and Hiromitsu 2004; Yesilnacar and Topal 2005; Nefeslioglu 2008). A detailed synthesis of these statistical approaches, their potential application and limitations have been substantially elaborated in the following scholarly literature over the years (Brabb et al. 1972; Carrara et al. 1977; Carrara et al. 1990; Greco et al. 2010). The above-discussed approaches are inefficient at modeling landslide susceptibility at small scales. This inefficiency is because the landslide conditioning factors require a considerable number of high-resolution datasets, which is usually not available for large areas in most parts of the world.

Recently, new soft computing methods have been applied to landslide suitability assessment studies, using evidential belief function models (Althuwaynee et al. 2012). These soft computing approaches have been reviewed in many articles in recent years (Alexander 2008; VanWesten et al. 2008). For in-depth Knowledge of the leading soft computing methods, see the following articles on artificial neural network model (Lee et al. 2004; Pradhan and Lee 2007, 2009, 2010), neuro-fuzzy high-tech mapping techniques (Kanungo et al. 2005; Lee et al. 2009; Pradhan et al. 2010d; Vahidnia et al. 2010; Sezer et al. 2011; Oh and Pradhan 2011), support vector machine (SVM) (Yao et al. 2008; Yilmaz 2010) , decision-tree (Nefeslioglu et al. 2010) and finally fuzzy logic (Ercanoglu and Gokceoglu 2002, 2004; Lee 2007; Pradhan and Lee 2009; Pradhan 2011; Gemitzi et al. 2011; Akgun et al. 2012; Osna et al. 2014; Alharbi et al. 2014; Chalkias et al. 2014).

Regional landslide susceptibility assessment methods encounter statistical problems due to the complexity of the landscape under investigation. The analytical approaches have the problem of terrain and data variability introducing in some cases of uncertainties to the analysis. Therefore, it is imperative to adopt a strategy that minimizes these uncertainties to provide a realistic model. Recent advancements in geographic information science (GIS) has improved the decision-making process significantly and revolutionized geospatial analytical processes using sophisticated approaches like multi-criterial probability distribution function (MCPDF) which can conduct an effective and efficient analysis and can be used to guide decisions of urban planners (Feizizadeh and Blaschke 2001). MCPDF is an intelligent approach used to convert spatial and non-spatial data into information that can together with expert knowledge be used to assist in making critical environmental and settlement decisions (Sumathi et al. 2008; Chen et al. 2010; Gbanie et al. 2013). It has the capability of handling different aspects of various elements of a complex decision-making problem such as organizing multiple aspects into hierarchical structures and studying the relationship between the individual components of the problem.

The fuzzy multi-criteria probability distribution function techniques involve a set of quantifiable spatial criteria: First data standardization in which the values of the datasets being analyzed are re-scaled between (0-1), where the mean is (0), and the standard deviation is (1). Secondly determination of relative importance of criteria. Here the individual criteria datasets are assigned weights based on their respective influence on landslides and slope instability. Thirdly Geospatial data integration. Here, weighted criteria values are aggregation or combined resulting in an overall landslide evaluation score for each spatial location in the study site.

The above techniques make multiple-criteria decision evaluation approach attractive for incorporation into a GIS (Malczewski 2004; Chakhar and Mousseau 2008; Chen and Paydar 2012). When it comes to landslide susceptibility models, multi-criteria decision analysis encounters the problem of non - linearity. This problem of uncertainty or (non-linearity) can be addressed by introducing the concept of fuzzy memberships (FM) or fuzzy measures (FM). Fuzzy measures are border concepts that include fuzzy set memberships. The standardization factor of MCPDF comes from a class of fuzzy measures and more specifically, instances of fuzzy set membership. It can be argued that this perspective provide a strong theoretical base for the standardization of landslide controlling factors and their subsequent aggregation (Jiang and Eastman 2000; Marjanovic et al. 2011). Fuzzy memberships (FM) can be integrated into multi-criteria probability distribution function (MCPDF) to deal with the problems of uncertainty and improve the accuracy of model results. The uniqueness of the (MCPDF) approach as compared to other statistical approaches such as logistic regression is that it uses the location of known objects such as landslides and expert knowledge base (EKB) to estimate weights or coefficients (Pradhan 2011; Pourghasemi et al. 2012). The combination of (FM) and (MCPDF) permits greater flexibility in the assessment of outputs and decision making. A fuzzy multi-criteria probability distribution function (FMCPDF) still retains all the uniqueness and advantages of the (MCDA) specifically the way this approach handles multiple criteria and combination of qualitative and quantitative data. It creates a hierarchical structure making decomposition and pairwise comparison easy, hence generating priority vectors and reducing inconsistencies. This approach somewhat reflects human thought in that it processes and uses appropriate information as well as uncertainty to create maps that support decision making (Kahraman et al. 2004). These capabilities make (FMCPDF) a proper and efficient tool for creating landslide susceptibility and subsequently hazard risk maps that can assist in making complex decisions in environmental management systems.

The models created in this study exploited information obtained from landslide inventory maps created for the study area indicating areas where landslides have occurred in the past. Such information was used to predict possible areas where landslides may occur in the future. Finally, considering that landslide susceptibility and hazard assessments models using a combination of fuzzy multi-criteria decision analysis (FMCDA) and a probability distribution function (PDF) at a parcel level scale has not yet been created for the study area, this contribution provides originality to this study.

3.2. THEORETICAL FRAMEWORK

This research hinges on a variety of integrated quantitative methods. Therefore, it is essential to establish a framework to describe the progression of methods and the subsequent integration of each technique's results. A successful landslide inventory analysis generally depends on a set of widely accepted assumptions that act as guiding principles for the theoretical framework of the analysis (Radbruch-Hall and Varnes 1976; Varnes et al. 1984; Carrara et al. 1991; Hutchinson and Chandler 1991; Hutchinson 1995; Dikau et al. 1996; Turner and Schuster 1996; Guzzetti et al. 1999). The assumptions herein include:

I) When landslides occur, they leave unique discernable features on the surface of origin showing the zone of rupture that can be recognized, classified and cataloged as inventory data in the field or through spatial analysis of high-resolution aerial imageries. In the field, most landslides can be identified as exposure scars, vegetation, and canopy break points. These signs are morphological as they indicate changes in the form, position, and appearance of a topographical surface.

II) The nature, magnitude, trigger mechanism and type of landslide (fall, flow, slide, complex and compound) usually dictates the morphological signature and rate of movement of slope failure (Varnes 1978; Cruden and Varnes 1996). In general, under the same morphological and physical condition, a landslide will have a somewhat similar and predictable morphological behavior. From the morphological signature of a landslide, the areal extent of failure, as well as impact and movement type can be determined. The physical characteristic and appearance of a landslide scar in the field can shed light on its age, the degree of activity and depth of failure. However, caution should be taken when classifying landslides through visual interpretations of field characteristics of exposure scars, because landslides especially, complex falls can be a combination of different morphological landslide failure types and may have multiple signatures.

III) Landslides are a result of geophysical processes triggered by mechanical and physical processes that can be empirical, statistically and deterministically inferred, calculated and modeled (Aleotti and Chowdhury 1999; Guzzetti et al.

1999).

IV) Landslides are governed by the principle of uniformitarianism, a principle that states 'the past and the present are keys to the future'. This principle can be interpreted as landslides in the future will occur under the same conditions in which they occurred in the past and present or slope failures in the future will be more likely to occur under the same conditions which led to the past and present instability. Mapping of current slope failures is imperative to comprehend the spatial distribution and arrangement of historic landslides. Sophisticated landslide inventory maps containing historical landslide datasets can provide crucial information that can be used to forecast zones of future landslide occurrence (Carrara et al. 1991; Hutchinson 1995; Aleotti and Chowdhury 1999; Guzzetti et al. 1999).

The above assumptions are crucial to achieving a successful model with a high predictive capacity and accuracy. Failure to consider the above assumptions can undoubtedly limit the applicability of an inventory map and their derivative products such as landslide susceptibility and hazard exposure quantification regardless of the approach employed. The assumptions outlined above are generally agreed upon by landslide scholars. However, there is still some disagreement amongst geoscientist as to the degree of influence between each assumption and how best to incorporate them into modeling landslide susceptibility (Guzzetti et al. 1999). For this research, all the above-stated interpretations are assumed to be true.

3.3. CONCEPTUAL FRAMEWORK

The landslide susceptibility or geophysical risk model was accomplished in five steps; (I) the preparation of landslide inventory location data collected from visual analysis of aerial photographs. (II) the identification of landslide conditioning or causative factors and determination of the frequency of landslide occurrence for each class of the conditioning factors. (III) Fuzzification (Standardization) of conditioning factors into fuzzy membership groups. (IV) Production of landslide factor fuzzy maps or weighted index maps within a GIS and Finally, (V) validation of landslide susceptibility index maps by conducting statistical analysis such as the receiver operating characteristic curves (ROC) and calculating the area under the curve (AUC). A schematic flowchart of the conceptual framework for the landslide susceptibility modeling process is illustrated in (Figure 9) below.

The primary criteria factors for this landslide susceptibility analysis included slope, aspect, topographic elevation, curvature, terrain ruggedness, land use land cover (LULC), precipitation, fires, proximity to roads, proximity to fault lines and soils. Landslide location points within the study area were identified and digitized from a 2016 1-meter resolution aerial imagery downloaded from the National Agriculture Imagery Program (NAIP). Each criteria factor was then processed and converted into a raster data layer within a geographic information system (GIS) and projected into the appropriate coordinate system, in this case, NAD 1985-UTM-Zone-11N. A total of 599 landslide points were identified through surface scars and soil debris flow directions and subsequently digitized into vector polygons. The landslide sample data was randomly split into two groups using a sample randomization subset function in ArcMap. One group of 499 landslides were used to model the spatial structure and produce a landslide susceptibility model (training data) and the second group of 150 landslides was used to compare and validate the landslide susceptibility model (validation data).

To assess the degree to which a location in the study area is susceptible to landslides using data from multiple conditioning factors, a multi-criteria evaluation approach is employed which involves the aggregation of weighted criteria factors. It is important to note that this analysis operates under the underlying assumptions that landslides occur because of the influence of causative and triggering factors as backed by geomorphological literature and that landslides will happen in the future under similar conditions as in the past (Carrara et al. 1991; Hutchinson 1995; Aleotti and Chowdhury 1999; Guzzetti et al. 1999). Therefore, landslides occurrence within the study area will occur under conditions that can be characterized by the spatial distribution of criteria factor datasets, which are considered as predisposing or conditioning factors. In order to reflect reality in the output of the model and to make the analysis more objective, fuzzy membership values, or weights, were calculated based on the frequency of landslide occurrence on all raster class intervals of the landslide related criteria factors and expert opinion as per the expert knowledge laid down by the United States Department of Agriculture (USDA) as well as the Natural Resources Conservation Service (NRCS) in regards to vulnerability of soil types to landslides.

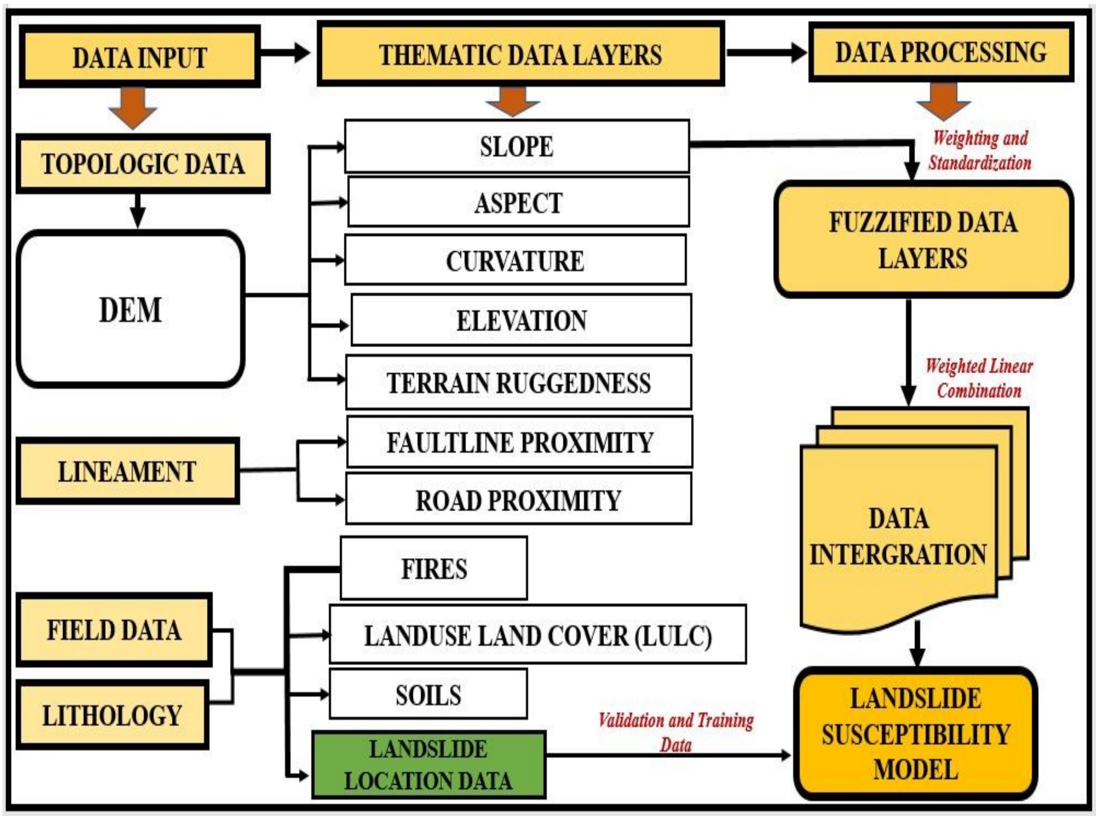

Figure 9. Conceptual Framework, Flowchart for the Geophysical Risk Model.

3.4. DATA AND ANALYSIS

A concise but extensive inventory of the causative factors is essential for improving our understanding of landslide susceptibility and hazards. In this study, extensive aerial photo interpretation and GIS techniques were used to characterize the landslides and construct thematic data layers. Due to the absence of prior landslide location data for the study area, a total of 599 landslides were mapped within the study area to assemble a database of landslides. Landslide points and exposure scarps were digitized into vector polygons and used to analyze the relationships between landslide occurrence and landslide causative or conditioning factors. These landslides were detected from aerial photographs by visually interpreting breaks in the forest canopy, bare soil and typical geomorphic characteristics of landslide scars. Using the full movement of the landslides can introduce noise to the data and therefore result in inaccurate susceptibility maps. Care must be taken to accurately delineate the rupture zone to establish a statistical relationship with causal factors.

To precisely identify the position of landslide scars, a high-resolution color four band 1m × 1m cell size resolution Naip aerial imagery of the study area was used to determine landslide scars, which were subsequently digitized into vector polygons. The input data comprises of several layers of map information outlined in (Table 5). Slope, curvature, elevation, terrain roughness and aspect were calculated from a high pixel cell size resolution 9 m × 9 m Digital Elevation Model (DEM). The lithology data were acquired from the United States Department of Agricultural (USDA) Web Soil Survey and roads and fault lines were extracted from the United State Geological Survey (USGS). *A*fter processing all datasets, the vectors layers were converted into a cell-based database, and the whole study area consisted of over 64,710,274 pixels with each pixel corresponding to a 9 m × 9 m cell size on the ground. The datasets were converted into one unified coordinate system NAD 1983 UTM Zone 11 using ArcGIS 10.4. Given that landslides are strongly related to environmental factors, multi-source spatial data collection and processing have proven crucial to assessing landslide susceptibility (Ruiqing et al. 2013). The landslide causative datasets were grouped into three primary categories namely; topographic, geologic and seismic datasets which can further be subdivided into other fundamental factors as shown in the table below (see Table 5). The essential factors are usually the environmental factors and include elevation, slope, aspect, curvature proximity to the road, proximity to fault lithology and slope roughness.

Table 5. Datasets

Spatial database	Data Scale	Data Types
Landslide Data		Landslide location polygon coverage
Topographic Data Sets	1/3 arc-second (10m)	Slope
	1/3 arc-second (10m)	Slope Aspect
	1/3 arc-second (10m)	Slope Elevation
	1/3 arc-second (10m)	Slope Curvature
	1/3 arc-second (10m)	Terrain Roughness
Geologic Data Sets	1:12,000 to 1: 63,360	Lithology (Soils)
Seismic Data Sets	1:100,000	Proximity to Faults
Lineation Datasets	1:100,000	Proximity to Roads
Hydrological Data	1:100,000	Precipitation
Surface cover Datasets	1:100,000	Land use land cover
Cal Fire	1:1,000,000	Wildfires

3.4.1. Soil Map Unit Symbols and Soil Descriptions

The lithology layer is one of the most vital landslide conditioning factors in this study area. The study area is covered by 89 different soil types with varying codes of soil and vulnerabilities to landslides. Table 6 illustrates the various lithological compositions, characteristics and their description.

Table 6. Soil Map Unit Symbols and Soil Descriptions

Soil Group	Soil Symbol	Soil Component Name/ Slope percentage
Group 1	GxG/BdG/CaF/LaF/SnG	Gullied land, Badland, Calleguas (50%), Landslide, Sedimentary rock land. - Very Unstable Soils with 30 – 50% slope

Table 6. Continued.

Soil Group	Soil Symbol	Soil Component Name/ Slope percentage
Group 2	MaF/HuD2/Cc/OsE2/OsD2	Malibu (85%), Huerhuero (85%), Camarillo (85%), Ojai (85%), Unstable soils with 30 – 50% slope
Group 3	NaD2/DbD/LeE2/SoE2/SeF/SeE/DbE/ScE2/HuC2/SwC LoF/GaC/RcE2/LeD2/ChD2/LoD2/SzD/LoE2/ AcC/CyC/GcB/MoC/HuE3/McC/SoF/GbC/PcC/CnB/ LkF/T	Nacimiento (85%), Diablo (85%), Linne (85%), Sespe (85%), Santa Lucia (85%), Diablo (85%), San Benito (85%), Huerhuero (85%), Sorrento (85%), Los Osos (85%), Garretson (85%), Rincon (85%) Chesterton (85%), Sorrento Variant (85%), Anacapa (85%), Cropley (85%), Mocho (85%), Huerhuero (70%), Mets (85%), Pico (85%), Coastal Beaches (95%), Lodo (70%) - Moderately unstable soils with 9 – 30% slope eroded
Group 4	Rw/XA/W/DA	Sandy alluvial land, Xerorthents (100%), Water (100%), Dam (100%)
Group 5	ScG/ScF2/MaE2/LeF2/MhF/DbF/NaE2/CfD2/AuD/AuC2/ScD2/ZmC/SvF2/ShF2/SsE2	San Benito (85%), Malibu (85%), Linne (85%), Millsholm (45%), Diablo (85%), Nacimiento (85%), Castaic (45%), Azule (85%), Zamora (85%), Soper (85%), Saugus (85%),
Group 6	SoG/CbF2/CfF2/NaF/CfE/ MmF2/PxG/NaG/AsF	Sespe (85%), Calleguas (50%), Castaic (45%), Millsholm (45%), Sandy alluvium land (5%), Nacimiento (85%), Arnolds (85%)

3.4.2. Landslide Identification and Recognition

Landslides can be identified and mapped using a variety of techniques and tools, including but not limited to the following: geomorphologyogical field mapping

(Brunsden 1999), interpretation of vertical or oblique stereoscopic high-resolution aerial photographs (air photo interpretation, API) (Turner and Schuster 1996), surface and sub-surface monitoring geographic terrains (Petley 1984; Franklin 1984) and the use of innovative remote sensing technologies such as the interpretation of high-resolution multispectral images (Zinck et al. 2001; Cheng et al. 2004).

Over the years, a more traditional approach to the visual interpretation of stereoscopic aerial photographs has been at the forefront of identification and mapping of landslides (Turner and Schuster 1996). National and local governments, geological surveyors, environmental protection agencies, research organizations and private companies have long obtained stereoscopic aerial photographs for a variety of purposes and across a wide range of landscapes and have made the datasets available for public use. Because of such convenience, aerial photograph visual interpretation techniques have long been the most utilized technique to recognize, identify, and collect landslide training datasets as well as map landslide inventory data for the majority of landslide assessment research and certainly for this analysis.

3.4.3. Mapping of Landslide Inventory Datasets

A crucial aspect of any landslide susceptibility assessment is the mapping of existing landslides. The presence of prior landslide data is imperative for creating the statistical relationship between landslide distribution and the conditioning factors. Considering that detail or extensive data of previous landslides is absent for the area of study, an approximate sum of 599 landslide scars or exposure surfaces were digitized through visual interpretation using high-resolution aerial imagery in a GIS environment to serve as landslide training and validation point data. From the visual analysis of aerial imagery of the study area, most of the landslides or slope failures identified were related to rotational slides, debris, and earthflow in accordance with the forms of slope failure types suggested by Varnes (1978) (Figure 10). From a collected sample of approximately 599 landslide locations acquired from the aerial imagery, 499 of the mapped landslides were randomly selected for use as susceptibility model training datasets while the remaining 150 landslides, were used to verify and validate the accuracy and predictability of the final landslide susceptibility model.

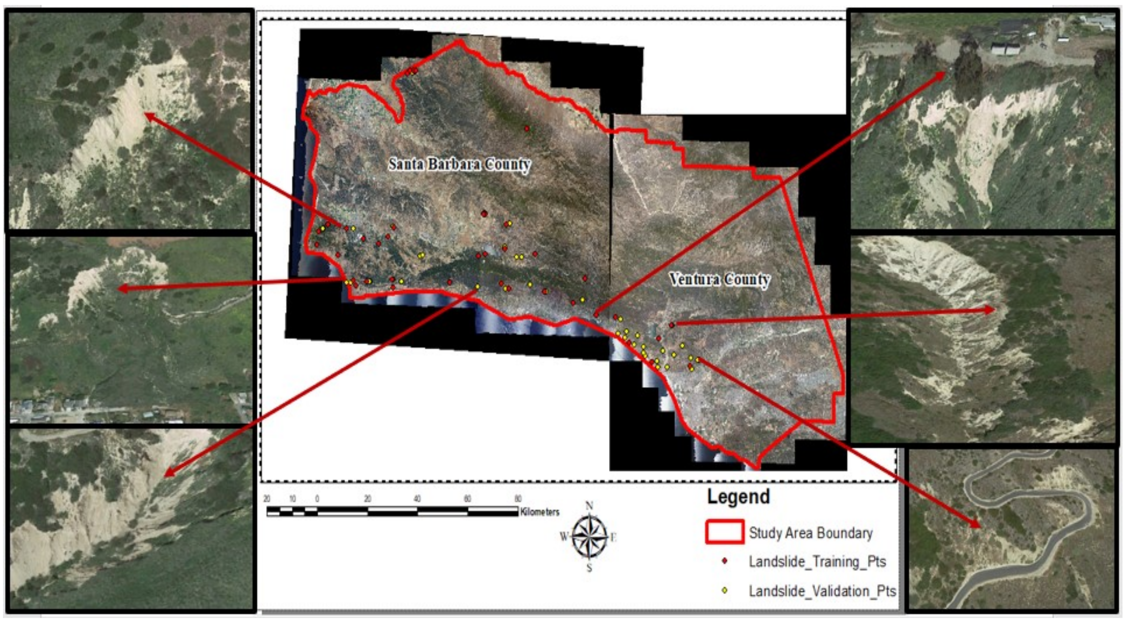

Figure 10. Hill Shaded Map Indicating Landslide Locations and Landslide Examples Visually Interpreted and Identified on a High-Resolution Aerial Imagery.

