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Predicting Landslides in Costa Rica Using Self-Organizing Map Machine Learning

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ABSTRACT

Landslides are natural hazards commonly understated in both number of occurrences and cost of economic impacts. The Costa Rican terrain is predominately geologically young and therefore, severely impacted by landslides. It has limited resources and infrastructure and with a large portion of the population being poor, this causes communities to build in hazardous locations and infrastructure that can be easily crippled by landslides. Being able to identify where and when landslides are going to occur is key to mitigating the effects, either by stabilizing the slope or by evacuating communities. Machine learning is one method that has been increasingly used to monitor and predict landslides in recent times. These methods do not have the shortcomings of traditional analytical methods and can be easily adapted for different locations, changing or missing data, and number of factors studied. This research proposes that Self Organizing Maps (SOM) can be used as a versatile and effective method for landslide prediction. The results of this study have shown how SOM can be used for multi scale susceptibility analysis and for prediction with use of precipitation data, by producing significant results identifying high risk areas with a varying number and combination of variables. It has also shown that when precipitation data is used, it can identify high risk locations based on precipitation amounts and static variables (slope, TWI, curvature, NDVI, etc.). At the five-time scales tested, four of the tests produced correlations between increased precipitation and higher landslides risk (6 hour r^2 = 0.38, 12 hour r^2 = 0.36, 1 day r^2 = 0.24, 1 month r^2 = 0.33). This study has shown the versatility and effectiveness of SOM by producing significant results, as well as being able to use current weather conditions to produce landslide prediction analysis.

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1. Introduction

Landslides are a natural geomorphological process that play an important role in sediment redistribution and landscape evolution. The majority of earths surface has been influenced and formed by a combination of episodic large-scale landslides and more frequent small-scale landslides. Landslides, along with fluvial systems are main driving forces of slope evolution. Landslides are important for basin evolution and provide large amounts of sediment carried by rivers but can also dam rivers and cause rerouting (Sidle, et al., 2006; Korupe, et al., 2010).

Often, *landslide* is used as a synonym for all mass movements, however, slides are a specific category of mass movement, for the remainder of this study, the term landslide will often used in place of mass movement (Johnson et al. 2017; Pradhan & Tariq, 2019). There are many types of mass movement, which can be categorized by the type of movement, material, failure mechanism and, the velocity the movement occurs. One of the most common classifications has been done by Varnes (1978), all movements were divided into five broad categories based on the type of movement was occurring and by the material, this can be seen in (Table 1.). There were six main classes identified by Varnes (1978), which include falls, topples, slides (rotational and translational), spreads and, flows. Falls occur on cliffs or very steep slopes with material that drops, leaps, bounces or rolls down slope often being air bourn for a portion of the decent after being detached from the source material. Topples are a cohesive block of material, often rock, topples and overturns by tilting or rotating from the source material,

Table 1. Categories of mass movements by Varnes (1978).

Type of movement	Slides Material		
	Bedrock	Predominantly Coarse	Predominantly Fine
Falls	Rock fall	Debris fall	Earth fall
Topples	Rock topple	Debris topple	Earth topple
Slides (rotational and translational)	Rock slide	Debris slide	Earth slide
Lateral Spreads	Rock spread	Debris spread	Earth spread
Flows	Rock creep	Debris creep	Earth creep

caused by joints, cleavage or bedding planes. Slides are movements where there is a distinct slip surface where the failure occurred, either occurring on planer surface or a curved surface, commonly triggered by earthquakes and periods of heavy rain. Spreads which frequently has elements of slides and flows, is the near horizontal extension of material, often being triggered by earthquake shaking. Flows occur when a material takes the properties similar to that of a viscous fluid, often being a mixture of material and a high-water content but can also form in dry material such as rockslides, flows often follow channels and only terminate at low slope areas or at obstacles.

This classification method was then expanded on by Dikau et al. (1999), which took these limited classifications and expanded them into eight categories (Table 2.). These classifications can help in identifying the processes that can result in failures, primarily in soil-based movements, these processes are often calculated using the factor of safety.

Table 2. Expanded categories of mass movements by Dikau et al. (1999).

Process	Materials		
	Rock	Debris	Earth
Fall	Rock fall	Debris fall	Earth fall
Topple	Rock topple	Debris topple	Earth topple
Rotational slide	Slump	Single, multiple, and successive	Single, multiple, and successive
Translational slide	Block slide	Block slide	Slab slide
Planer	Rock slide	Debris slide	Mud slide
Lateral spreading	Rock spreading	Debris spread	Earth spreading
Flow	Rock flow and creep	Debris flow and creep	Earth flow and creep
Complex	Rock avalanche	Flow slide	Slump-earth flow

1.1 Factor of Safety

Mass movements occur when the stable state of the slope is shifted into an unstable state. The stability of a slope can be represented though a factor of safety equation:

$$\text{Factor of Safety:} \qquad F_s = s \,/\, \tau \qquad (1)$$

where τ is the forces acting on the potential slip surface (shear stresses) and s is the forces resisting the shear forces (shear strength):

$$\text{Shear Stress:} \qquad \tau = c + \sigma' \tan \phi \qquad (2)$$

where c is cohesion, ϕ is angle of internal friction and, σ' is the effective normal stress acting on the failure plane (Duncan et al., 2014). The shear stress of the slope is the measure of the gravitational forces acting on the slope or the load on the slope from the weight of the material, vegetation, water or anthropogenic loading (Duncan, et al., 2014):

$$\text{Shear Strength:} \qquad s = \sigma' \tan \phi \qquad (3)$$

where ϕ is angle of internal friction and σ' is the effective normal stress acting on the failure plane (Duncan et al., 2014). The materials that make up the slope system are very important, a weak material will have a lower ability to resist failure in comparison to stronger materials or rock slopes, causing the slopes more susceptible to failures and more often. Each type of material will have different properties that will change the strength and how each reacts to the mechanisms acting on the slopes. Slope failure occurs when the shear stresses become greater than the shear strength (Sidle et al. 2006). The shear strength can be defined as the measure of a slope's resistance to gravitational sheer stress, made of a combination of friction, cohesion, and normal load along the potential failure plane (Crozier, 1986). The shear strength is dependent on the density; higher density results in a greater strength of the soil by having larger interparticle contact forces and interlocking, increase shear strength. The importance of these factors can be seen by the angle of repose, especially in granular materials, such as soils. Pore pressure, the pressure that is present in the void areas in soils, can be altered by increasing or decreasing water content within the void areas. An increase of water will increase the pore pressure which decreases cohesion and internal friction between the soil particles (Duncan et al., 2014). The angle of repose is the steepest the material can be heaped while remaining stable, therefore, materials that have stronger cohesion, internal friction and, density, may be able to maintain steeper slopes (Beakawi Al-Hashemi & Baghabra Al-Amoud, 2018).

Slope systems have processes that are continually acting upon them, where two categories of processes cause slopes to weaken and fail. One being slow acting passive effects and the other being a relatively quick transient effect. In most cases, slopes are affected by the passive effects that slowly decrease stability, followed by a transient effect that initiates the failure (Figure 1.). Passive effects are long-term processes that cause the slope to lose its shear strength over time, such as weathering. These passive factors do not cause failures directly but work gradually on moving the slope toward instability. Weathering is caused by three different processes, physical, chemical and, biological weathering.

Physical weathering is caused by the breakup of the source material for slopes, through stress release, frost action, changing temperatures and, changing moisture levels. These processes increase the surface area of the material that leads to further weathering. Chemical weathering, changing the chemical make up of a material, often driven by water. Either the chemical changes weather the material directly or allow for other forms of weathering to act on the material. Biological weathering is caused by vegetation and other living organisms and is often has the greatest impact in warm humid climates. These can indirectly break down material changing the chemistry of the material leading to chemical weathering and large vegetation, such as trees, can have a direct physical impact by widening cracks and changing how water moves through the material. Transient effects are factors that initiate a movement, most commonly known as triggers. These take the form of an event that rapidly changes the strength and stresses acting on the slope (Crozier, 1986; Bell, 2002). The mechanisms that trigger movements can be classified within four categories, increase and addition of water, increase in slope, increase in weight, and earthquake loading. Classifications have been done on these mechanisms or