3.4.4. Thematic Data Layers of Criteria Factors

The elements that affect slope stability are numerous and interact in complex and often subtle ways. The selection of conditioning factors and preparation of corresponding thematic data layers is a crucial component of any landslide susceptibility assessment. According to Wu and Sidle (1995), these factors can be grouped into intrinsic factors which actively contribute to landslides (e.g., topography, geology, and hydrology) and extrinsic factors that serve as landslide triggers such as precipitation, earthquakes, and landscape modification (e.g., road construction, urbanization, and mining). In the case of Southern California, an obvious trigger mechanism of landslides is precipitation. Precipitation frequently causes landslides and mudslides in this area by saturating the colluvium bedrock interface. Precipitation within the study area is generated by atmospheric moisture emerging from the southwest (offshore to onshore). The steep mountains around the coastal landscape contribute to significant orographic rainfall in the region. Rainfall increases as elevation increase towards the south and west facing slopes (Beighey et al. 2003). On the lee side of the mountain (north and east facing slopes) precipitation decreases. It is obvious that precipitation is one of the dominant landslide triggering factors and is responsible for most of the slides that occur in the study area. The instability governing factors used in this study included; geology, slope angle, slope aspect, curvature, elevation, lithology, terrain roughness, proximity to roads, Precipitation, wildfires, and proximity to fault lines. The selection of these factors and their corresponding classes were based on observation of landslide occurrence frequency and associated terrain factors.

3.4.4.1. Slope Angle

A principal landslide causative factor is slope degree (Ercanoglu and Gokceoglu 2001; Lee and Min 2001 and Porghasemi et al. 2012). Steeper slopes have direct influence because of their higher shear forces (Dai et al. 2001; Neifeslioglu et al. 2008). Because of its relationship with landslides, slope angle is a crucial factor in landslide susceptibility assessment as such it is frequently used in creating landslide susceptibility maps (Clerici et al. 2002; Lee et al. 2004 and Lee 2005). In this study, a slope degree map was generated from a high-resolution Digital Elevation Model (DEM), and in accordance with the conditions and configurations of landslide occurrence, the study area was divided into 5 slope categories: (0º – 7º), (8º – 17º), (18º – 26º), (27º – 35º) and (36º – 68º) Shown on (Figure 11a). In this study, substantial attention was given to factors such as slope and lithology. The configuration and steepness of slope in conjunction with lithology were most significant for the susceptibility model.

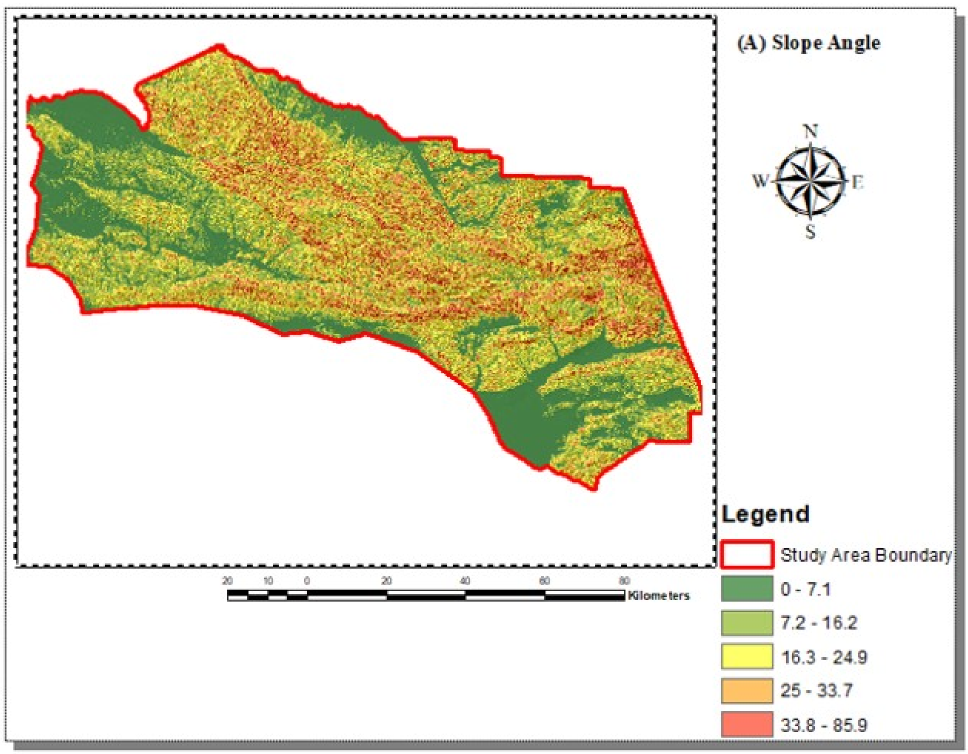

Figure 11A. Slope Angle

3.4.4.2. Slope Aspect

Slope aspect as a landslide conditioning factor has been considered in several other studies (Ercanoglu and Gokceoglu 2004; Lee et al. 2004; Yalcin 2005 and Pourghasemi et al. 2012). According to (Ercanoglu et al. 2001), in the early 1990's there were debates about the relationship between slope aspect and mass movement as there was no general agreement on such relationship (Carrara et al. 1991). Some scholars in their research considered aspect as a factor (Carrara et al. 1991; Maharaj 1993; Gokceoglu and Aksoy 1996 and Nagarajan et al. 2000) while other scholars did not (Uromeihy and Mahdavifar 2000). Slope aspect gravely affects hydrological processes such as evapotranspiration, weathering, and vegetation growth particularly in arid environments and areas with weak soil types (Sidle and Ochiai 2006). Meteorological events and characteristics such as rainfall and rain direction, amount of sunshine respectively have a tremendous impact on the propensity of landslides. Slopes that receive intense amounts of rainfall reach soil saturation faster. During this process, the pore water pressure of the slope forming materials change, resulting in slope failure. The slope aspect for the study area was divided into ten categories with each aspect falling with a specific range: Flat (-1), North (0-22.5), Northeast (22.5-67.5), East (67.5-112.5), Southeast (112.5-157.5), South (157.5-202.5), Southwest (202.5-247.5), West (247.5-292.5), Northwest (292.5-337.5), and North (337.5-360) (Figure 11b).

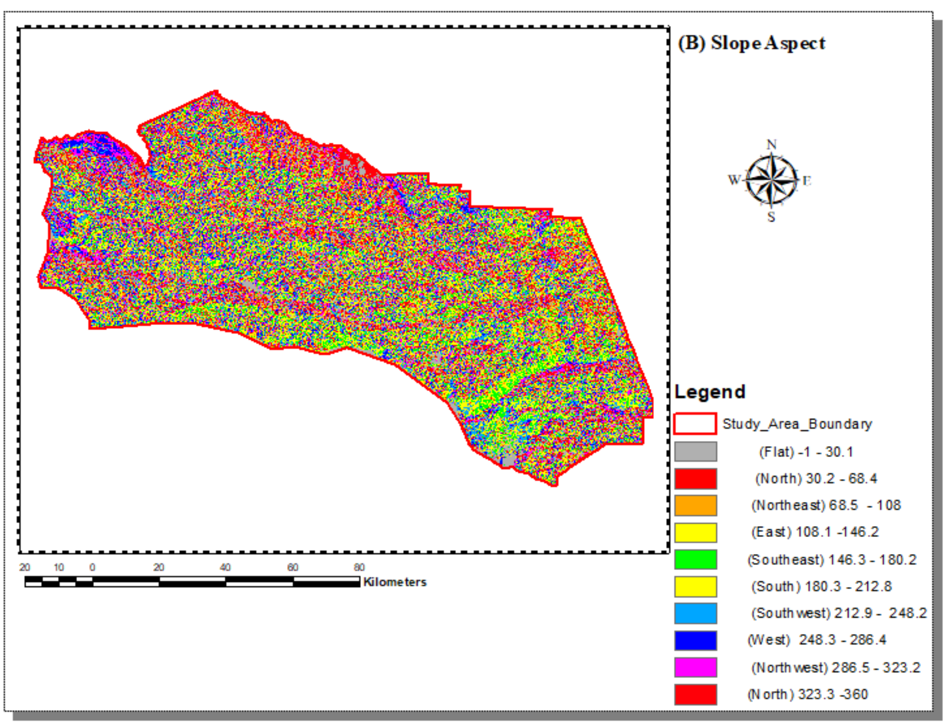

Figure 11B. Slope Aspect

3.4.4.3. Slope Curvature

The curvature is a parameter commonly used in landslide susceptibility modeling that needs further investigation (Ohlmacher 2007). It is the curvature of a hillside in a horizontal plane. Hillsides can be divided into concave outward plan curvatures called hollows and convex outward plan curvatures called noses. The curvature value can be evaluated by calculating the reciprocal value of the radius of curvature of that direction (Nefeslioglu et al. 2008). When curvature values of broad curves are small, the tights ones have higher values.

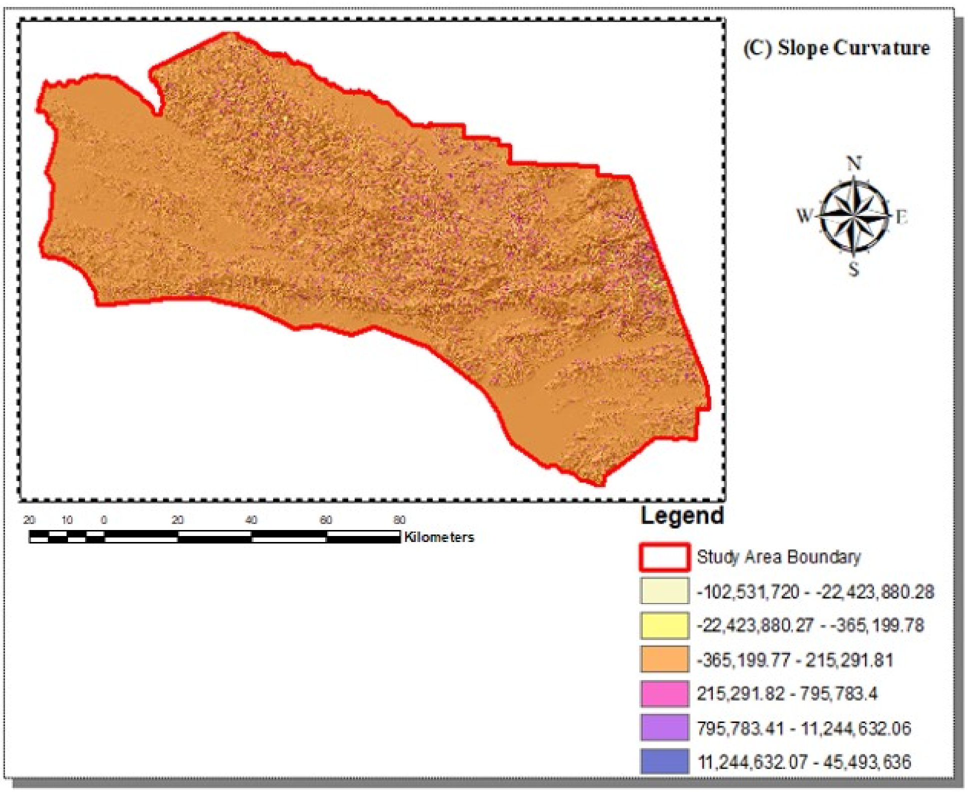

Figure 11C. Slope Curvature

Plan curvature contributes to slope failure by influencing erosion processes such as convergence and divergence of water during downhill flow (Ercanoglu and Gokceoglu 2002 and Oh and Pradham 2011). Because of its influence on erosion processes, it was considered as one of the conditioning factors to landslide hazards or slope failure susceptibility. A thematic map of plan curvature is shown on (Figure 11c).

3.4.4.4. Lithology (Soils)

Sedimentary rocks of Cretaceous-era including shale, mudstone and sandstone, Tertiary igneous rocks batholiths of granodiorite and multiple deposits of the Quaternary geological epoch such as alluvium, colluvium, clays and mixed deposits include the principal lithologies of the study area. Colluvium occurs on the gentle slopes, bedrocks along some of the steep ridges and fluvial deposits occupy the valleys. Lithology is a critical component in landslide susceptibility and slope failure. Under the influence of rainfall and seismic activities, various lithological units within the study area units show substantial differences in landslide susceptibility (Dai et al. 2001; Yalcin 2005, and Song et al. 2012). A lithological map of the study area was obtained from the United States Department of Agricultural (USDA), Natural Resource Conservation Service (Soil Survey) and designated into specific types of soil using the USDA textural classification regarding unique characteristics including texture, cohesion, slope and erosion class. Multiple types of lithological formations cover the area. The geological setting of the lithology of the study area thematic map is shown in (Figure 11d), and the characteristics and properties are shown on (Table 6).

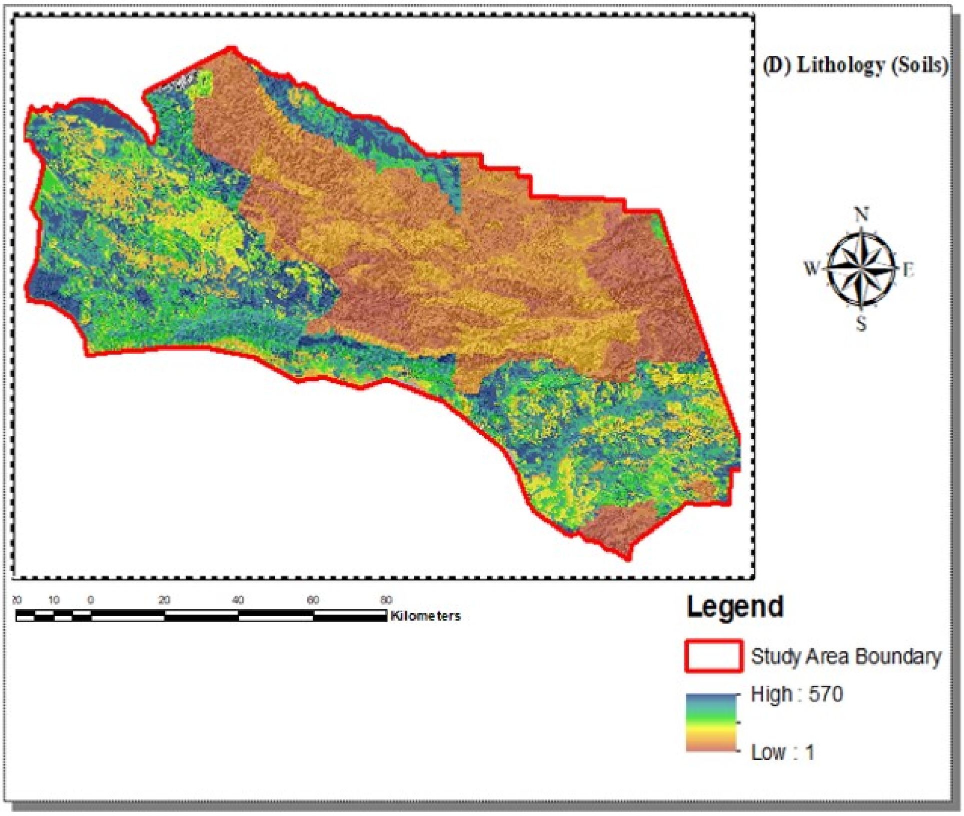

Figure 11D. Lithology (Soils)

3.4.4.5. Slope Elevation

The elevation is significant in landslide susceptibility modeling because weather and climate vary at different elevations. This variation can cause differences in soil formation, soil types, and vegetation (Aniya 1885). Elevation controls multiple geologic and geomorphological processes such as freeze and thaw at high altitudes increase weathering of rock while lower elevations turn to accumulate thicker colluvium and other deposits (Dai and Lee 2001; Ayalew et al. 2005 and Pourghasemi 2008). Elevation-derived from the high-resolution DEM was classified into six categories: (-0.6 - 59.27), (59.28 - 160.78), (160.79 - 249.28), (249.29 - 340.38), (340.39 - 447.1) and (447.11 - 663.13) in meters. An elevation thematic map was derived from a 9m ×9m resolution DEM as shown in (Figure 11e)

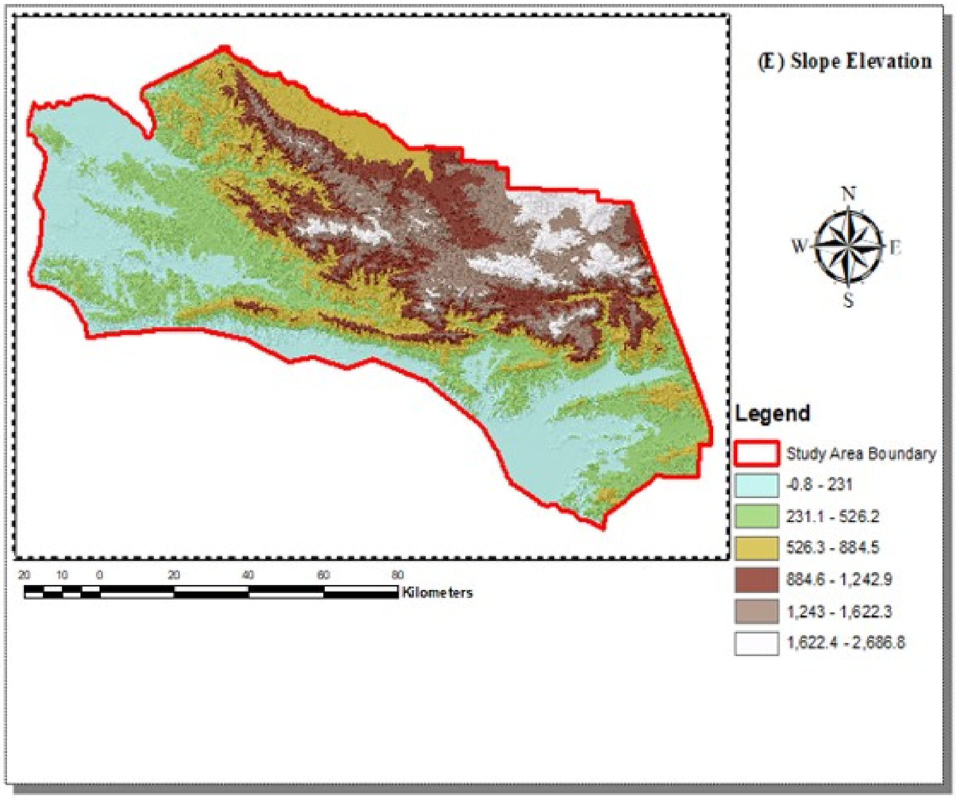

Figure 11E. Slope Elevation

3.4.4.6. Terrain Ruggedness

Surface roughness reflects geophysical parameters of a landform such as the distribution of crenulations and degree of erosivity. A considerable number of methods have been developed to calculate surface roughness based on different parameters (Grohman et al. 2011). For this study, terrain roughness was calculated on bases of surface area ratio because it measures topographic roughness and convolutedness. It was calculated using the equation below;

$$\mathrm{SAR}\ (\frac{\mathrm{A}}{\mathrm{A_S}}) \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{Equation (1)}$$

Where:

A is the surface area of region and A_S is planimetric area (Jennes 2002).

The analysis showed that high roughness slopes were more susceptible to slope failure because the changes in slope gradient favored infiltration of surface runoff water into the soils, thus increasing instability. The Terrain roughness thematic map is shown on (Figure 11f).

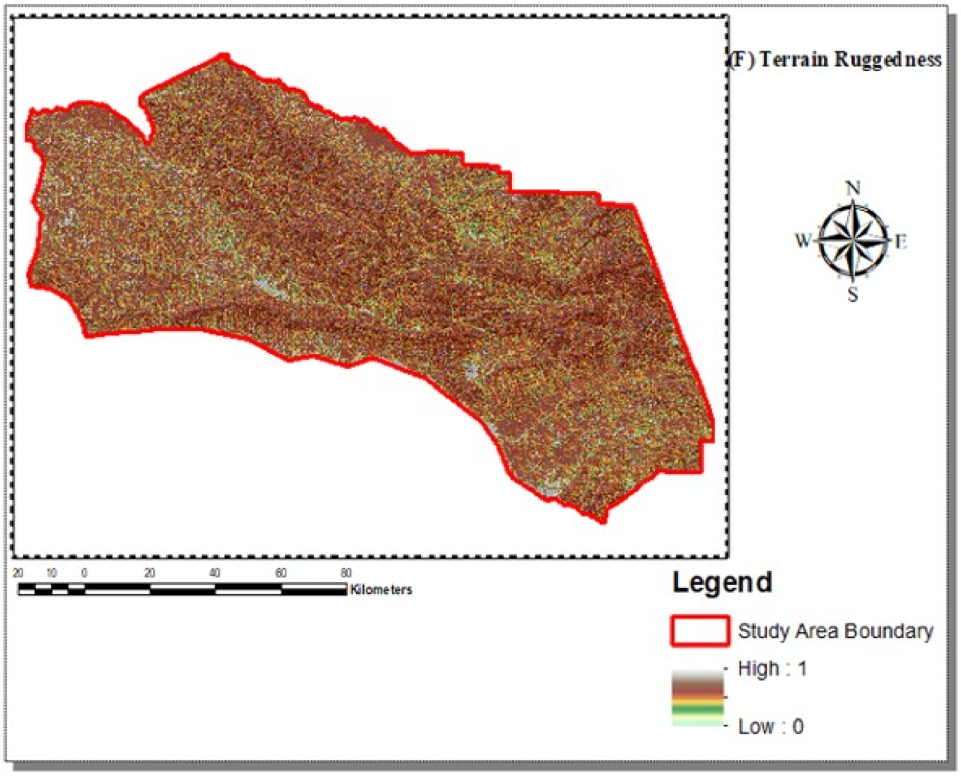

Figure 11F. Terrain Ruggedness

3.4.4.7. Proximity to Roads

Road networks constructed along the sides of slopes in mountainous areas can cause a decrease in the load on both the topography and on the toe of the slope. The steepening of a slope due to excavation, additional load, change in hydrology and drainage may affect stress state and slope equilibrium. For this reason, road proximity can be considered as a parameter for the generation of a landslide susceptibility model (Yacin 2008). During the analysis, it was observed that many landslides scares were found in close proximity to road networks. Subsequently, a 150 meters Euclidean distance buffer composed of two categories was created to determine the frequency of landslide occurrence to road network proximity classes. The Euclidean distance was divided into two categories: (0 – 49) and (50 – 99) in meters with a frequency of landslides scares appearing closest to the sloped walls of the road network as shown in (Figure 11g).

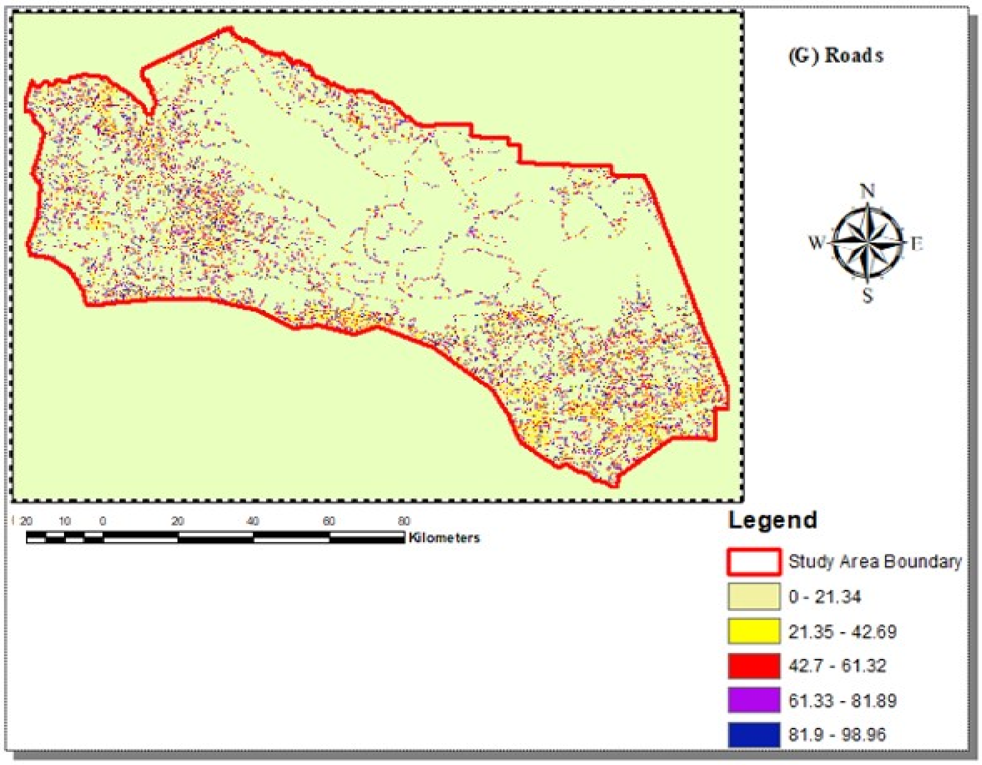

Figure 11G. Roads

3.4.4.8. Proximity to Fault-Lines

Distance to fault lines is an obvious causal factor for landslide manifestation. In most cases, fault lines act as triggers to landslides in already unstable slopes. Topographic movements along fault lines result in the weakening of rocks and compact soil triggering landslide incidents (Foumelis et al. 2004). To designate the influence of fault lines on slope stability in the study area, a 150-meter Euclidean distance buffer divided into two classes (0 – 49) and (49.1 - 98.9). The fault lines data for this study was acquired from exposed and unexposed fault lines from the United States Geological

Survey map service. A considerable number of landslides were found in the area with the closest proximity to fault lines and decreased as we move further away from the fault lines. This is because of the selective erosive nature of surface flow along fault lines planes which promote a weakening of slopes. A Faultline proximity thematic model is shown on (Figure 11h).

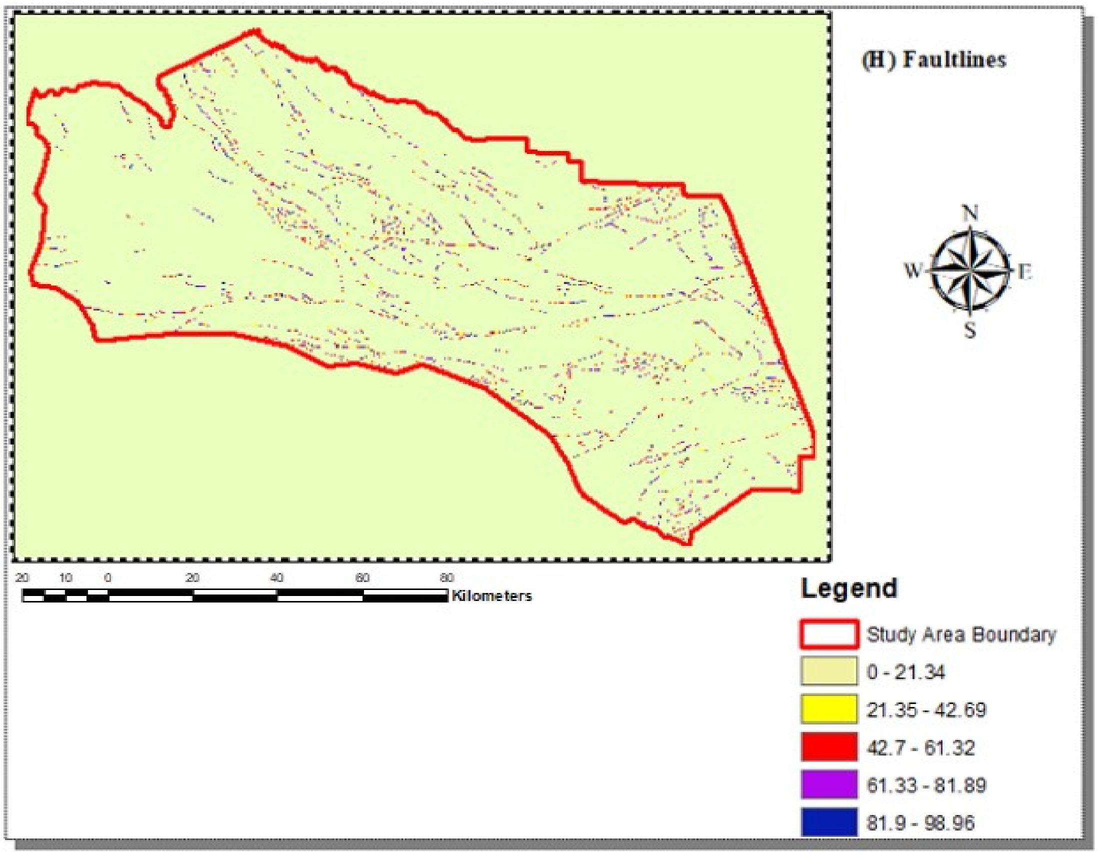

Figure 11H. Fault-Lines

3.4.4.9. Wildfires

Wildfires can have profound effects on the hydrologic response of watersheds. Consumption of the rainfall-intercepting canopy, soil-mantling litter, intensive drying of the soil, combustion of soil-binding organic matter, and the enhancement of water-repellent soils can change the infiltration characteristics and erodibility of soil, leading to decreased rainfall infiltration and exacerbating overland flow, runoff in channels and movement of soil (Wondzell and King 2003). Removal of obstructions by wildfires through consumption of vegetation can also enhance the erosive power of overland, flow resulting in accelerated erosion of material from hillslope. The wildfire thematic map is shown below (Figure 11i).

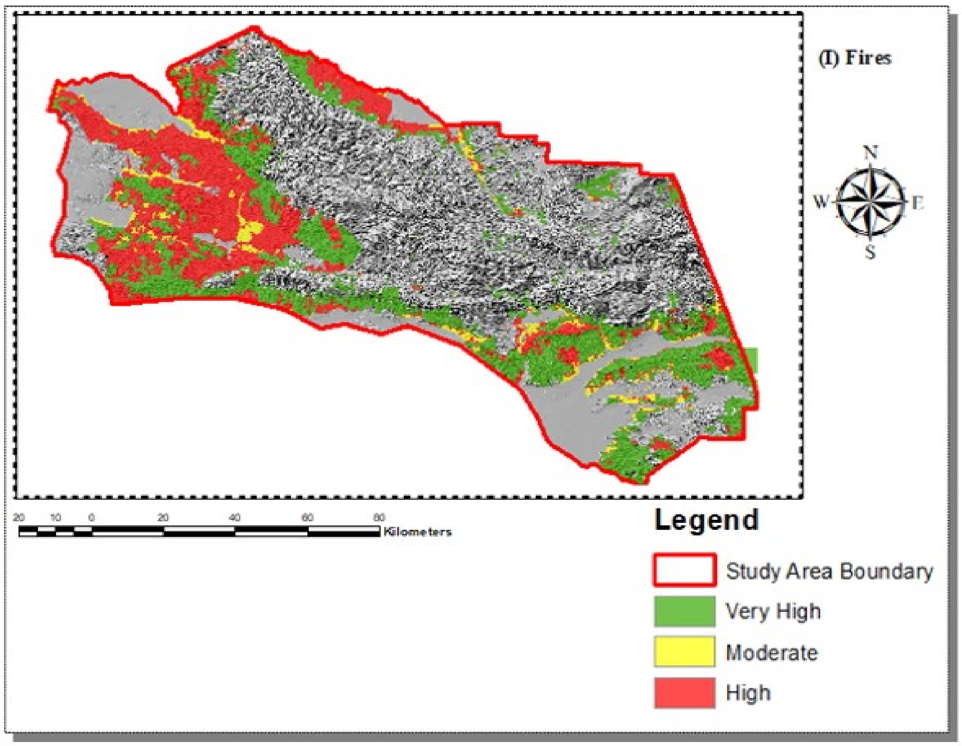

Figure 11I. Fires

3.4.4.10. Land Use and Land Cover

Land use and land cover play a significant role in influencing landslides. A considerable number of landslides occurred on slopes with sparse vegetation or bare surfaces as compared to other urban or developed and mixed vegetation surfaces. Rapid changes in land use and land cover, as well as land degradation processes, are precursors to mass movement events (Alcántara-Ayala 2006). The land use land cover thematic map is shown below (Figure 11j).

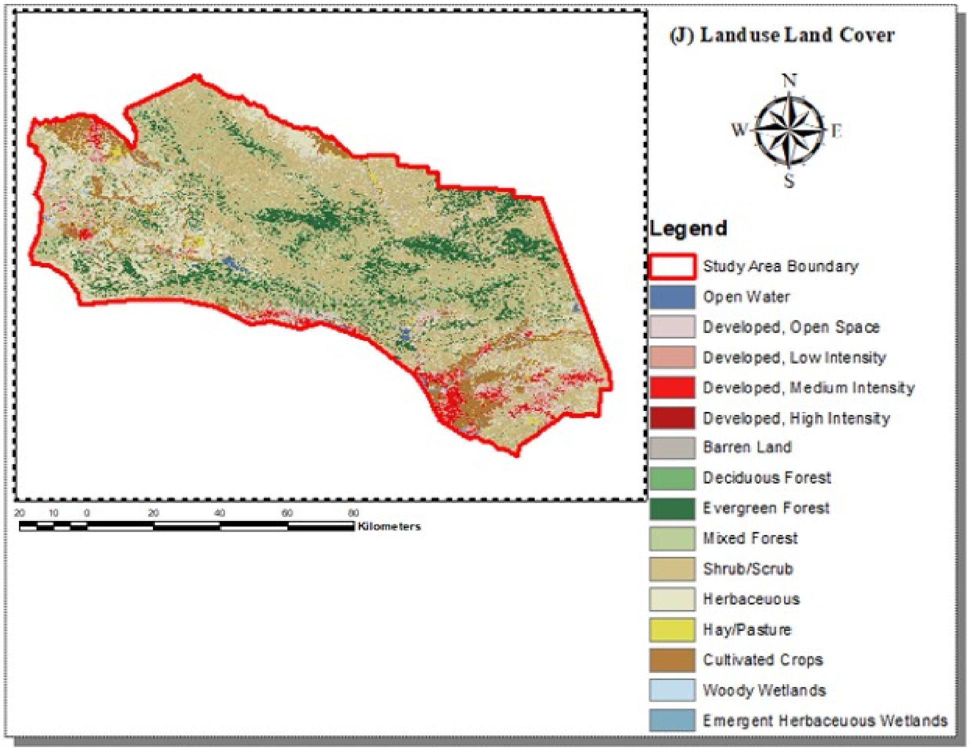

Figure 11J. Land Use and Land Cover

In this study, landcover classes were extracted from a Landsat ETM image using object-based classification approach. The segmentation function and classification method were performed using the image analysis software eCognition, which has been determined to produce better landcover classes with parameters at different data resolutions. The object-oriented segmentation not only segregates pixel groups using their spectral characteristics but can also distinguish various classes in the images based on other attributes such as shape and texture. A Landsat imagery for the study area was classified into a variety of different land cover types and classes. Identified land cover types that were reclassified included the following; open water, Developed Open space, Barren land, Deciduous forest, Evergreen forest, Mixed forest, Shrub/Scrub, Herbaceous, Hay/Pasture, Cultivated Crops, Woody Wetlands, Emergent Herbaceous Wetlands, sparse forest, settlements. A segmentation technique is used to build up a hierarchical network of image objects. This spectral image analysis software allows the advanced automatic image analysis, relying on image objects by using tools for object-oriented classification including details such as contextual and shape information. The spectral image analysis software differs from other pixel-based classification techniques in that it does not classify single pixels, but rather image objects, which are extracted in a previous image segmentation step. This spectral analysis technique makes a better argument for analyzing groups of spectral pixel signatures as objects instead of using the conventional pixel-based classification unit. This will reduce the local spectral variation caused by crown textures, gaps, and shade.

3.4.4.11. Precipitation

Spatial patterns of precipitation (Rainfall) are always associated with landslides initiation and occurrence (Glade 1998). High precipitation rates always bring about an increased risk of landslide occurrence. Excessive precipitation throughout Southern California, especially in October, usually is a source of concern for local governments and residents living in landslide susceptible regions. Precipitation is a significant trigger or causative agent of landslides and earth flows. This is because rainfall has the effect of changing the hydrodynamic state and characteristics of soils. When precipitation occurs, and the soil becomes saturated, the adhesive force that binds soil particles together is lost or weakened. As a result, any changes in slope angle or tremors can initiate landslides. Also, the absence of precipitation can leave the soil particles dry and lose hence susceptible to landslides Prior research on rainfall data in Southern California indicated that when monthly precipitation exceeds about 150 percent of the average, the occurrence of landslides becomes more likely throughout the coastline region. The thematic map of rainfall is illustrated below (Figure 11k**).**

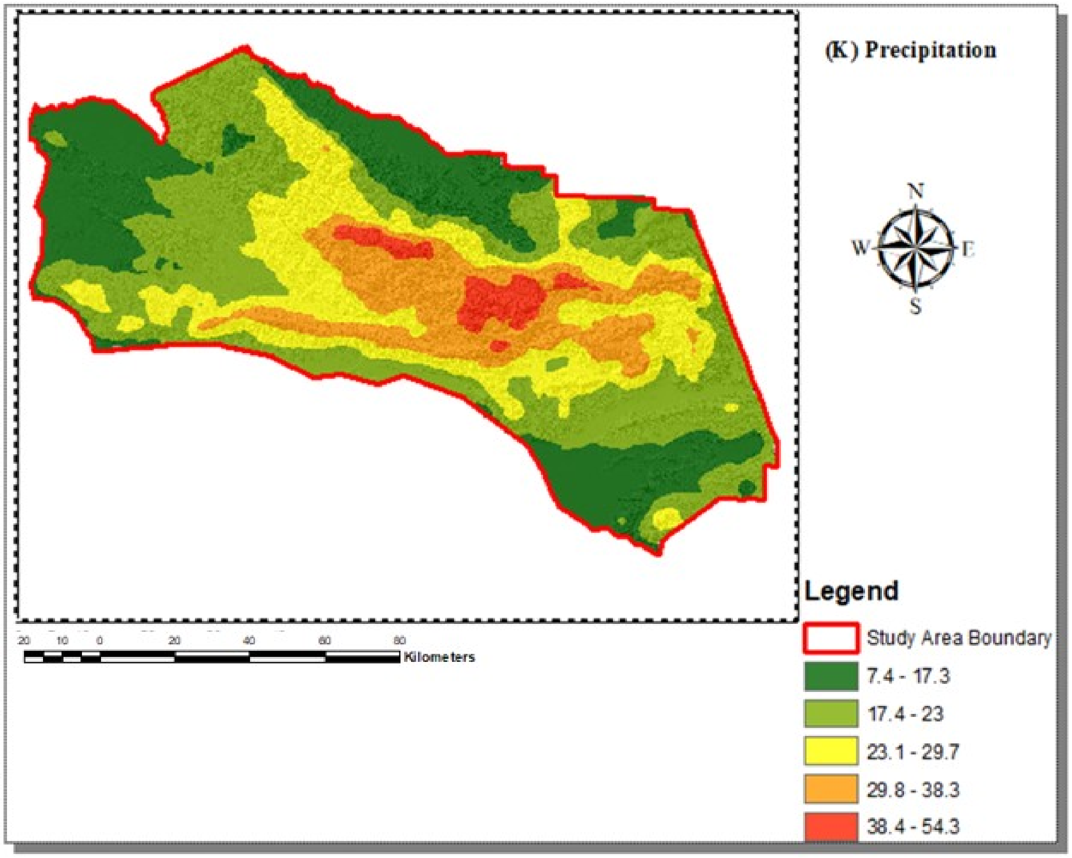

Figure 11K. Precipitation

Determining the suitable driving factors that affect landslides is crucial in analyzing slope instability and failures. Any such analysis needs a spatial database of both spatial and temporal datasets. The above criteria factors and their thematic maps below represents such a spatial database that has been designed for this study.

3.5. METHODOLOGY

3.5.1. Geophysical Landslide Susceptibility Modeling

A multi-criteria analysis (MCA) functions by selectively choosing and combining several criteria ensuring continuity and consistency to generate a complex evaluation index. The functionality of the criteria is primarily controlled by the influence of criteria components such as; factors (which can decrease or increase suitability) and constraints (which provides exclusion and limitation of factors). The most prominent advantages of the multi-criteria analysis (MCA) approach is its ability to maneuver, manage and incorporate both qualitative and quantitative data types (Feizizadeh et al. 2014). One such approach is a fuzzy set theory, introduced by Zadeh (1965). This method has been widely employed in susceptibility analysis over the years especially for modeling complex systems that are difficult to define in precise values. The main strength of this approach is its ability to deal with vague, imprecise, and ambiguous data that most often contains some uncertainty (Balezentiene et al. 2013). For a fuzzy set with two objects (A, Z), if Z denotes a space of objects, then the fuzzy set (A) in (Z) is a set of ordered pairs expressed mathematically as;

$$A \, \{z, MF\,(z)\}, \, z \in Z \text{ .... Equation (2)}$$

- Where the membership function MF (z) is the set A's degree of membership to Z.

Fuzzy logic considers spatial objects on a map as members of a set. In classical set theory, an object has a membership of 1 if it belongs to a set and 0 if it does not. While in fuzzy set theory, membership can take on any value between 1 and 0 reflecting the degree of certainty of membership (Zadeh 1965). This concept is important to the categorization of data and for decision making because it produces results with specific degrees of accuracy. Regarding the relevance and applicability of fuzzy measures in decision-making processes, any decision takes into consideration two sets (suitability and nonsuitability). To arrive at an appropriate conclusion, the degree to which a decision belongs to a set 'suitable' is determined from the assessment of suitability range. In this case, suitability is expressed in varying degrees of fuzzy membership with respect to some attribute of interest. When geospatial raster data types are involved, the attributes of interest are analyzed over discrete raster class intervals, and membership functions expressed as tables or graphs of raster class intervals against membership functions (Pradhan 2011). A fuzzy logic approach is attractive because it is simple to understand and implement. It can be used with data of various scales, and the assignment of fuzzy membership weights is entirely depended on the frequency of landslide occurrence and general interaction of the evidence collected for each site as well as field specialist opinion, (Ayalew et al. 2004; Kritikos and Davies 2011). Its ability to accommodate and accurately analyze complex combinations of weighted maps within a GIS has made this approach increasingly popular among geospatial analyst interested in Landslide suitability modeling.

In a multi-criteria decision analysis (MCDA) process, similar to a multicriteria analysis (MCA) and the fuzzy set theory, a data series reflecting different objectives is scrutinized with the aim of extracting alternative possibilities from the data sets given various criteria. A multi-criteria decision analysis, functions by selectively choosing and combining several criteria ensuring continuity and consistency to generate a complex evaluation index. The functionality of the criteria is primarily controlled by the influence of criteria components such as criteria factors which impacts (decrease or increase of suitability) and constraints (which provides exclusion and limitation of alternatives of factors under study).

For this study, a series of qualitative (expert-derived datasets) and quantitative datasets (appreciation of observed relationships between raster class intervals and frequency of landslide occurrence) were employed. The spatial relationship between each landslide criteria factor, the frequency of landslide occurrence for raster each class interval and the assigned fuzzy membership values are illustrated in Table 7 below.

Table 7. The Spatial Relationship between each Landslide Related Criteria Factor and Landslide Frequency and Fuzzy Membership Values.