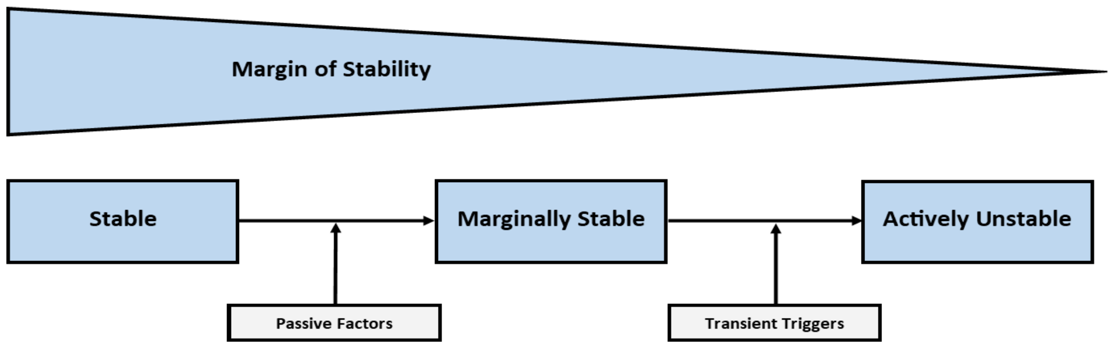


Figure 1. Progression of stability in slope systems (Thiebes, 2012).

triggering event. A model was created by Bell (2002), which sorts movements by the triggering event, the type of material and how the triggering event causes the movement (Table 3.).

The addition of water, when introduced over short time periods, influences both the shear strength and stresses acting on the slope. High intensity storms that introduce high amount of water to the slopes in a short period of time often cause small shallow fast movements. The water will infiltrate down to the failure plane, causing higher pore pressures and swelling that increase in the void ratio of the soils, decreasing density, friction, and cohesion resulting in a reduction of shear strength (Sidle et al. 2006). In locations where precipitation is less intense, but occurs over extended durations, such as the length of the rain season, will not cause a movement in the same method as large amounts of precipitation in a short time period will. The slower introduction will actively raise the ground water level thereby decreasing the shear strength as it reaches the failure plane, causing larger deep slides (Sidle, et al., 2006). There are also effects caused by decreased moisture, when the soils dry, shrinking and cracking occur, once a crack is formed all the strength along that plane is lost. The formation of cracks also allows for increased infiltration rates once precipitation returns (Sidle, et al., 2006; Duncan, et al., 2014; Mukhlisin, et al., 2018).

The shape of the slope is one of the most important factors in slope stability, and there are major impacts when the slope is altered. Processes occurring through natural or anthropogenic methods, result in either increasing the slope angle, removal of the slope toe or changing the shape of the slope. Actions such as rivers or glacial retreat eroding the bottom of slopes and road development employing the cut and fill technique, increase the amount of stress and decrease shear strength acting on the failure plane (Sidle, et al., 2006; Duncan et al., 2014). Outside slope gradient, there are three main shapes a slope can take, planer, divergent and convergent. Divergent slopes are generally found to be the more stable, followed by planer and then convergent. Diverging slopes, tend to have both surface and subsurface water movement more dispersed, resulting in lower pore pressures and perched water tables. Whereas convergent slopes concentrate water movement into the valleys found in slopes which can lead to rapid pore pressure increases during storms, resulting in more shallow rapid movements occurring on slopes which have the convergent shape (Sidle, 1984; Fernandes et al., 1994; Montgomery et al., 1997; Tsuboyama et al., 2000; Sidle, 2006). The addition of weight to a slope increases the amount of shear stress acting on it, weight is increased by the addition of water and anthropogenic development. Once water is added to a slope, the mass of the water is now acting on the slope, increasing the normal load acting on the failure plane, further moving the slope toward instability. Anthropogenic development such as the building of roads and structures on top of slopes are major additions of weight, further increasing the normal load. The final trigger that is most commonly associated with movements are the effects of earthquakes. Earthquakes cause vertical and horizontal accelerations that result in cyclic variations in the stresses acting on the slope, increasing them above the static values for short periods of time (Duncan et al., 2014). If the stresses are increased above the stable threshold then their results in a movement. Frequently, when the earthquake is large enough, many movements are triggered.