Criteria	Class	No. of pixels in Class	No. of Landslides	Attribute Ranking	FM Value of Classes
Slope (°)	0 – 7.1	30911108	12	0	0.001
	7.2 - 16.2	26694097	30	25	0.25
	16.3 - 24.9	29297260	75	50	0.5
	25 - 33.7	24891363	114	78	0.78
	33.8 - 85.9	12684327	90	100	1
Aspect	Flat (-1)	11614979	0	1	0.001
	N (0-22)	10959990	85	68	0.68
	NE (22-67)	10384964	34	30	0.30
	E (67-112.)	12344281	14	1	0.01
	SE (112-157)	16045099	96	75	0.75
	S (157-202)	15870007	245	100	1
	SW (202-247)	13592870	82	50	0.50
	W (247- 292)	12577240	65	50	0.25
	NW (292- 337)	12417460	12	1	0.01
	N (337- 360)	13756459	7	1	0.01
Curvature	Concave (-37-1)	11196212	246	100	1
	Convex (2 – 36)	12716565	77	50	0.5
Elevation (m)	-10.8 - 231	31062435	23	25	0.25
	231.1 - 526.2	29576304	326	100	1
	526.3 - 884.5	21114979	87	78	0.78
	884.6 - 1242.9	17382206	12	1	0.01
	1243 - 1622.3	16277034	6	1	0.01
	1622.4- 2686	6155641	2	1	0.01

Table 7. Continued

Criteria	Class	No. of pixels in Class	No. of Landslides	Attribute Ranking	FM Value of Classes
Terrain Roughness	0 - 0.341	7770975	36	25	0.25
	0.342 - 0.447	49114223	78	50	0.50
	0.448 - 0.525	30356574	152	78	0.78
	0.621 - 1	9184188	186	100	1
Precipitation	7.4 - 17.3	4179	46	25	0.25
	17.4 - 23	2017	121	100	1
	23.1 - 29.7	3303	94	78	0.78
	29.8 - 38.3	5399	58	50	0.50
	38.4 - 54.3	4179	23	1	0.00001
Soils	Group 1	354070	173	100	1
	Group 2	57733	126	90	0.9
	Group 3	511086	69	78	0.78
	Group 4	22202	32	50	0.5
	Group 5	414130	28	30	0.3
	Group 6	554097	17	0	0
Road proximity	0 - 49	13783271	78	100	1
	50 - 99	12344069	52	78	0.78
Fault-line Proximity	0 - 49	2768581	36	50	0.50
	50 - 99	2859357	14	25	0.25
Wildfires	1	0	0	0	0.0001
	1.01 - 2	19855515	168	78	0.78
	2.01 - 3	24553926	256	100	1

3.5.2. Application of Fuzzy Membership Functions (fmf)

For this study, all criteria raster pixel values associated with landslides were converted into fuzzy scores or values. The membership of each raster pixel was standardized and normalized on a scale of (0-1) based on the fuzzy and crisp membership function, where 0 represented least susceptible and 1 represents most susceptible. Prior to fuzzification of criteria factors, the classes of each conditioning factor were statistically ranked. Then the scores of each raster pixel were computed and ranked in increasing order, to determine the order of rank of assigned scores. Pixels with the smallest scores had a value of 0 while the pixels with highest scores had a value of 1. These pixels were then statistically normalized so that the pixels with the highest predictive capacity were assigned a value of 1 or 100. While there are no standard rules for choosing fuzzy memberships for criteria factors, some researchers have defined their fuzzy membership values based on expert opinion (Bonham-Carter 1994) while others are based on statistical analysis of data (Ercanoglu and Gokceoglu 2002). For this study, the assigned fuzzy membership function values for each criteria raster class interval was based on a linearized sigmoidal membership function (monotonically decreasing and increasing) in association with user-defined linear membership functions for selected parameters. A linearized sigmoidal function was chosen because of its ability to deal with data that had problems of non-linearity efficiently. In the linearization process of a sigmoidal function, a log-logit function is used to transform a sigmoidal curve with a single inflection into a straight line. The linearized sigmoidal function is expressed mathematically below;

$$\mu(x) = 0 \text{ if } x < \min,\ \ \mu(x) = 1 \text{ if } x > \max, \quad \text{...} \quad \text{Equation (3)}$$

$$\text{Otherwise} \qquad \mu(x) = \frac{(x - \min)}{(\max - \min)} \quad \text{..} \quad \text{Equation (4)}$$

- Where min and max are user inputs.

Lower susceptibility values were assigned to areas with less suitable criteria data formation and high susceptibility values assigned to an area with high suitability criteria data formations. Subsequently, the classes of all fuzzified criteria raster datasets were classified on the basis of landslide susceptibilities.

3.5.3. Landslide Frequency and Fuzzy Membership Graphs for Criteria Factors

Frequency graphs were created for each landslide related criteria factor showing the number of observed landslides in each raster class interval. From these frequency values, each criteria factor's raster class interval was quantified into appropriate membership values of susceptibility, ranging between 0 (low susceptibility) to 1 (high susceptibility). The membership function landslide frequency graphs for each criteria factor analyzed for the study area is illustrated from Figure 12a - Figure 12j below.

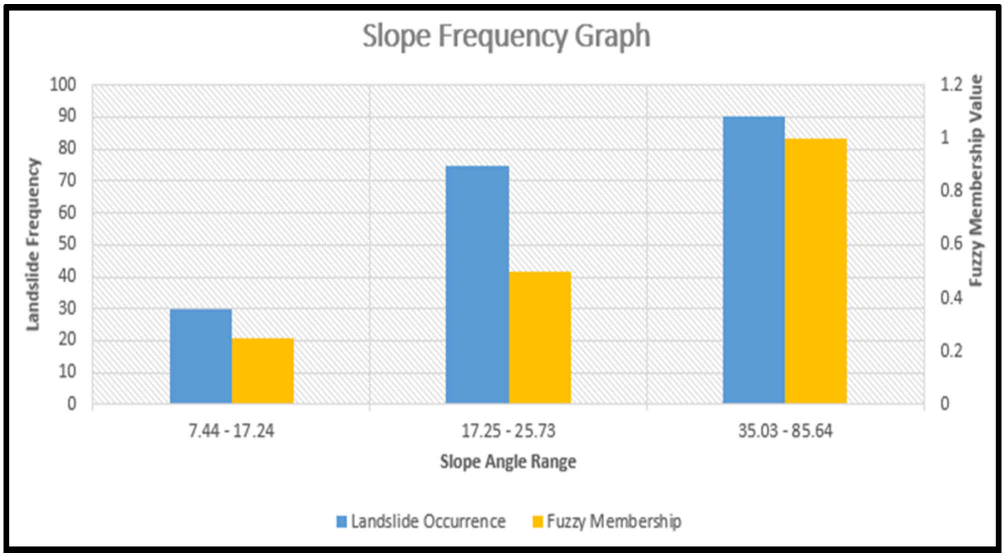

Figure 12A. Slope Landslide Frequency Graph

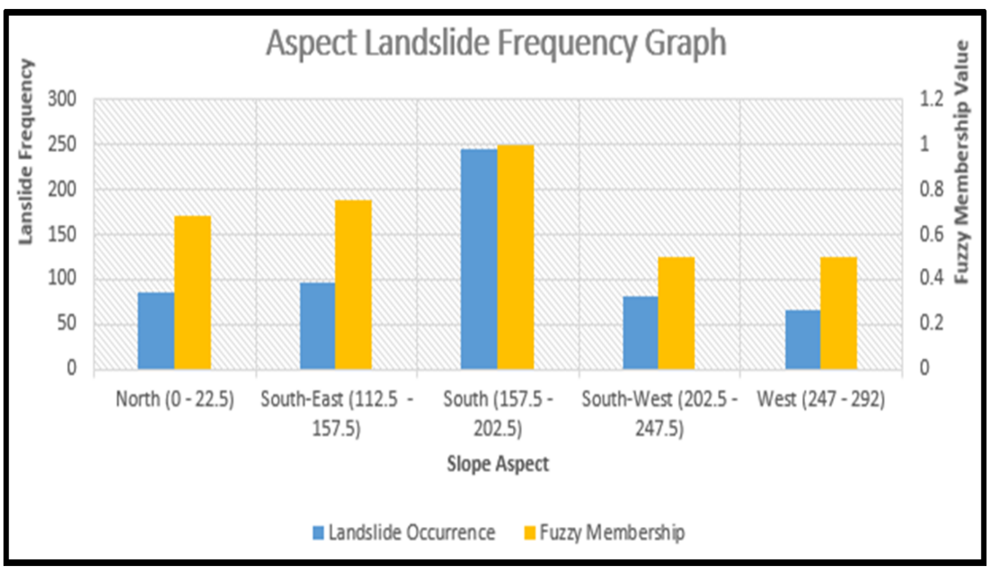

Figure 12B. Aspect Landslide Frequency Graph

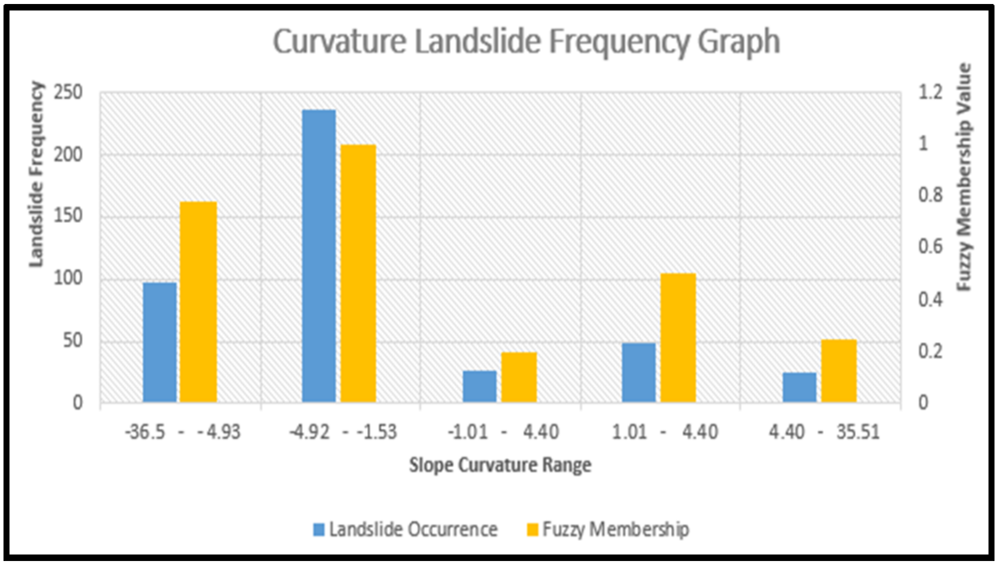

Figure 12C. Curvature Landslide Frequency Graph

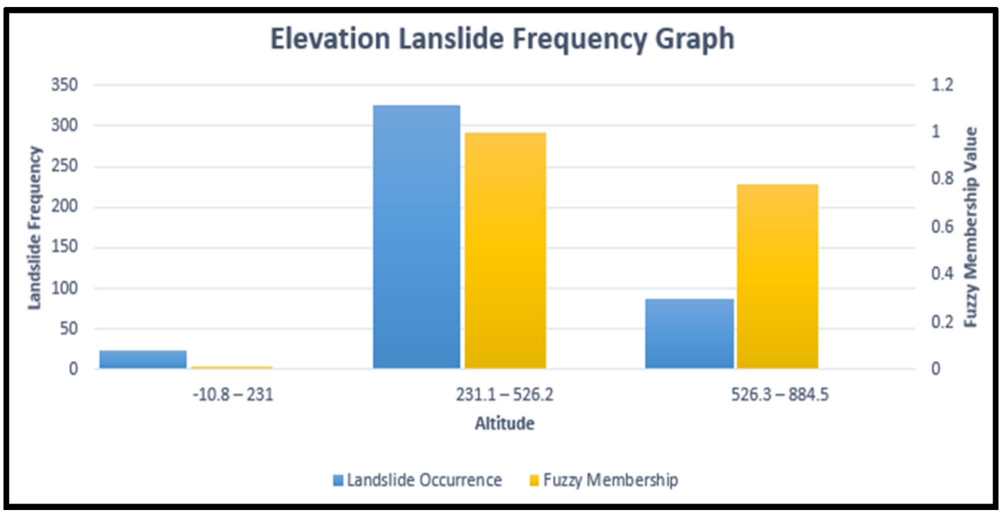

Figure 12D. Elevation (Altitude) Landslide Frequency Graph

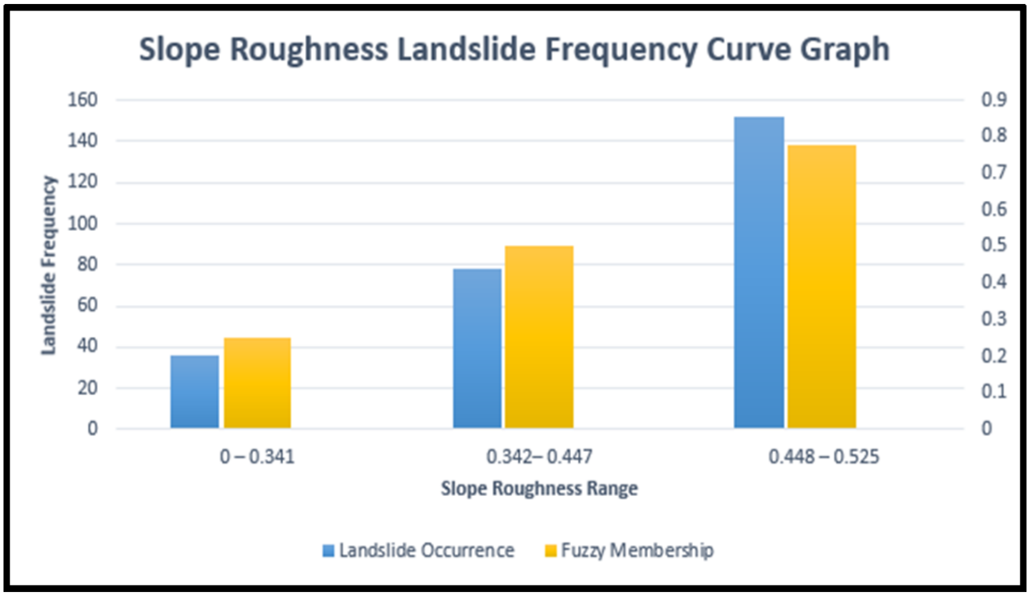

Figure 12E. Slope Roughness Landslide Frequency Graph

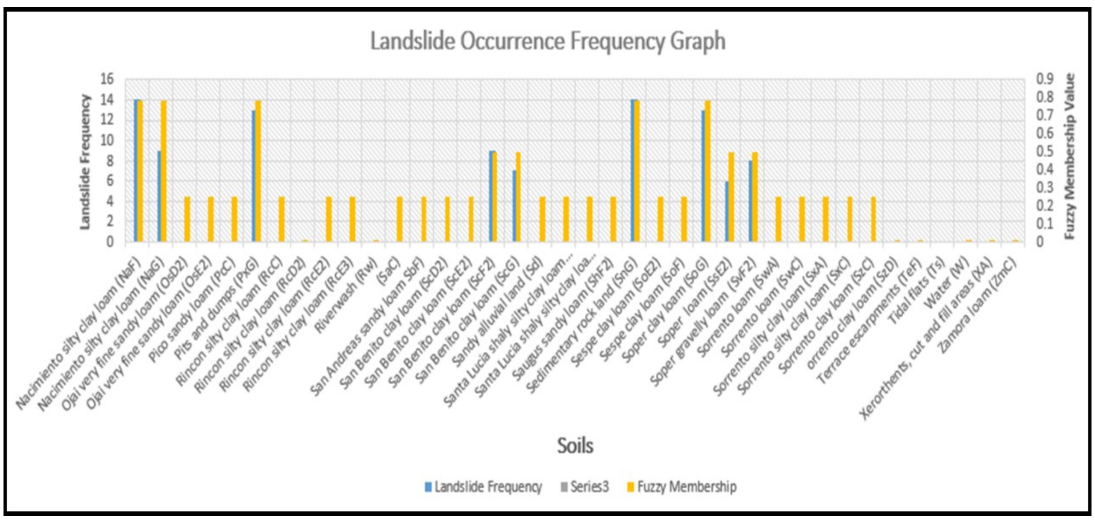

Figure 12F. Soils Landslide Frequency Graph

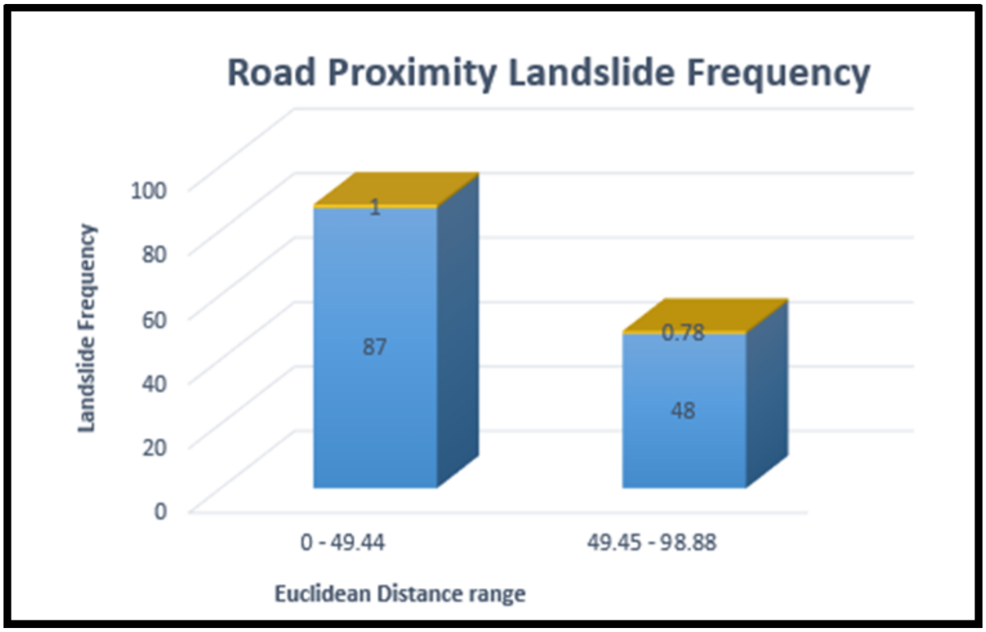

Figure 12G. Road Proximity Landslide Frequency Graph

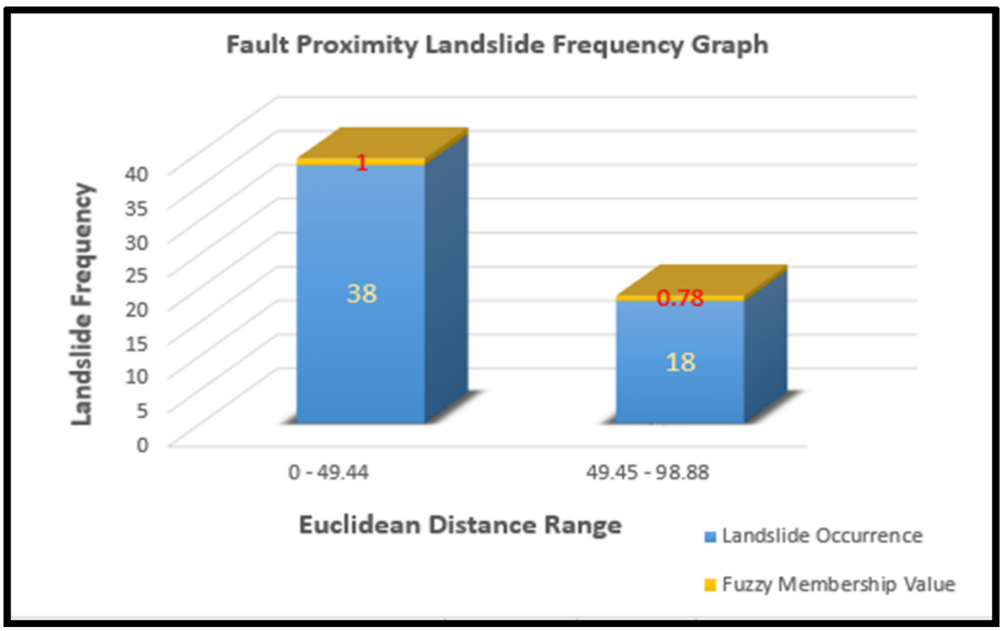

Figure 12H. Fault-line Proximity Landslide Frequency Graph

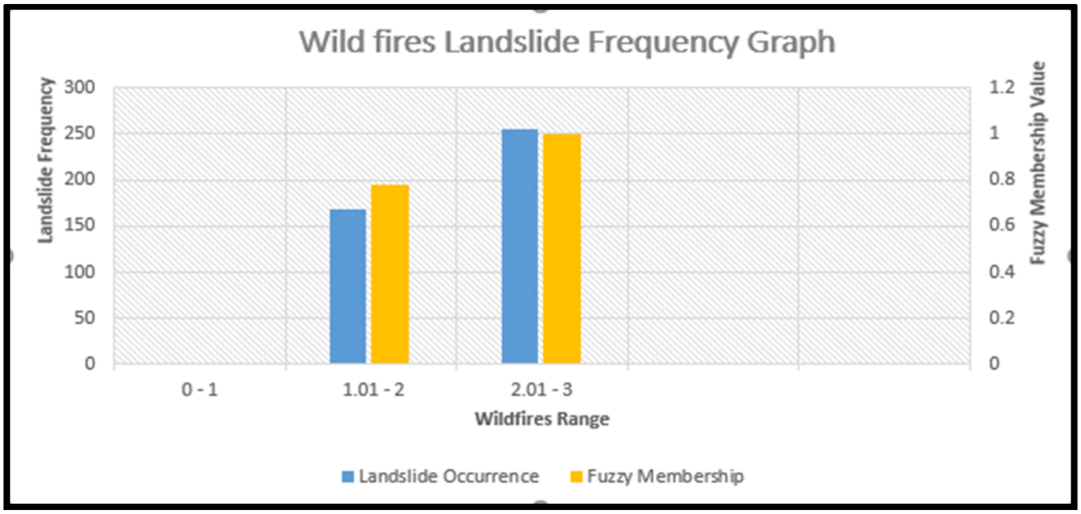

Figure 12I. Wildfires Landslide Frequency Graph

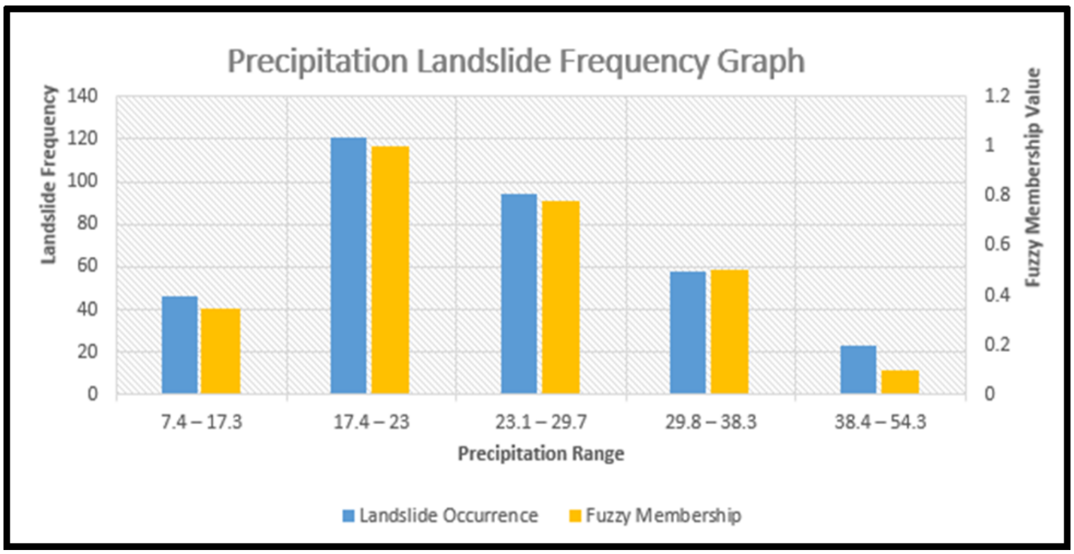

Figure 12J. Precipitation Landslide Frequency Graph

3.5.4. User Defined If-Then Rules Used for this Analysis

The use of fuzzy set functions has made it possible to represent more accurately and correctly datasets that appear to be ambiguous and vague (Juang et al. 1992). With that concept in mind, the fuzzified frequency graphs of landslide-related criteria factors above were used to create the following user-defined If-Then Rules for the fuzzy analysis (See Table 8).