When slopes fail, it is often due to multiple mechanisms working on the slope to cause the failure. Unless the triggering mechanism is sufficiently impactful, it is the effects of multiple mechanisms that weaken the slope then a triggering event which initiates the failure. Such is the case with many movements caused by earthquakes, slip surface may have been previously weakened by weathering, recent precipitation, slope modification, or weight loading that have brought the slope closer to failure and the earthquake results pushed past the failure point. There are also two potential impacts that can occur on slopes after a movement event. The movement may cause more movements by increasing slope angle, removing slope toe reducing strength, resulting in more movements up slope, an increase of erosion and infiltration will occur due to the removal of vegetation. Further movements are likely to continue occurring until a stable state is reached. There can also be a stabilization effect that can occur after a movement, caused by the removal of weakened material from the slopes leaving only the stronger more stable source material. This effect can also occur though reducing the slope angle and changing the slope shape.

Table 3. Mass movements sorted by type of material and triggering event by Bell (2002).

Name of Agent	Event or process that brings agent into action	Mode of action of agent	Slope Material Most Sensitive Action	Physical Nature of significant actions of agent	Effects on equilibrium conditions of slope
Transporting Agent	Construction operations or erosion	Increase of height or rise of slope	Every material	Changes state of stress in slope-forming material	Increase of shearing stresses
			Stiff fissured clay, shale	Changes state of stress and causes opening of joints	
Tectonic stresses	Tectonic movements	Largescale deformations of Earth's crust	Every material	Increases slope angle	
Tectonic stresses or esxplosives	Earthquakes or blasting	High frequency vibrations	Every material	Produces transitory change of stress	Decrease of cohesion and increase of shearing stresses
			Loess, slightly cemented sands, and gravel	Damages intergranular bonds	
			Medium or fine loose sand in saturated state	Initiates rearrangement of grains	Spontaneous liquefaction
Weight of slope forming material	Process that created the slope	Creep on slope	Stiff fissured clay, shale remnants of old slides	Opens up closed joints, produces new ones	Reduces cohesion
		Creep in weak stratum below foot of slope	Rigid materials resting on plastic ones		
Water	Rain or melting snow	Displacement of air in voids	Moist sand	Increases pore water pressure	Decrease of frictional resistance
		Displacement of air in open joints	Jointed rock,shale		
		Reduction of capillary pressure associated with swelling	Stiff fissured clay and some shales	Causes swelling	Decrease of cohesion
		Chemical weathering	Rock of any kind	Weakens intergranular bonds (chemical weathering)	
Frost		Expansion of water due to freezing	Jointed rock	Widens existing joints, produces new ones	Decrease of frictional resistance
		Formation and subsequent melting of ice layers	Silt and silty sand	Increases water content of soil in frozen toplayer	
Dry Spell		Shrinkage	Clay	Produces shrinkage cracks	Decrease of cohesion
Rapid Drawdown		Produces seepage towards foot of slope	Fine sand, silt, previously drained	Produces excess pore water pressure	Decrease of frictional resistance
Rapid change of elevation of water table		Initiates rearrangement of grains	Medium or fine loose sand in saturated state	Spontaneous increase of pore water pressure	Spontaneous liquefaction
Rise of water table in distant aquifer		Causes a rise of piezometric surface in slope-forming material	Silt or sand layers between or below clay layers	Increases pore water pressure	
Seepage from artifical source of water		Seepage towards slope	Saturated silt	Increases pore water pressure	Decrease of frictional resistance
		Displaces air in the	Moist, fine sand	Eliminates surface tension voids	
		Removes soluble binder	Loess	Destroys intergranular bond	
		Subsurface erosion	Fine sand or silt	Undermines the slope	Increase of shearing stresses

1.2 Impacts of landslides

Though a natural process, landslides can be triggered by anthropogenic activities and are considered a natural hazard. Increasing development, slope destabilization practices (deforestation, slope undercutting, poor land use, etc.) on steep slopes and unstable terrains have put human life and infrastructure at risk in developed regions (Crozier, 1986; Sidle, et al., 2006). Vulnerability to landslides is the greatest in developing nations and poor communities, where there is limited knowledge of the hazard and few, if any, mitigation measures in place. In these locations there are often limited resources and methods for recording the impacts and often are underestimated or unreported. Therefore, causing an uneven and misrepresentation when quantifying the economic cost and human lives lost.