Table 8. User-defined If-Then Rules Used in Study Area

Criteria Factor	Antecedent Condition	Antecedent Consequence
Slope	If slope is very low If slope is moderate If slope is high If slope is very high	Landslide susceptibility is low Landslide susceptibility is very high Landslide susceptibility is high Landslide susceptibility is very low
Aspect	If aspect is flat - E If aspect is East - SE If aspect is S - W If aspect is NW - W	Landslide susceptibility is non-susceptible Landslide susceptibility is low - moderate Landslide susceptibility very High Landslide susceptibility is low
Elevation	If elevation is very low If elevation is low If elevation is moderate If elevation is high or very high	Landslide susceptibility is non-susceptible Landslide susceptibility is very high Landslide susceptibility is high Landslide susceptibility is very low
Curvature	If curvature is concave If curvature is convex	Landslide susceptibility is low Landslide susceptibility is high- very high
Terrain Ruggedness	If terrain is smooth and flat If terrain is rough and steep	Landslide susceptibility is low Landslide susceptibility is high
Soils	If lithology is (Group 1) If lithology is (Group 2) If lithology is (Group 3) If lithology is (Group 4) If lithology is (Group 5) If lithology is (Group 6)	Landslide susceptibility is very high Landslide susceptibility is high Landslide susceptibility is moderate-high Landslide susceptibility is moderate Landslide susceptibility is low Landslide susceptibility is very low
Precipitation	If precipitation is high If precipitation is low	Landslide susceptibility is high Landslide susceptibility is low
Fault-line Proximity	If proximity to fault is small or very small If proximity to fault is moderate If proximity to fault is high If proximity to fault is very high	Landslide susceptibility is very high Landslide susceptibility is high Landslide susceptibility is low Landslide susceptibility is very low

Table 8. Continued

Criteria Factor	Antecedent Condition	Antecedent Consequence
Road Proximity	If proximity to roads is high/very high If proximity to roads is moderate If proximity to roads is small/ very small	Landslide susceptibility is very low Landslide susceptibility is moderate-high Landslide susceptibility is very high
Wildfires	If wildfires are present If wildfires are not present	Landslide susceptibility moderate to high Landslide susceptibility is low
Land Use Land cover (LULC)	If covered by pavement If covered by mixed vegetations	Landslide susceptibility is low Landslide susceptibility is moderate to high

These if-then rules in association with landslide occurrence frequency data were subsequently used to generate landslide susceptibility maps for the individual conditioning factors as shown in (Figure 13 a - k) below.

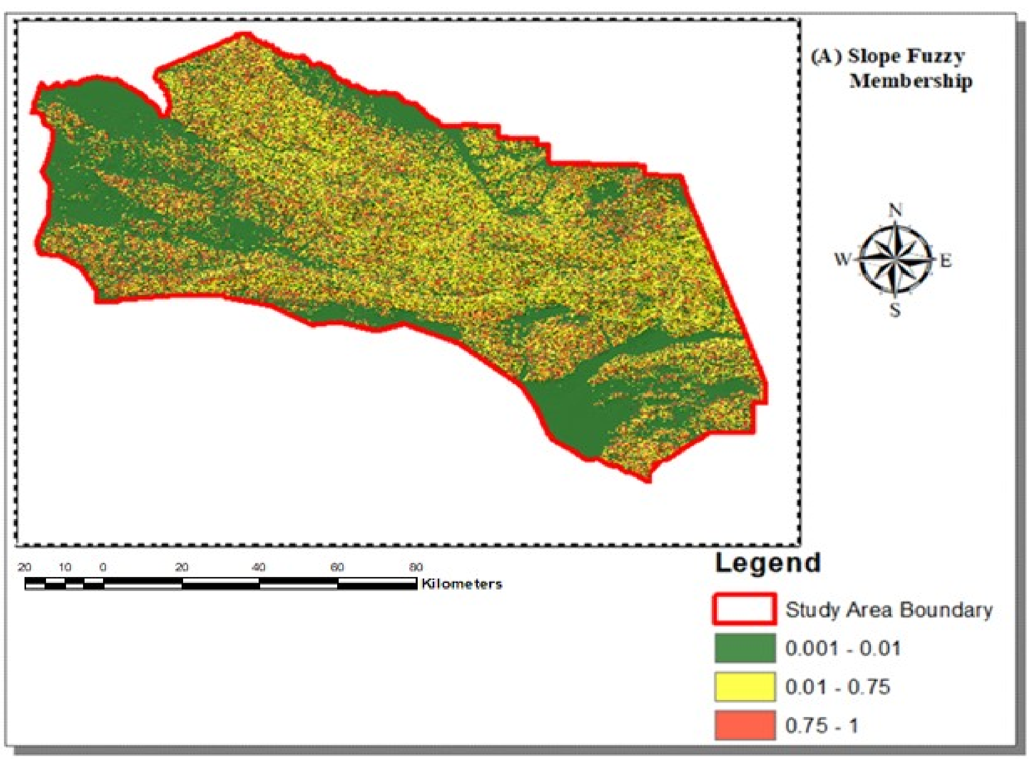

Figure 13A. Slope Angle Fuzzy Membership

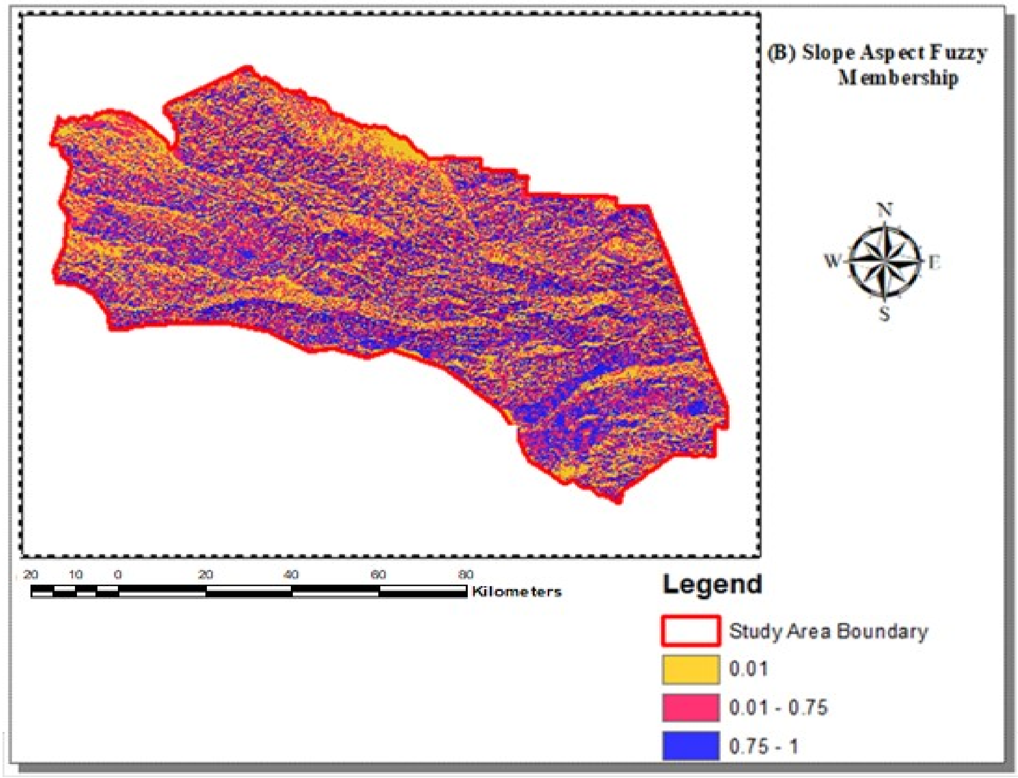

Figure 13B. Slope Aspect Fuzzy Membership

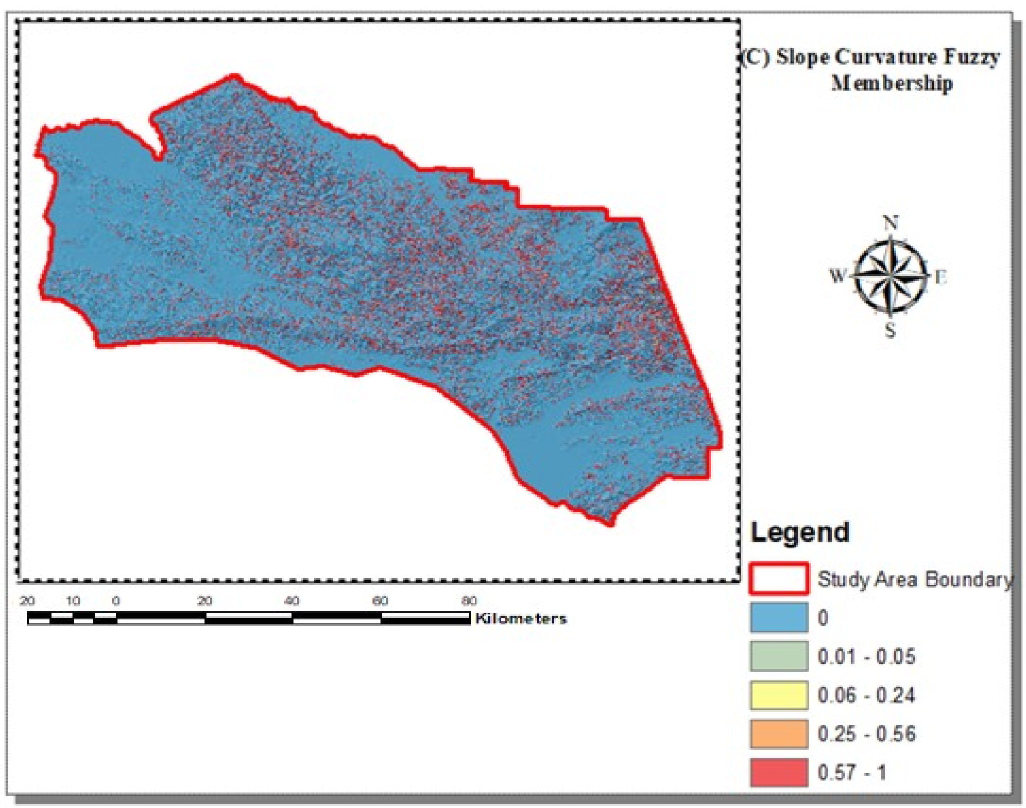

Figure 13C. Slope Curvature Fuzzy Membership

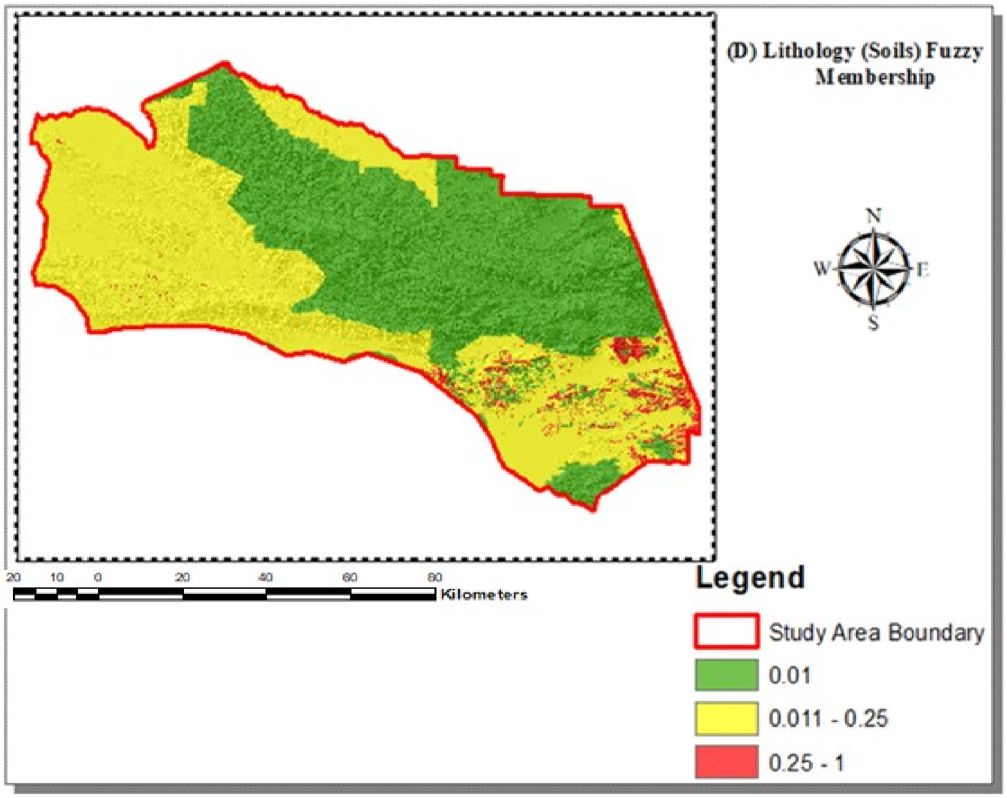

Figure 13D. Lithology (Soils) Fuzzy Membership

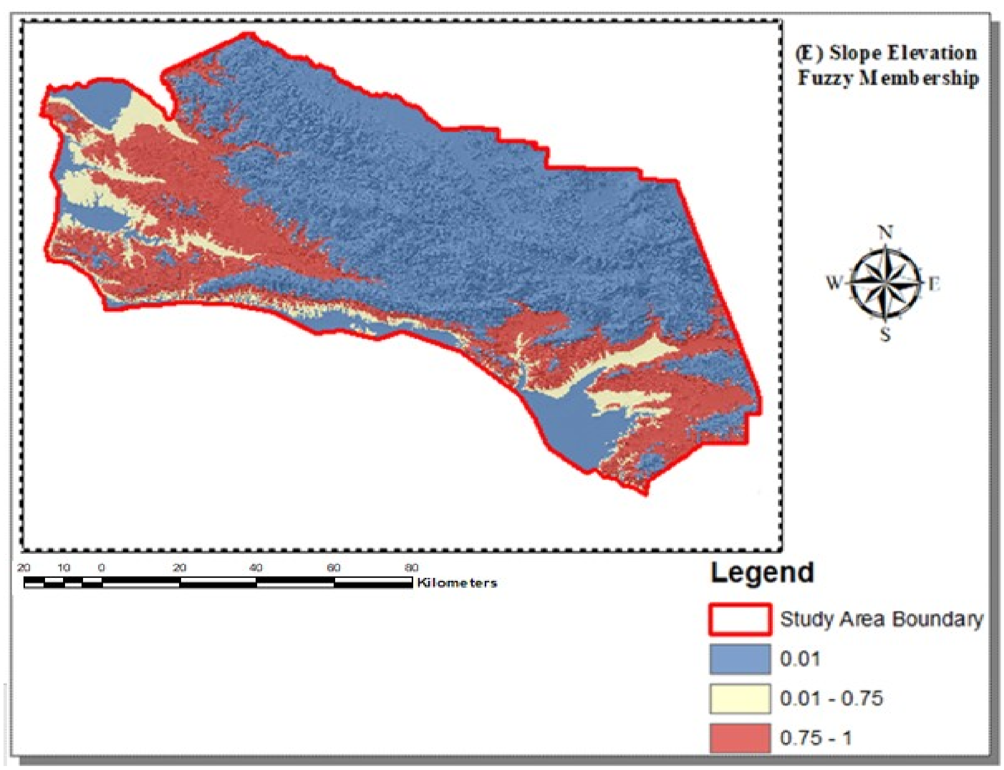

Figure 13E. Slope Elevation Fuzzy Membership

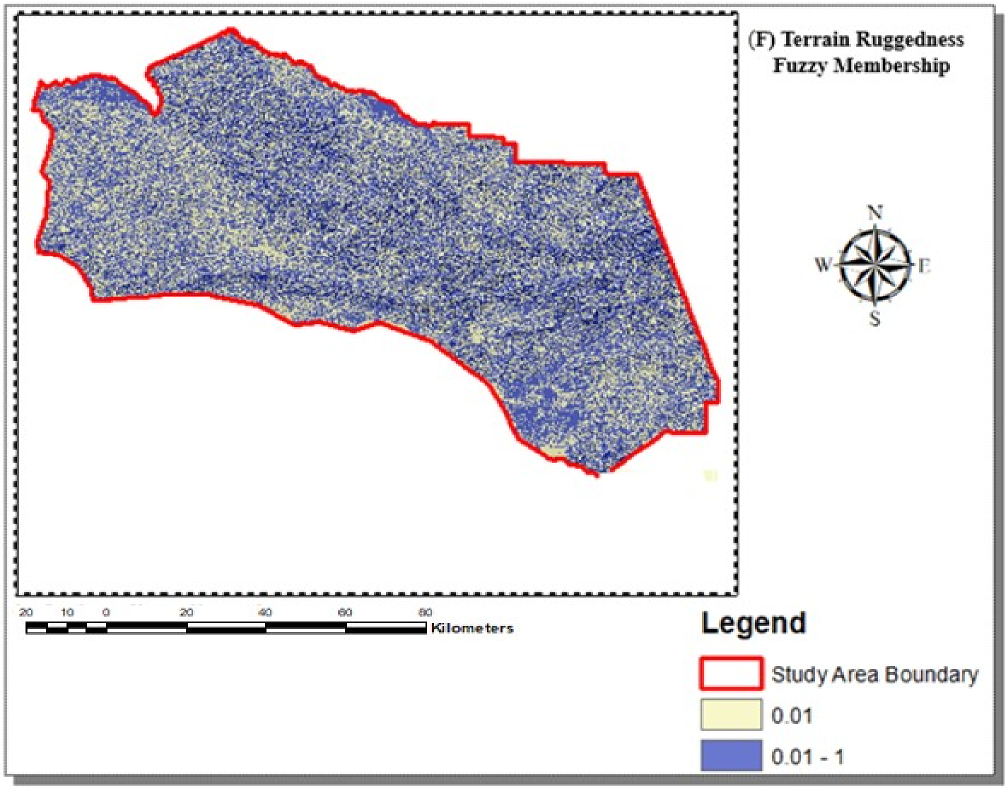

Figure 13F. Terrain Ruggedness Fuzzy Membership

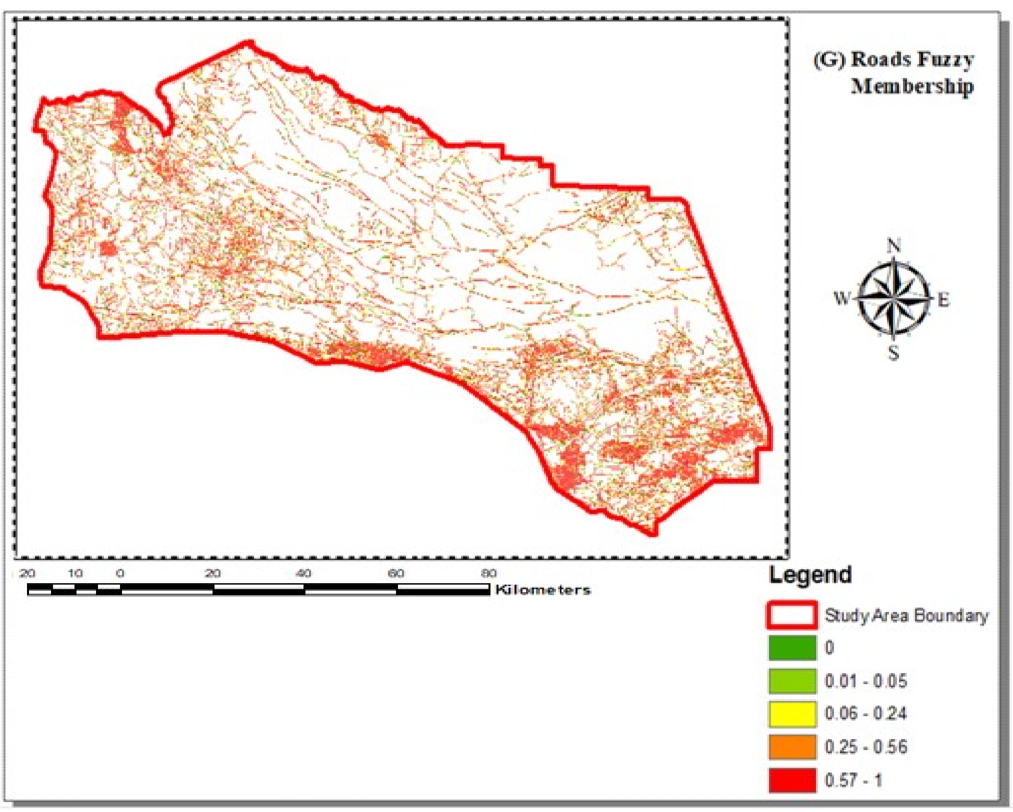

Figure 13G. Roads Proximity Fuzzy Membership

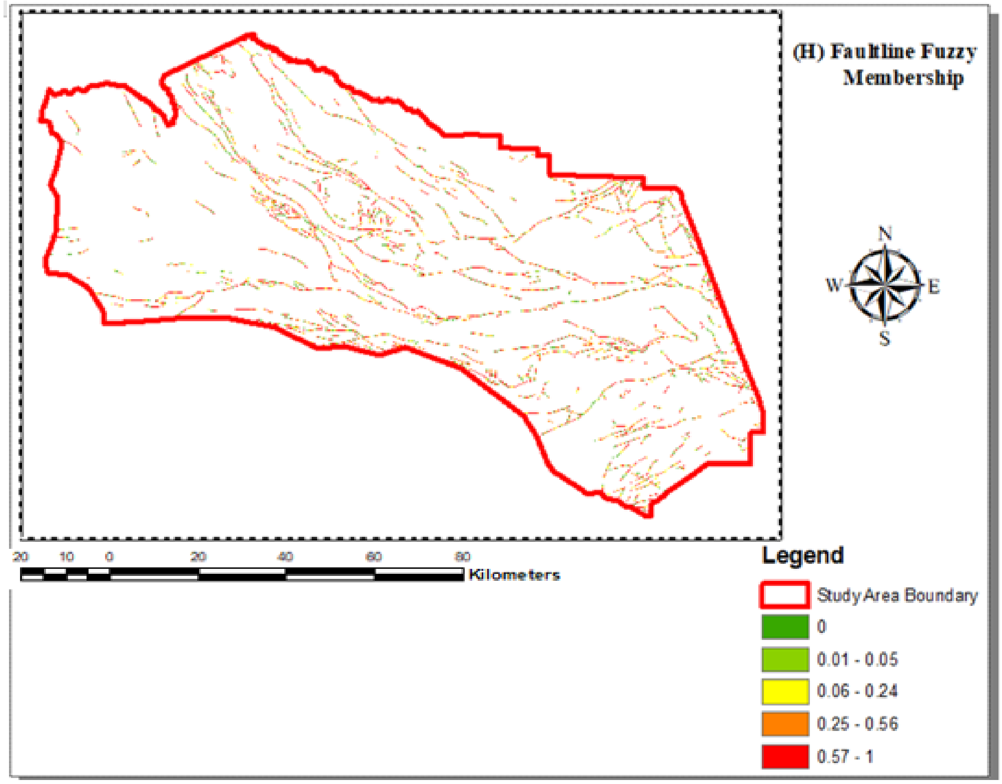

Figure 13H. Fault-line Proximity Fuzzy Membership

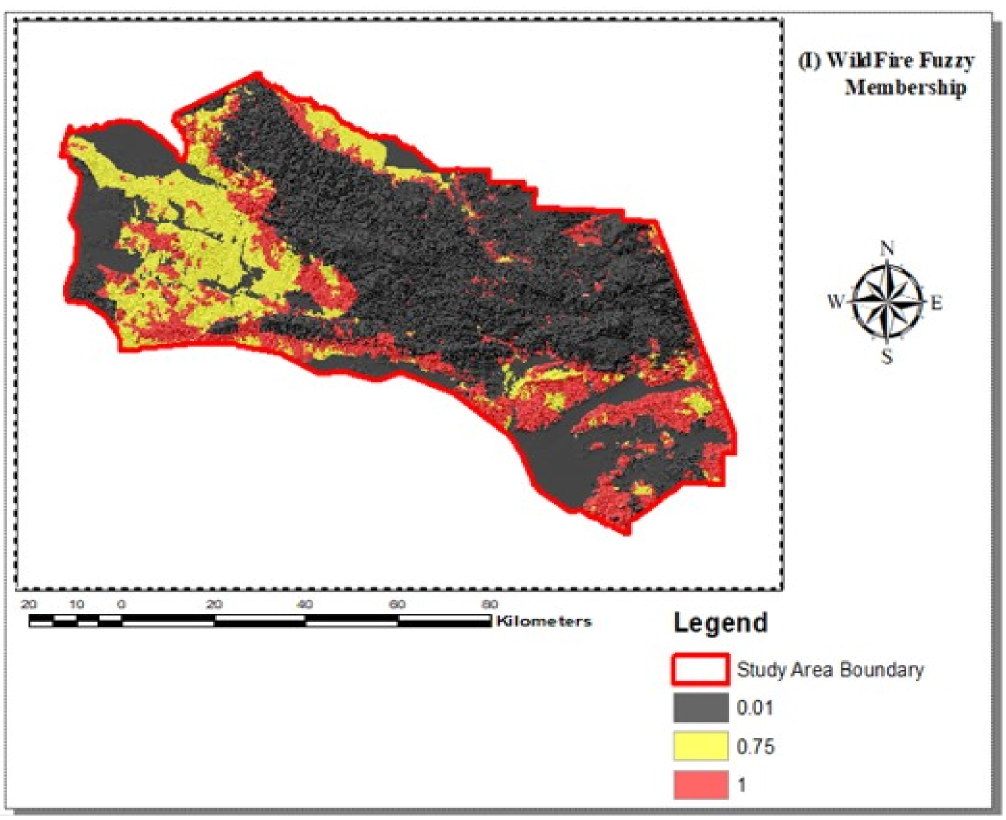

Figure 13I. Wildfires Fuzzy Membership

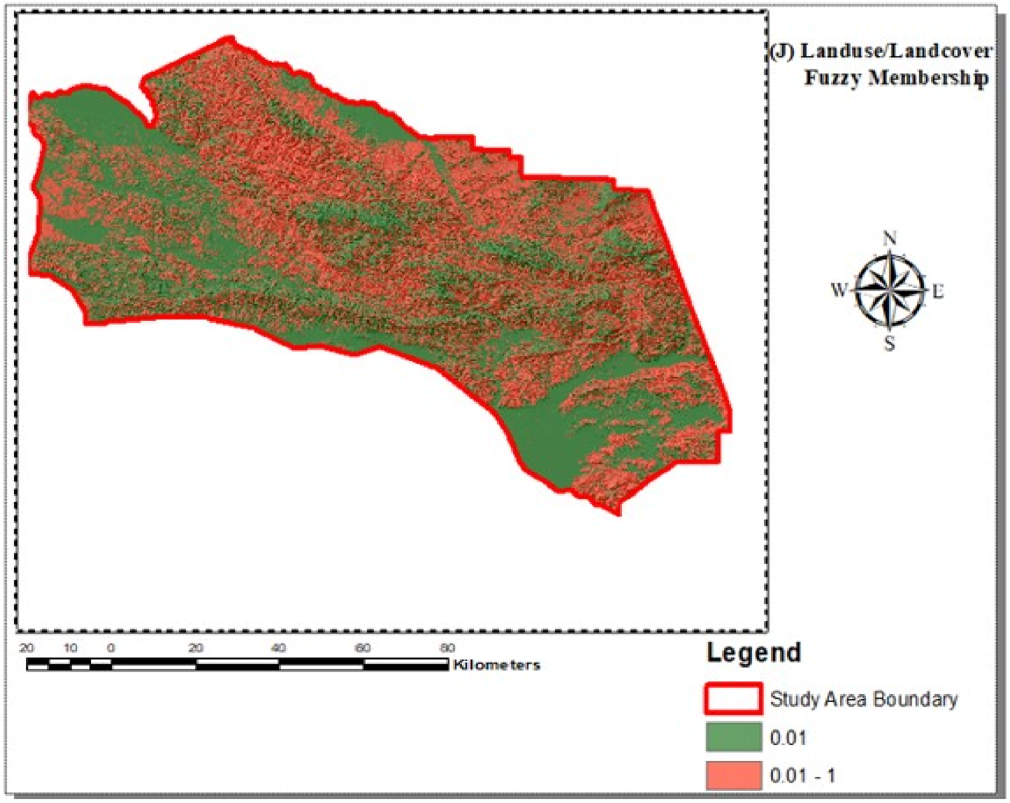

Figure 13J. Land Use and Land Cover Fuzzy Membership

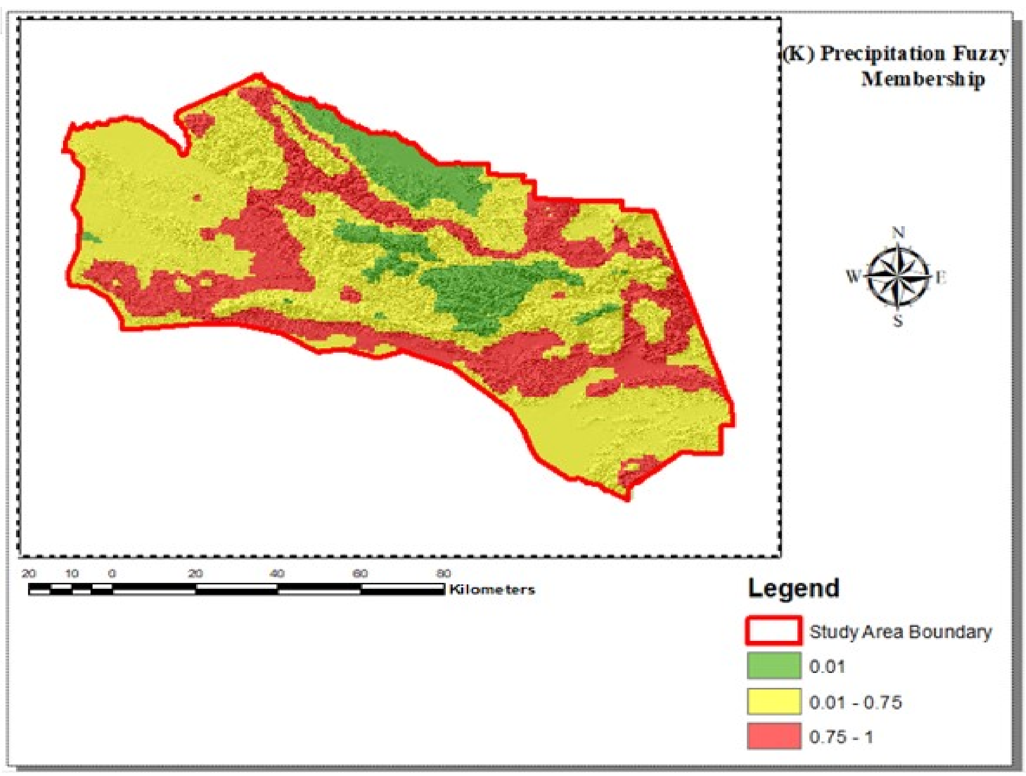

Figure 13K. Precipitation Fuzzy Membership

To obtain a final landslide susceptibility map, a fuzzy overlay technique of multi-criteria aggregation was used to combine the weighted fuzzified raster layers of criteria factors. Several fuzzy operators can be employed to efficiently integrate or overlay the weighted membership classes of criteria factor layers. For this analysis, the following data integration operators were tested: Fuzzy (And), Fuzzy (Or), Fuzzy algebraic Product, Fuzzy algebraic Sum and Fuzzy Gamma (Bonham-Carter 1994; Jiang and Eastman 2000; Pradham et al. 2009). These operators were selected over other statistical combination techniques because they provide greater flexibility than other statistical techniques, for example, the weighted-sum or weighted-overlay techniques let the expert incorporate greater sensitivity based on knowledge of how the evidence interacts. The Fuzzy (And) and Fuzzy (Or) operators are very popular but have limitations in that, one of both operators significantly influences the results of the output combination while the other does not influence the combination. This analysis assessed all five fuzzy operators with the goal of identifying the operator that produces the best results for the model. The Fuzzy (And) is similar to the Boolean AND (logical intersection). In this operator, the minimum of all the values defined the output of the model and is expressed mathematically by equation (5) below.

$$\mu(x) = \min(\mu_{a,}\ \mu_{b,}\mu_{c,}, \ldots \ldots . \mu_{d),} \text{...} \quad \text{Equation (5)}$$

Where:

$\mu(x)$ is the calculated fuzzy membership function, $\mu_{a,}$ is the membership value of map A at a particular location and $\mu_{b,}$ is the membership value of map B at a particular location.

The Fuzzy (Or), Similar to the Boolean OR (logical union), the output model is determined by the maximum score or value of any of the input data as expressed mathematically by equation (2) below.

$$\mu(x) = \max(\mu_{a,}\ \mu_b, \mu_c \ldots \ldots \mu_d) \text{.......................... Equation (6)}$$

Where: $\mu(x)$ is the calculated fuzzy membership function, $\mu_{a,}$ is the membership value of map A at a particular location and $\mu_{b,}$ is the membership value of map B at a particular location etc.

The Fuzzy Algebraic Product produces output functions lower or equal to the lowest function given and expressed mathematically by equation (3) below,

$$\mu(x) = \pi_{a=1}^{n} \mu_a \text{.......................... Equation (7)}$$

Where: μ_a is the fuzzy membership function for the a-th map, and a = (1, 2, 3….n) maps are to be combined.

The Fuzzy Algebraic Sum compliments the algebraic product by producing output functions higher than the values of the input data but never above 1. Expressed mathematically in equation (4) below,

$$\mu(x) = 1 - \pi_{a=1}^{n} \mu_a (1 - \mu_a) \text{.......................... Equation (8)}$$

Finally, a fuzzy gamma operator was assessed. This operator function is defined regarding the fuzzy algebraic product and fuzzy algebraic sum. This final operator allows for optimization of the membership combination. On one extreme of this operator for example when gamma is 1 ($\gamma = 1$), the combination is the same as in algebraic sum and when ($\gamma = 0$), the combination is the same as in the algebraic product as expressed in equation (5) below,

$$\mu(x) = (\text{FuzzySum})^{\gamma} \text{ - } (\text{FuzzyProduct})^{1-\gamma} \text{.......................... equation (9)}$$

Where: γ is a user input gamma value chosen in the range between (0, 1)

The raster data values in between (0, 1) allow for the combination of evidence between two extremes and possibly different than Fuzzy (Or) or Fuzzy (And). Fuzzy Gamma operator is a compromise between the increasing effect of Fuzzy Sum and the decreasing effect of Fuzzy Product. The Fuzzy Gamma operator generates a relationship between multiple input criteria factors and does not merely return the value of a single membership as does Fuzzy (Or) and Fuzzy (And) operators.

To successively combine the overlaid fuzzy memberships of the different criteria factors using the various operators discussed above, the extreme membership values of (0 and 1) were replaced with approximations such as (0.1 and 0.9) using a raster calculator tool. Then the criteria factor memberships were combined using various fuzzy gamma operators. In this combination process, the paired attributes of similar origin are grouped together. An equal interval cut-off point was used for the categorization of pixel distribution

3.5.5. Results and Model Validation

Initial landslide susceptibility model results indicated that the gamma operator had the best model results. To fine-tune and optimize the results, the fuzzy gamma operator values between ($\gamma = 0.7 - 0.9$) were further analyzed to improve accuracy. The accuracy of these models was determined by calculating their respective Areas Under the Curve (AUC) using the Relative Operating Characteristics (ROC) (Fawcett 2006; Nandi & Shakoor 2009) and observing the number of landslides that fall within the various categories of the landslide susceptibility model. The ROC operator characteristic is useful in representing the quality of the deterministic or probabilistic detection and forecast system while the AUC characterizes the quality of the forecast system by demonstrating the system's ability to anticipate accurately the occurrence or non- occurrence of a pre-defined event, (Negnevitsky 2002; Brenning 2005). In an ROC curve, the false positive rate is plotted on the x- axis and false negative rate plotted on the *y*- axis. When calculating the ROC value, AUC values close to 1.0 indicate high levels of accuracy of the model while results close to 0.5 indicate inaccuracies in the overall model (Yilmaz 2010). When the validation landslide data were overlaid onto the landslide susceptibility model at different fuzzy gamma values (γ –values), different AUC values were achieved. The tested AUC values for the fuzzy gamma operator ranged from ($\gamma = 0.7 - 0.9$) and the AUC value results were between 0.79 to 0.882 (See Table 9).

3.5.6. Results Verification Using ROC and AUC Curves

Table 9. Verification Results Using Area Under the Curve (AUC).

Fuzzy Operator	**Prediction Accuracy (%)**
Fuzzy And	77.5
Fuzzy Or	77.6
Fuzzy Algebraic Sum	75.9
Fuzzy Algebraic Product	81.4
Gamma (γ) = 0.7	73.2
Gamma (γ) = 0.8	79.9
Gamma (γ) = 0.9	**88.2**

The AUC values were verified using the 150 landslide points set aside at the beginning of the analysis as data to be used for validation of the final landslide susceptibility model (LSM). The best model performance regarding the (AUC-value) prediction output was achieved at ($\gamma = 0.9$) and the AUC value was 0.882 and a standard error of 0.006. The result showed that about 60% to 80% of the landslides occurred in areas of high (H) or very high (VH) susceptibility zones, thus making it the parameter of choice for the final landslide susceptibility model (LSM). The resulting Final landslide susceptibility model was generated by ranging the continual values into five categories of relative susceptibility namely: Very Low – VL, Low – L, Moderate – M, High- H and Very High- VH, illustrated in (Figure 14) and (Figure 15a-b).

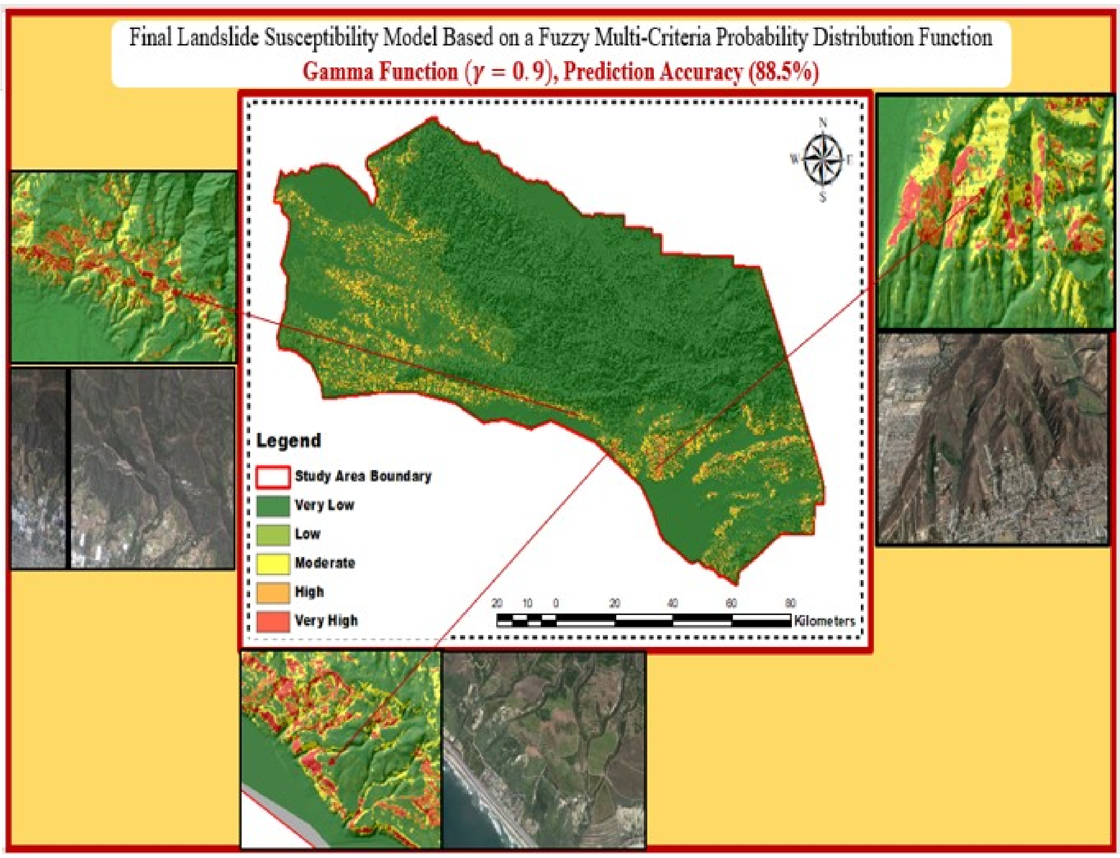

Figure 14. Landslide Susceptibility Model at Fuzzy Gamma Function Value of (γ=0.9)

LA CONCHITA LANDSLIDE SUSCEPTIBILITY ILLUSTRATION

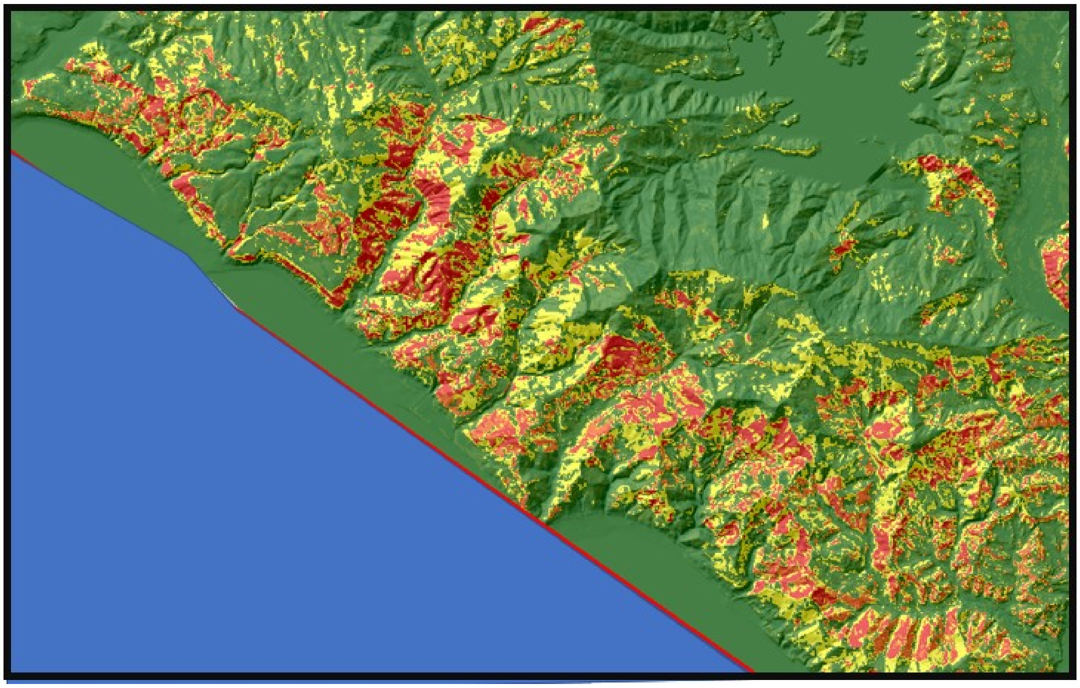

Figure 15A. Detail Landslide Model Illustration

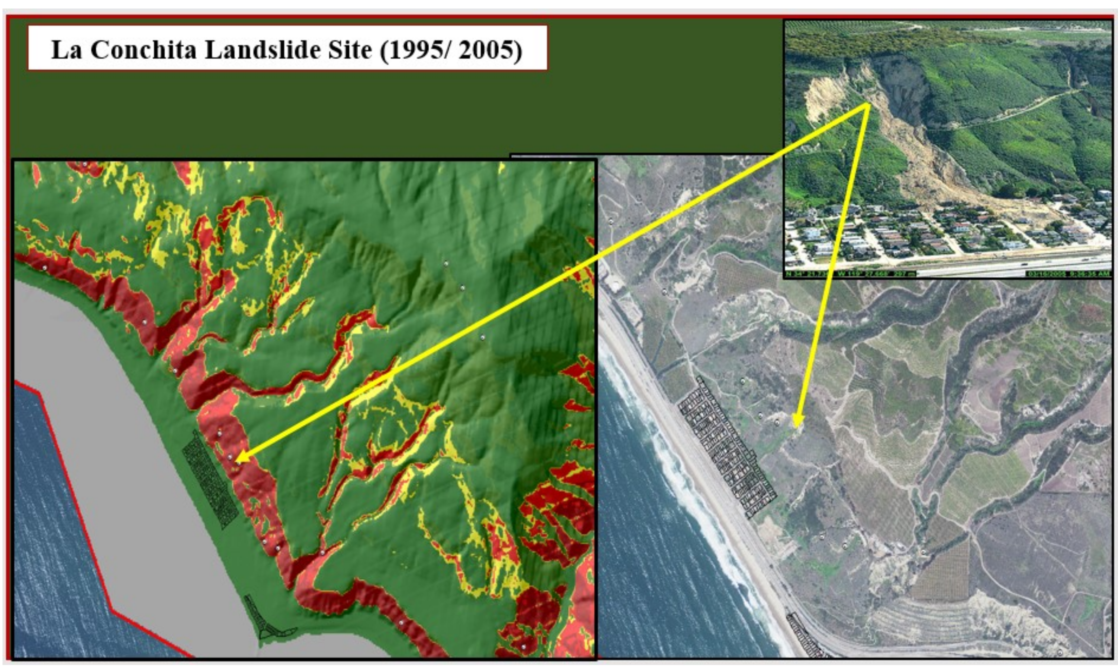

Figure 15B. Model Sample Showing La Conchita Landslide Site.