As a natural hazard, landslides are understated in both occurrence and impact when compared to other more prominent hazards such as earthquakes, hurricanes, and floods, causing issues when calculating the total cost associated with landslides (Thiebes, 2012; Houser et al., 2019). Furthermore, landslides are often caused by other natural hazards (earthquakes, hurricanes, typhoons, etc.), these cause the effects from the landslides to be calculated under the event that may have triggered the movement (Crozier, 1986; Sidle et al. 2006; Thiebes, 2012). Inaccuracies can arise from the method in which the economic impacts and loss of life are determined, by using different scales, local or regional, or using differing calculation methods. There are also large biases in the locations that have been studied for losses, more developed countries that are prone to landslides are represented more than that of developing nations that do not have the ability or data to accurately assess the impacts (Sidle & Ochiai, 2006). The economic costs are the direct impacts of the landslides, buildings, transportation networks, water systems, and telecommunications systems are often the main sources of cost analysis. The indirect costs are such things as productivity loss (industrial and personal), healthcare, landslide mitigation, loss of agricultural land, moving costs, property devaluations, increase use of emergency and healthcare services, and decreased tourism (Sidle et al. 2006). These losses are often overlooked and can account for the majority of the impact (Burke et al., 2002; Schuster, et al., 2007). The best estimates available are that landslides cause about 4,600 fatalities and $1.4 trillion worldwide in economic loss annually (Dilley et al. 2005). The ability to predict where and when landslides are likely to occur can influence the land use planning and help policy makers avoid situations where there can be significant loss of life and infrastructure due to landslides.

3. Landslide Modeling, Prediction, and Early Warning Systems

An Early Warning Systems (EWS) can be defined as a non-structural risk mitigation measure that monitor one or more variables that can potentially influence or trigger mass movements and discern meaningful spatial and temporal warning information (Sagoni et al., 2018). These systems are primarily focused on using threshold values of precipitation established by empirical or statistical correlation between landslides inventories and precipitation fall, as the triggering mechanism (Chae, et al., 2017; Segoni, et al., 2018). EWS and the prediction of landslides, spatial and temporally, are important for the prevention of loss to those at risk, by providing vital information to local governing bodies and those responsible for the safety of those at risk. Unlike susceptibility mapping, where the likely location information is generated, EWS uses real time data to add an accurate current conditions component to landslide analysis (Chae et al., 2017).

Warning systems are designed as one of two operating systems, empirical or physical. Empirical models use comparison of precipitation fall values to threshold values to assign risk, where once the precipitation fall reaches a certain value there is a movement likely to occur. The assumption is that where landslides have occurred, they are likely to occur again under similar slope weakening and failure triggering conditions (Goetz et al. 2015). A majority of regional methods use empirical systems, systems designed where it is not necessary to have on going monitoring equipment and systems for specific locations. Physical based systems are most often used for local methods, such as on single slopes where it is less costly to install monitoring equipment. These systems monitor the physical processes and behaviors for each slope, such as movement and water levels (Alfieri, et al., 2012).

EWS are classified as one of three type of methods, prediction, warning, and alarm or reaction (Thiebes, 2012; Stahli, et al., 2015). Prediction or forecasting type systems are commonly applied on a regional scale. Completed daily by experts using sensor data or models assessing the risk of rapid mass movements across the region, the results are similar to a daily suitability map. Such systems are used as general risk management tools or to inform the other types of EWS. One example of a prediction or forecasting system is in place in San Francisco, where a network of precipitation gauges and weather forecasts that are tested against predefined threshold values are used to issue warnings for the upcoming 24 hours (Thiebes, 2012). Warning is often done on a smaller scale than prediction and is a process of where experts use technology to detect changes in the environment, often based on defined thresholds of precipitation, cracks openings or slope movement. These types of systems are focused on slow moving mass movements where there are gradual stages to failure (rockslides, deep-seated slides/slumps, etc.), this allows experts to apply intervention measures before complete slope failure occurs. Reaction is dependent on the decision and policy makers implementing plans to initiate action for the public at risk (Thiebes, 2012; Stahli, et al., 2015). An example of a warning system that is being used is in Switzerland, where the use of monitoring sensors along the landslide channels in use with alarms and lights used for warning if an event is detected. (Graf et al. 2006). The final and most important EWS class is alarm or reaction, the goal is to get the information to the public so that there is response to a coming hazard. This is achieved by direct messages through text alerts, warnings on television and radio or sirens. Alarm systems use the detection of movement of a hazard to automatically trigger the alarms. Although this is the only method where the hazard is actually occurring this means that there is very little lead time to react whereas the other systems give risk information before the movement occurs (Thiebes, 2012; Stahli, et al., 2015). There is a alarm system that is being used in Japan, sensors are in place across a catchment basin to detect ground movement, vibrations or occurring debris flows (Stahli, et al., 2015).