The southern Californian coastal region has experienced and will likely continue to experience, a rather bewildering variety of landslide hazards. Different landslide scenarios are likely to occur because of different specific rainfall conditions, and no part of the local community can be considered safe from landslides. Landslide susceptibility maps have proven to be crucial and informative in the decision-making process for urban development. Unfortunately, cuts in funding of environmental agencies have resulted in prioritization of hazard response as such leaving some communities exposed to hazards. Local planners, urban developers and hazard mitigation teams currently do not have regional parcel level high-resolution landslide susceptibility maps, extensive high-resolution landslide analysis, pre-historic landslide data inventory and the understanding to accurately forecast what might happen in the future regarding possible changing rainfall scenario. Considering the nexus between past landslide hazards events and extreme climate thresholds, prudence will undoubtedly dictate, however, that there will be renewed landslide activity during or after future periods of prolonged and (or) intense rainfall and earthquakes (Jibson 1995). Hence, a comprehensive landslide susceptibility analysis at a parcel level scale is vital to both community and city planners in making decisions regarding hazard assessment, settlement, and mitigation. These hazard mitigation decisions can be in the form of technical countermeasures, regulatory management or combination of both. The results of this study can help local developers, community planners, and slope management engineers by providing them with efficient, effective, cheap and readily replicable landslide susceptibility maps of high resolution. Also, this susceptibility map can change the community's approach to landslide hazards from mitigation and response to prevention by creating landslide predictive maps ahead of hazardous events as opposed to localized site-specific geotechnical analysis after a landslide has occurred. The landslide susceptibility map results of this study can efficiently reduce the constraints of geotechnical slope analysis such as data requirements, associated cost, and location specificity. This contribution has the potential of helping the communities and local planners change their overall action framework to landslide hazards from mitigation and response to warning and deterrence. This change will bolster better development and settlement decisions' given the hazardous nature of the southern coastal region of California.

IV. PHASE TWO:

LANDSLIDE HAZARD EXPOSURE MODELING

Natural hazards are geophysical processes that, when encroached upon by human development, have the potential to cause loss of life or destruction to property. By definition, “natural hazards constitute a threat to society” (Montz et al. 2017, p.9). Although the potential for an adverse event to occur may be recognized, there is often uncertainty as to the timing and magnitude of the event. Thus, the threat from landslide hazards is usually expressed in terms of likelihood or probability of occurrence of a given event of a specific magnitude and over particular area and time. In quantitative terms, the level of risk is a combination of the likelihood of something hazardous or adverse occurring and the consequences of the impact of the adverse event if it does occur. The risk exposure levels emerge from the intersection of the adverse event with the elements at risk, in this case (human-built environmental systems) usually expressed in terms of vulnerability as illustrated in (Figure 16a - b) below.

Figure 16A. Montecito, CA. Mudslide Hazard, Jan.10, 2018. Courtesy of AP Courtesy of Matt Udkow /AP

Figure 16B. Camarillo Springs, CA, Dec. 2014 Mudslide Hazard, Courtesy of Jonathan/Reuters

Landslides generate a small but essential component of the spectrum of hazards and increasing risk that faces mankind (Alcántara-Ayala 2002). In an ideal scenario, people would settle in areas that are safe and far away from landslides, earthquakes, earth tremors and environmentally unstable zones. However, in most areas, for example, the Pacific coastline settlements of southern California, there is no guarantee that there is sufficient knowledge of hazards and risk to allow people to make informed decisions. Often, the residents are placed at the mercy of nature because of population growth and pressure, shrinking resources, urbanization and economic structures (cheaper land parcel prices in hazardous regions). The threats posed by landslides have driven national and international assessment and discussions about hazard risk reduction. In most cases, these threats are difficult to calculate or record because of the absence of historically recorded data. This failure can be attributed to changing population density, settlement patterns, variability in observational techniques and social awareness. The ultimate test of a landslide hazard prediction model is predicting places where and when an adverse event will occur as well as what its impacts will be. The difficulties of quantifying the spatial conditions and the complexity of the temporal conditions severely limit our ability to forecast landslide hazards effectively. For this reason, landslide hazard exposure models are usually expressed in terms of the probability and likelihood of hazard occurrence relative to the built environment.

Increasingly, choropleth maps are being used to communicate risks to the public especially those that are environmental by nature depicting information such as potential exposure to hazards. In research, the terms risk and hazard are often used interchangeably and often contextualized improperly (Blaikie et al. 2014; Gorokhovich et al. 2016;

Baumert 2016). Risk is the likelihood of something adverse occurring while a hazard is a phenomenon that has the potential to cause damage or loss to an element at risk (e.g., buildings or people). Proximity hazard exposure maps are useful tools for planning and mitigation because they illustrate the geographic distribution of risk and hazards allowing managers to make spatial decisions in response to assessed risks, to avoid hazards (Severton and Vatovec 2012). The purpose of this research, is to create a GIS hazard model, that will offer local community managers landslide hazard exposure maps at a high enough resolution to enable neighborhood-scale decision-making when it comes to settlement and development.

4.1. PROBLEM STATEMENT

The current state of hazards especially landslides, mudslides, and rockfalls in southern California are of primary interest to the public, local communities and various governmental entities in the state of California. Although this preliminary analysis and evaluation of landslide hazards do not cover the entire southern Californian region, reasonable observations and inferences can be learned from the area currently modeled in this study and the results extrapolated to the different areas of the state. Historical accounts and geologic evidence show that hazards of various types and scales have been occurring at and near the southern Californian coastal region for many thousands of years and on a relatively frequent basis for example Dec. 10th Montecito, Santa Barbara, California mudslides that killed 20 people. Considering the radical changes in climatic conditions in recent years, there is no reason to assume or believe that this pattern of hazard occurrence will change. Even in the absence of additional significant rainfall, the remnants of prior landslide hazards could still remobilize, especially slides such as the deep slump earth flows of La Conchita in 1995. These forms of mass movements are usually slow but still could pose severe hazards to property and perhaps, life. If rainfall values significantly exceed the average thresholds, several landslides scenarios are possible; 1) earth flows on adjacent hillsides, 2) mobilization of deposits into rapid debris flows from nearby slopes particularly in ravines and 3) triggering of subsidiary landslides from accumulated deposits or scarps. These landslide scenarios highlighted above could potentially be hazardous to the communities within these regions as evident by past and most recent hazards in southern California. Hence the modeling of the hazardous nature of the southern Californian coastal region and the quantification of the hazard exposure of the elements at risk (human-built environments) based on their respective proximities to the landslides zones can be crucial in improving the hazard consequence on the elements at risk.

4.2. LITERATURE REVIEW

Population growth and the expansion of human settlement over hazard susceptible regions have increased exposure to the impact of natural hazards such as landslides, both in the developed and third world countries (Rosenfeld 1994; Alexander 1995). The economic loss and casualties due to landslide hazards are more significant than recognized and generated a yearly loss of property more substantial than from many another natural hazard (Schuster and Fleming 1986; Alexander 1989; Swanston and Schuster 1989; Olshansky 1990; Glade 1998). According to Schuster and Fleming 1986, casualties as a result of slope failures are more pronounced in third world countries, because of the difficulty affording the high cost of controlling and managing landslide hazards through major engineering ventures and rational land use planning. While economic losses are more severe in developed nations due to structural investment reluctance to risk reduction. However, recent trends in landslide hazard response has been geared towards the development of warning systems and the utilization of regulations aimed at minimizing the loss of life and damage to property without investing in long-term, costly projects of slope stabilization (U.S. Geological Survey 1982; Kockelman 1986; Schuster and Fleming 1986; Schuster 1995). Despite the realization of the importance of landslide planning strategies, minimal attempts have been advanced to introduce landslide hazard exposure considerations in building codes or civil protection strategies (Brabb and Harrod 1989) with a few recognizable examples including; San Francisco Bay area (Nilsen and Brabb 1977; Brabb 1995) and the Los Angeles area in the United States. Adoption of a suitable and flexible hazard framework can be vital in mitigating the associated hazard risk by providing much-needed context and aid to the progress that has been achieved so far.

Research in quantitative hazard assessments indicate that many developments have taken place in the last decade, and that quantitative hazard risk assessments on a site investigation scale or for the evaluation of linear features such as pipelines and roads is feasible (Wu et al. 1996; Morgenstern 1997; Einstein 1997; Fell and Hartford 1997; Hardingham 1998; Lee and Jones 2004). However, the generation of quantitative high-resolution proximity-based landslide hazard exposure maps still seems a step too far, especially at a parcel level scale. Beyond the general complex nature of the hazard exposure quantification process, many hazard researchers question whether there is a need for such types of information at the parcel level scale. Considering that risks maps produced at medium scales have been successfully used in the past for the development of settlement planning and emergency response decisions. Analysis of hazard exposure for urban and local settlements in quantitative and spatial frameworks are essential for urban and rural public safety. Hazard exposure in quantitative terms is consistent with the standard notion of risk in actuarial principles and leads to cost-effective analysis as a basis for evaluating hazard risk mitigation options. When conducting a spatial hazard exposure assessment (framework), there is usually acknowledgment that exposure to hazards is a geospatial process that has considerable spatial variations in environmental factors driving the likelihood and the intensity of dangerous phenomenon as well as the human and asset vulnerability (Salvi and Debray 2006). Increasingly, quantitative and spatial frameworks are being employed by countries with major sophistication like China, to make informed hazard risk related management decisions (Zhao and Chen 2014). The natural situation of human settlement in hazardous areas is primarily a geospatial issue and refers to the spatial patterns and natural geographical conditions of urban and local systems. As the availability of high-resolution geospatial data (temporal, spatial scales) increases over time, research in hazard risk, risk calculation, model quantifications and mapping have increased significantly as well. The spatial technology software (GIS), increasingly has played an essential role in geospatial information processing of vast datasets and evaluating hazard risk at different geospatial scales (Delvosalle et al. 2006; Sebos et al. 2010; Herrero-Corral et al. 2012; La Rosa and Martinico 2013; Thompson et al. 2015).

In recent years, a series of techniques have been developed and tested to access potential landslide hazard risk from different perspectives. When it comes to urban and settlement planning, three main approaches of possible hazard evaluation can be used; (i) generic separation distance, (ii) consequence-based approach and (iii) risk-based approach (Christou and Mattarelli 2000; Kontić and Kontić 2009; Sebos et al. 2010; Pasman and Reniers 2014). In literature reviews of the above approaches, the risk-based methodology has proven to be the most widely accepted, efficient and comprehensive in regard to quantifying potential hazard risk of an element exposed to a hazard (Bottelberghs 2000; Cozzani et al. 2006; Kontić and Kontić 2009; Sebos et al. 2010; Pasman and Reniers 2014). The risk-based method is a quantitative probabilistic approach (QPA) that focuses on assessing the likelihood of potential hazard occurrence and the consequences of that hazard occurrence on the element exposed to the underlying hazard. In the QPA, individual hazard risk focuses on the potential hazard risk of a specified location on the geospatial landscape. The results of the QPA are usually presented as particular risk and or location specific risk. The level of risk or risk index is determined based on risk exposure, specific risk acceptability, and vulnerability for each site on the geospatial landscape (Christou and Mattarelli 2000). From the QPA results, countermeasures and risk mitigation can be implemented in the form of reducing hazard incident probability and implementing effective settlement deterrence plans around hazardous landscapes (Kontić and Kontić 2009; Zhao and Chen 2015). Despite the advancements of the above approaches in hazard assessment, hazard assessment like most research frameworks have their limitations. This approach fails to appreciate the fact that other factors can influence the spatial distribution pattern of risk and hazard vulnerability such as the relative importance of each exposed target and the heterogeneity of different risk targets around the hazardous terrain. These attributes are seldom considered in hazard assessment, as such their integration will, therefore, represent a contribution to the body of knowledge (Salvi and Debray 2006; Tixier et al. 2006).

Quantifying the hazard exposure of an element at risk at a parcel level scale and producing risk maps of higher resolutions is essential for evaluating the potential exposure of urban, and local communities to adjacent landslides. Such analysis is significant for public safety and environmental protection.

Hazard exposure internally is the degree of vulnerability and potential loss of an element at risk within a landslide threatened area (Fell 1994). Hazard exposure characterizations are usually based on the geographic location of an element at risk in space and the vulnerability of the element at risk. Landslide hazard exposure quantification research is still very preliminary as compared to other hazard phenomena. Hazard exposure index classes can be assigned to structural analysis of buildings but require expert knowledge (Leone et al. 1996; Spencer et al. 2004). Techniques and procedures for assessing landslide geophysical risk and vulnerability to landslides are relatively well established, accepted and documented. On the contrary, assessment of hazard exposure of elements at risk specifically (building parcels and persons) in relation to landslides still requires significant efforts. The primary loads that a landslide can exert on an exposed element at risk (building parcel) depend on displacement and related deformations in the form of tilting, impact pressure, accumulation from transport and undercutting from erosion (Leone et al. 1996).

Within an extensive landslide geospatial landscape, there are delicate areas where the consequence (damage) is going to be enormous irrespective of the forces and processes associated with the landslide displacement. This noticeably occurs along landslide boundaries (heads and scarps) where tensile stresses build up creating tension cracks and rotational slides. During this process, an exposed building may be able to resist the impact of falling blocks but won't be able to avoid the expansion of the tension cracks due to displacement from translational slides (Fell 1994; Fell and Hartford 1997).

The scope of a landslide hazard problem usually determines the approach used to analyze hazard exposure. In terms of assessment, the approach used in a regional hazard analysis differs from that employed in discreet high-risk site analysis. The nature of the information used to assess hazards may also vary depending on whether susceptibility sites have natural or artificial slopes. Also, the presence or absence of prehistoric landslides (site inventory data) allows for the utilization of different methodologies. Irrespective of the approach employed, the initial concern is to determine the problem and model what physical hazards exist (landslide risk) and how they are likely to behave in relation to the elements at risk (landslide hazard).

It is imperative to distinguish between landslide probability models and landslide hazard exposure models. Both concepts have different objectives within the framework of landslide risk and management. A landslide probability model is a document that is not directly intended for use in urban development and settlement planning because they reflect the current situation of damage but not the spatial distribution of the hazardous zones (Cascini et al. 2005). When modeling landslide probability, as was done in Phase (I) of this research, the conditioning (preparatory) factors which make the slope susceptible to failure need to be considered (Brabb 1984; Hervas and Bobrowsky 2009). Landslide hazard modeling, on the other hand, takes into consideration the Spatio-temporal probability of land sliding (Brabb 1984; Chacon et al. 2006). Landslide hazard maps identify the most exposed and vulnerable elements and assess the level of risk of the element. Based on the information provided by these maps, protection and reinforcement works can be envisioned to minimize the subsequent levels of risk (Cascini et al. 2005). When modeling landslide hazards, both the conditioning factors and triggering mechanisms, which initiate movement, should be considered (Hervas and Bobrowsky 2009). In landslide hazard assessments, non -urbanized areas are often classified as low-risk zones or low hazard zones, irrespective of the presence of landslides. The time dimension of a landslide hazard is usually established by studying the frequency of landslides or the trigger mechanisms (Wilson and Wieczorek 1995; Soeters and Van West 1996; Zezere et al. 2004, 2005, 2008; Guzzetti et al. 2005, 2007). The activation process of a landslide can significantly influence the size and type of the resulting landslide, which in turn has implications for landslide hazard mapping (Chacon et al. 2010).

When it comes to analyzing natural hazards caused by the intersection of landslide zones and the human-built environmental systems especially in southern California, a mixture of empirical and process-based approaches can be utilized. Empirical and process-based approaches are used to model behaviors, intersection, and character of debris flow paths, flow directions and flow speeds in relation to human-built environmental systems (Glade 2004, and Jensen 2004). Using a deterministic or geotechnical probability framework, the probability of failure of individual slope areas can be determined. Depending on the adopted hazard assessment approach, this information can be used in combination with other factors to produce hazard exposure maps. The calculation of the safety factor (F) of slope areas (probability of failure) is a crucial component of the quantitative process of hazard assessment. Although research has been conducted regarding proximity to natural phenomena especially in social and behavioral sciences (Zhang et al. 2004; Arlikatti et al. 2006; Cutter 2008), modeling the hazard exposure of human-built environmental systems based on proximity to landslides still remains vastly uninvestigated especially in landslide hazards susceptible areas like Ventura and Santa Barbara counties of Southern California. This study aims at contributing by creating a proximity-based landslide hazard exposure quantification model for building parcels within the hazardous regions of southern California.

4.3. CONCEPTUAL FRAMEWORK.

Proximity-based hazard exposure analysis can be quantified in a series of ways using the following as guiding principles; 1) creation of buffer zones quantifying the distance between high landslide susceptibility zones in relation to exposed building parcels, 2) Identification and digitization of building parcels within the hazard area, 3) calculation of the linear distance (Euclidean distance assessment) between landslide raster pixels and building parcel raster pixels within the hazardous area and 4) assessment of adjusted distance of debris flow using a distance decay function.

A combination of the above guiding principles were used as the basis for the proximity-based hazard exposure analysis. The hazard zones were determined based on the intersection between the landslide geophysical risk zones and the human-built environmental systems, or elements at risk. The proximity-based hazard exposure assessment involved a four-step process model in which the hazard exposure of the human-built environmental systems or building parcels within the study area were quantified and ranked on a scale from low – high representing risk exposure levels based on landslide proximity to building parcels and impact probability as illustrated on the conceptual framework below (see Figure 17). This model assumes that there is always enough sediment stored on slope surfaces or in gullies that will be available for flow during a landslide incident. (Glade 2004).

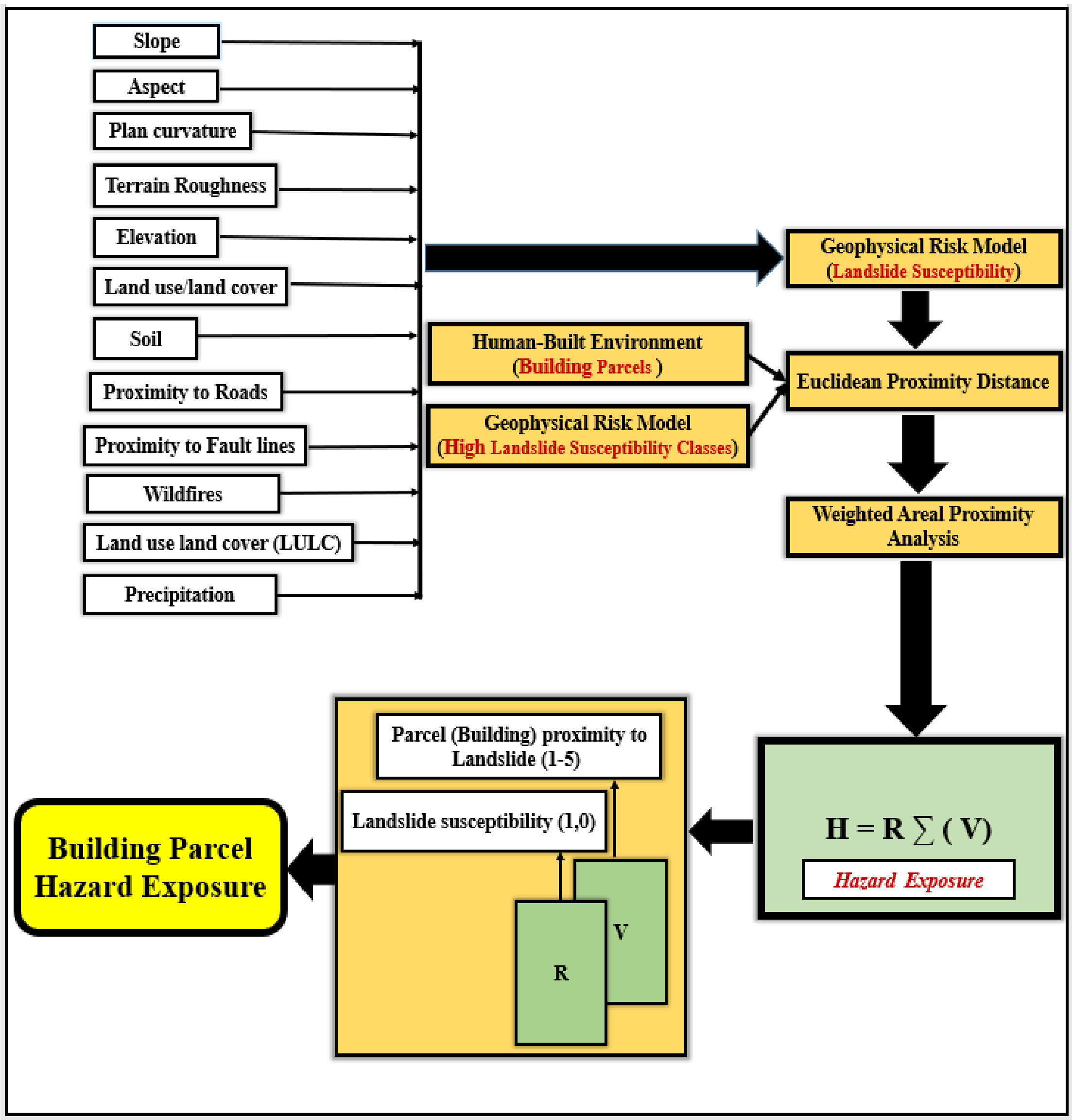

Figure 17. Proximity-Based Hazard Exposure Conceptual Model and Schematic Work Flow.

4.4. DATA AND METHODOLOGY

The above four-step schematic workflow of the proximity-based hazard exposure analysis (PBHEA) process can be further elaborated on as follows;

Step (I) - Involves calculation of the Geophysical landslide risk of the study area. The result of the geophysical risk model is a landslide susceptibility raster layer classified from low to high landslide occurrence probability.

Step (II) - Involves calculation of the Euclidean proximity distance from the human-built environmental systems or building Parcels to the landslide probability risks classes.

Step (III) - Involves calculation of the weighted areal proximity analysis of slope debris flow, flow-cost, and terrain flow path cost taking into consideration the horizontal cost (Speed of debris movement), vertical cost (surface friction affecting debris movement) and linear cost factors for high landslide probability classes.

Step (IV) - Involves a statistical integration or overlay of the calculated weighted aerial proximity of the human-built environmental systems or building parcels and flow path cost of slope debris over the landslide geophysical risk probability classes.

The proximity-based hazard exposure model (PBHEM) discussed above, takes into consideration the combined surrounding risk, respective distances from the human-built environmental systems and geospatial situation within the landslide terrain. The PBHE model assesses the combined associated risk of each location within the study area, in this case (raster cells) based on the combined sum of mapped risks in that area. Hazard risk was represented as a continuous field controlled by risk measurements (Sum) taken for each raster pixel or cell location and at each point in space. Each location on the map was assigned a numerical geophysical risk value. When the locations with assigned risk values were used as input datasets in the hazard exposure assessment, the input numerical geophysical risk dataset values ended up defining the hazard exposure values of the output. The results of the combination of the proximity-based hazard exposure model (PBHE) with the geophysical risk (landslide susceptibility or probabilistic) model as input data, is an index risk map categorized from low to high. This proximity-based hazard exposure model makes a series of assumptions; 1) each hazard location has a direct complimentary relationship to the surrounding hazards, 2) the hazard magnitude for any raster pixel or cell location must reflect the mapped hazard value and may not have a higher classification than the sum of the combined hazard value for that specific location and 3) the relative intensity and influence of a hazard risk and exposure decreases with increasing distance from its nucleus.

In step three of this analysis, the areal weighted proximity analysis of slope debris flow, debris flowcost, and terrain flow path cost was calculated which accounted for the horizontal cost, vertical cost and linear cost of debris movement. The weighting technique employed for this analysis is expressed mathematically below;

$$\mathrm{PHB}(x, y) = \frac{\sum_{i=1}^{n} H(X_i, Y_i) W(X_{i,} Y_{i,} X_{i,} Y_{i,})}{\sum_{i=1}^{n} W(X_{i,} Y_{i,} X_{i,} Y_{i,})} \text{ .... Equation (10)}$$

Where a set of risks or hazards of values H_i defined at n locations (x_i , y_i), i =1,2,3,4…. n. From this, a set of W_i weights were used to assign hazard intensities values to (x, y) locations. Since the value of W_i varies from one location to another on the geospatial landscape, the values of the proximity-based hazard exposure map will equally vary from place to place in association with surrounding hazard combination values.

Hazard exposure is typically expressed as (vulnerability $\times$ amount/cost). However, for this analysis, an adapted version of the hazard exposure equation mathematically illustrated below was used, (Varnes 1984; Fell 1994; Leroi 1996; Lee and Jones 2004; and Van. et al. 2006).

$$\text{Hazard Exposure} = \sum (R \times 10) \sum V) \quad \text{(Equation 11)}$$

Where;

R – Geophysical Risk (landslide probability) expressed as the probability of landslide occurrence within a reference period (Spatial and temporal probabilities)

10 – In this case 10 is a multiplier to keep code simple and thus allows a quick attribution to the respective exposures

V - the Physical vulnerability of building parcels based on proximity to geophysical risk ranked from (0 – 1).

4.5. RESULTS

The results of the above analysis are a building parcel hazard exposure map that has been classified, categorized and ranked from low hazard exposure to high hazard exposure. The final exposure model shows each building parcel's hazard exposures in geographic space, based on their respective proximities to landslides probabilities (see (Figures 18a - b), (Figure 19a – b, c) and (Figure 20)) below. This analysis subsequently forms the basis for risk reduction, transfer and preparedness planning (Lee and Jones 2004).

Figure 18A. Study Site Block Group Building Parcels

Figure 18B. Illustrates a Proximity-Based Hazard Exposure Model of Building Parcels Draped Over an Aerial Imagery of Study Site.

Figure 19A. Study Area Building Parcel Hazard Exposure Model Site One

Figure 19B. Study Area Building Parcel Hazard Exposure Model Site Two

Figure 19C. Study Area Building Parcel Hazard Exposure Model Site Three

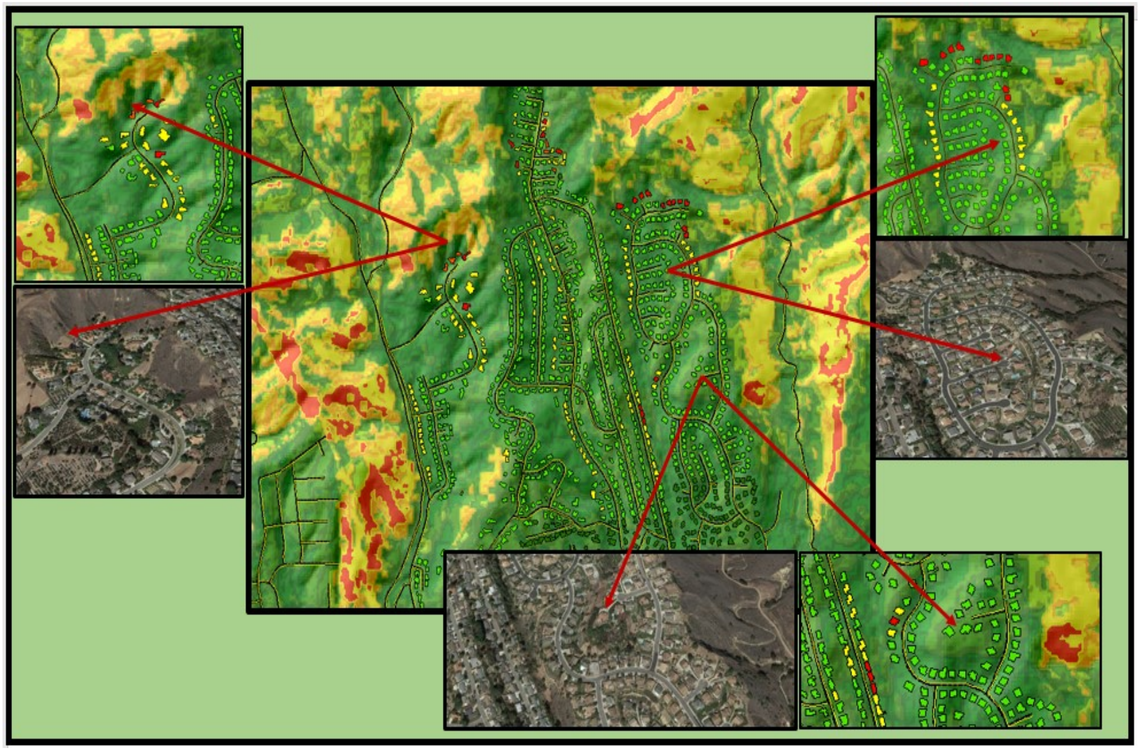

Figure 20. Illustrates a Proximity-Based Hazard Exposure Model of Building Parcels Draped Over a Landslide Susceptibility Model of Study Area.

It is important to note that proximity-based hazards exposure models (PBHEM), assess hazard risk of specific locations on a map based on the visual and spatial representation of hazards. For each location on a map, the mapped hazard values are used rather than the actual hazard data for that location. Given the complex nature of the geophysical landscape of study, the analysis did not consider many complex factors that may influence spatial variations in the distribution of various types of risk and hazards. For example, sub-surface soil water behavior and transport. Soil water may contain contaminants which may influence complex hydraulic processes such as hydraulic conductivity, which intern may affect slope and slope debris stability, landslide susceptibility as well as hazard exposure.

This study has demonstrated how the analysis of the exposure to landslide hazards has evolved from simple coincidence analysis and discrete buffer zones to more sophisticated techniques that are based on precise distance and terrain morphometric dynamics between landslide hazard locations and human-built environmental systems.

The results of this analysis suggest that local governmental agencies consider similar studies and findings in siting roads, public facilities, and residential areas. The proximity-based hazard exposure index map above provides sufficient justification for the application of precautionary steps to protect people from the deleterious effects of living near landslide hazard susceptible landscapes. Although economic and political forces will require stringent evidence that specific recommendations such as the creation of protective buffer zones around areas in close proximity to hazards will be effective, some practical ideas should be obvious such as prohibiting the siting of residential locations, and other sensitive land uses in close proximity to hazardous landscapes.

V. LIMITATIONS OF ANALYSIS

5.1. PHASE ONE: LANDSLIDE SUSCEPTIBILITY MODELING LIMITATIONS

Most successful landslide susceptibility mapping approaches are not without limitations. These limitations influence modeling processes by constraining researchers to a specific dataset, regions of study, methodologies, analysis and validation techniques. Although research limitations can affect research results, they can also act as guiding pillars or springboards for future or further research. In the case of this study, the following limitations were encountered;1) unavailability of pre-historic and current landslide inventory datasets for the study area. To address this problem, the high-resolution aerial imagery was used to identify and digitized old and fresh landslides through visual interpretation techniques. 2) The natural problem of geospatial terrain heterogeneity which makes interpolation of analysis a challenge. 3) Difficulties identifying landslide exposure scares and determining their respective ages through visual interpretation of aerial imagery. Despite the impressive advancements of the remote sensing technique, the identification, and interpretation of landslide features are not without limitations, because the appropriate completion of the landslide inventories still relies on immensely on expert opinion. 4) The analysis relies on assumptions based on the concept of uniformitarianism which states that current and future landslides will occur under the same conditions in which they occurred in the past. This assumption, however, is challenged by the fact that landslides are dynamic. When landslides occur, they change the geomorphic structure and morphology of that landscape such that preceding landslides may have different structures and morphology making replication or regional generalization of results challenging. Finally, 5) the analysis process was very laborious and time-consuming.

5.2. PHASE TWO: HAZARD EXPOSURE MODELING LIMITATIONS

It is imperative to mention here that despite the simplistic mathematical representation of the quantification of hazard exposure as expressed in (equation .11) above, the quantification of specific risk to a building or a person(s) in a building within a land parcel quickly becomes a complicated task. This complexity results from the difficulty in precisely locating the elements at risk versus the possible location and probability of landslide occurrence. The spatial and temporal probabilities that a landslide will impact a particular person(s) or building must be evaluated to identify the specific risk (Van. et al. 2006). Temporal probability can be determined by correlating landslide occurrence data to triggering factors provided such data is available (Van 2002). Spatial probability comes from evaluating the relationship between locations of past landslide incidents and a set of environmental factors to predict areas of landslide initiation with similar environmental factors. The lack of both complete, reliable and high-resolution data sets especially temporal, and associated ancillary building parcel datasets in many landslides threatened urban areas is a significant constraint to the achievement of high predictive maps. The modeling process also experienced some limitations in terms of analytical specificities for example, for a building structure, the expected damage may depend on three factors; (i) the type of landslide mechanism (rockfall, debris flows and slides), (ii) intensity (velocity and volume), and (iii) and the relative location of the exposed element at risk (building parcel) in relation to the trajectory of the landslide within the hazard threatened or affected area. When landslide risk zones are combined with spatial and temporal probabilities, the result is a landslide hazard map. Therefore, any hazard exposure map is limited by compounding assumptions embedded in the geophysical risk modeling technique, the hazard exposure model and the quality of data available.

5.3. DISCUSSION

Landslides and other forms of mass wasting have been a concern for communities living along the coastline of southern California for generations. Even a simple rainfall event, imperative for the region's agricultural industries, can bring about adverse mass wasting events, be it mudslides, flows and rock-falls. With expanding urbanization and decreasing funding at the state and federal level for hazard modeling, it is vital to develop a comprehensive, neighborhood-scale landslide analysis and a hazard exposure assessment for local communities and city planners. It is also important that these models be designed using publicly available data to ensure that they can be deployed across a variety of communities with equal confidence in the assessment. In this way, local planners, landowners and environmental agencies will be armed with the tools needed to make informed decisions regarding hazard prediction, evaluation, and mitigation. These decisions are usually in the form of technical countermeasures, regulatory management or combination of both. An example of such measures would be to create hazard zonation maps limiting habitation in very high susceptible zones or enforcing specific standards for occupancy in such regions.

In recent years, both the U.S. federal government and the State of California have reduced funding for landslide hazard and terrain analysis. These cuts were implemented under the auspices of saving money for higher priority programs. These cuts have weighed heavily on environmental agencies and their programs through reduction of work hours and personnel. Consequently, there has been a decline in the ability of most environmental assessment agencies to provide extensive analysis of hazard susceptible regions. Because the limited resources and personnel are focused on priority situations, potentially hazardous, underprioritized areas remain open to communities interested in settlement. For this reason, a comprehensive landslide susceptibility, and a hazard risk exposure quantification analysis on a fine resolution scale is vital to community and city planners. Such analysis will equip them with the tools they need to make decisions regarding hazard prediction, assessment, and mitigation. These hazard response decisions are usually in the form of technical countermeasures, regulatory management or a combination of both.

This study begins with the assumption that future landslides will occur under similar conditions in which they occurred in the past and present. To achieve the goals and objectives of this study, fuzzy measure techniques (F) were integrated into multi-criteria probability distribution function (MCPDF) technique to create landslide probability or susceptibility models (LSM). The landslide occurrence frequency was used as a calibration criterion for the fuzzy measures to develop fuzzy membership classes of criteria factors. The results showed that the fuzzy multi-criteria probability distribution function's (FMCPDF) did produce not only models with reasonable accuracy values but also introduced more flexibility in judgment and decision making as compared to other statistical techniques. In this process landslide occurrence frequency data were used to standardize and weight criteria factors. This technique overcomes the issues of uncertainty by using fuzzy membership functions (FMF) to assign memberships to criteria data. This method was desirable because it mirrors how a human brain processes criteria data.

The fuzzy approach is also capable of accommodating data of various scales and leaves the expert in control of criteria weighting and standardization processes. After a detailed analysis of the various fuzzy functions, the gamma operator at the gamma γ value of ($\gamma = 0.9$) had the highest accuracy value. When the model was validated using landslide validation data using the operating receiver characteristics ROC function and the Area Under the Curve (AUC) values calculated, it was determined that the model had an acceptable accuracy value of 0.885, (88.5%). From the results of this study, it can be fairly argued that the effects of choosing different gamma values from (0 – 1) is not large. Because the other gamma values ($\gamma = 0.7,\ 0.8$) had AUC values ranging from (78.2% to 80.2%) showing close similarities to the gamma ($\gamma = 0.9$) which was the best LSM model with the highest area under the curve as well as accuracy. The overall verification showed a satisfactory agreement between the LSM or probability model and existing data from landslide locations.

The second phase of this study was to assess the extent of hazard exposure as a result of the interaction between highly landslide-susceptible landscapes and human-built environmental systems, as well as to quantify hazard exposure into various index levels of exposure based on distances of the human-built environments or building parcels to highly landslide-susceptible landscapes. To achieve this goal, a proximity-based hazard exposure model was created. This model assessed the risk associated with every map location based on a totality of mapped risks (geophysical and environmental) in the study area. For each raster cell in the study area, a calculated numerical value was assigned to represent the geophysical risk for that raster pixel or cell location. The hazard exposure as a result of the interaction between the landslide geophysical risk and the human-built environmental systems was modeled using a four-step process. The four steps included the following; calculation of landslide susceptibility (landslide probability), calculation of the Euclidean proximity distance between high susceptibility landslide locations and human-built environments, calculation of a weighted aerial proximity analysis of slope, debris flow, flow cost, and statistical overlay weighted datasets. Since the output products of the weighted raster layers varied from one raster cell (pixel) to the next, so too did the surrounding map hazards from one location to another. Even with a fixed set of hazards, the pattern of hazards from various locations is always different, thus hazard proximity (like hazard exposure) will vary over geographic space. The proximity-based hazard exposure model produced a continuous field of risk measurements taken at discrete points and specific distances in a geographic area. The final model output successfully quantified the hazard exposure of the building parcels in their respective geographic spaces, based on their proximities to highly landslide locations and categorized the model output into levels of exposure from high to low.

Landslide hazard and hazard exposure maps can help planners, engineers and citizens by substantially reducing or preventing financial loss and loss of life that may likely occur as a consequence of failure to prepare for future landslides and mudflows in the coastline region of southern California through mitigation, prevention, and (or) avoidance.

5.4. CONCLUSION

Over the last decades, several strategies for landslide and hazard risk management have been developed in response to the consequences of such disasters. The most pronounced of the above strategy include hazard and risk assessment methods. Past landslide incidents, knowledge gained from hazard literature and information obtained from several countries around the world have encouraged the use of hazard and risk assessment maps to improve urban development planning as well as minimizing the associated risk to human systems. Given the deadly nature of landslide hazards in southern California, a need exist for standardization and development of replicable, easy to read and use methods for assessing hazard exposure and hazard risk components. For some time now, the disaster response to landslide hazards in southern California has been reactionary. The inadequate-ability of the hazard response has been as a result of cuts in environmental and hazard research-related funds by the government. This action resulted in a prioritization type style of hazard research which for the most part has been reactionary. Non – structural hazard prevention measures such as prohibition or restrictions of buildings in hazardous areas and the establishment of warning systems in locations where hazards cannot be avoided have been a constraint because such countermeasures can only be put into practice if high-resolution landslide predictive models and hazard exposure maps are available for the area in question. Figure 21a and 21b below illustrates the difficulties associated with conducting an effective hazard response with hazard maps of low resolution. A side by side comparison between the resolution of the available CGS and USGS landslide hazard map and the resolution of the landslide susceptibility map from this study in southern California is illustrated below;

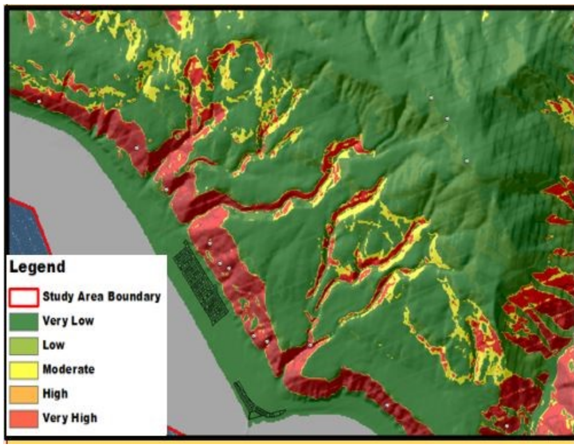

Figure 21A. Illustrates Resolution of Landslide Susceptibility Model for this Study

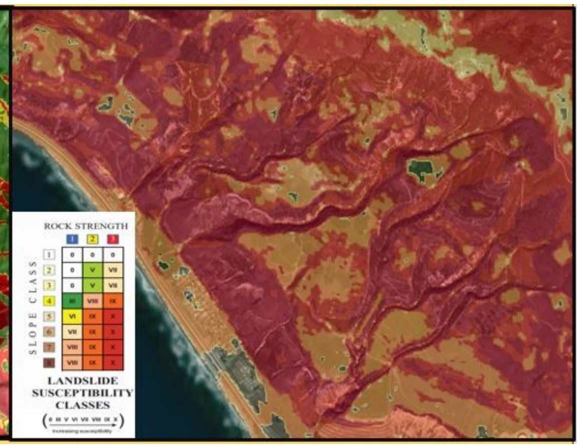

Figure 21B. Illustrates Resolution of Landslide Susceptibility Model from the CGS/ USGS

The hazard exposure map developed from this study can be used to make critical developmental, settlement planning, disaster warning and evacuations decisions in southern California. These evacuation and disaster warning systems can represent valuable safeguard measures for populations living in hazardous landslide regions. To ensure continual progress and efficiency in future hazard modeling endeavors, experimental observations must be tested in specific sample sites, and investigations carried out using advanced statistical approaches with the aim of individuating reliable threshold values of rainfall, debris flow, and debris displacement.

Finally, this study has successfully demonstrated that it is possible to model landslide susceptibility for a geospatial terrain and the resulting geophysical risk maps utilized to quantify or estimate the potential hazard exposure of an element at risk (building parcel) based on its location in a geographic space relative to a hazardous landslide landscape. This development is an essential step within the comprehensive research field of landslide hazard risk assessment. Future studies should focus on the detailed evaluation of spatially distributed information on landslide magnitude and frequency to perform a sound landslide hazard calculation which can then be used within a landslide risk analysis. Nevertheless, hazard exposure analysis that is related to other hazards would undoubtedly enrich the attempts towards a more sustainable planning approach.

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