Outside the examples above, there are a number of early warning systems that are used in countries around the world, each using different parameters, scales, methods, and monitoring techniques. Majority of these methods are focused on measuring precipitation fall infiltration on slopes and surpassing certain thresholds, with little regard for other variables. These systems are non-structural passive mitigation measures causing there to be a large range of methods that all have distinct characteristics from one another (Priciullo et al. 2018). Each of these systems follow similar steps: (i) knowledge of the hazard and the risks associated with it, (ii) monitoring and analysing the conditions of the hazard to make predictions on future events, and (iii) develop a system in which to communicate the warning to those who are in danger of the hazard (Priciullo et al., 2018). These systems use relatively few variables, having a main focus on slope angle, amount and intensity of precipitation, and infiltration rates. Using a small number of variables may cause an overlook of many important factors that can greatly increase the accuracy and efficiency of predictions. Modern machine learning techniques have made progress in incorporating a higher number of variables while achieving an 85% average success rate in determining landslide susceptibility.

There is a large variation of modeling methods, and each can be placed within two categories, local and regional. Local systems are designed to be applied to small areas or on single slopes. Physically-based methods are more common for local systems, the smaller scale allows for more detailed study using sensors and monitoring equipment and continuously analyzing the conditions, processes, and triggering of failures on the slope, such as rainfall thresholds (Segoni et al., 2018, Pan et al., 2018, Piciullo et al., 2018). Though the equipment needed results in an increased cost to implementing systems that allow for the detailed study across a slope, resulting in them being limited to these small locations. Another system that is primarily used in local systems is Limit-equilibrium, a mathematical based method that calculates the stability of two separate two dimensional cross sections of the slope. Two other methods used are continuum and discontinuum methods, these divide the slope into grids to calculate how each of the cells relate or effect one another for the stability of the slope.

Regional methods are designed to cover larger areas and are created as susceptibility or risk assessment maps over homogeneous zones (Thiebes, 2012; Calvello, et al. 2014). The main advantage of regional methods is that they are able to evaluate larger areas than local systems or individual experts can assess. There are two types of regional systems, landslide susceptibility and landslide risk (prediction). Landslide susceptibility is the probability of special occurrence of previous slope failures based on the geoenvironmental conditions, this method assumes that because landslides occurred in these conditions it can be used to predict where failures are likely to occur in the future. Landslide susceptibility methods, however, do not predict when or how frequently landslides will occur (Guzzetti et al. 2006). Landslide prediction as defined by Varnes (1984), is the probability of occurrence within a specified period of time and within a given area of potentially damaging phenomenon, therefore, prediction requires more information about the potential landslide than susceptibility.

There are five categories prediction models fall into: 1) inventory models, 2) heuristic models, 3) deterministic models and, 4) statistical models and 5) machine learning models (Yilmaz, 2009; Chae, et al., 2017; Canli, et al., 2018):

1) Inventory based methods analyse the distribution of landslides within a given area and the topography and conditions of where they occurred and use this as the basis for susceptibility and risk within the given area.

2) Heuristic methods use the knowledge of geomorphological and geotechnical experts to build susceptibility and hazard maps.

3) Deterministic models use physically based simulations to assess susceptibility as a factor of safety value. Using a combination of hydrology modelling, infinite slope model, and slope stability variables such as cohesion and internal friction to assign a factor of safety value.

4) Statistical methods are the most applied method within regional scales and are used to create susceptibility and risk maps as well as predict the location of future landslides. These methods calculate the relationships between the variables that cause landslides and past landslide locations and predict the location of future landslides (Thiebes, 2012).

5) Machine learning is a subset of artificial intelligence computer science and are mathematical models that can classify data that humans or other basic classification techniques cannot. The learning aspect comes from the model's ability to adjust and tune its parameters to better suit the problem or data it is given. Once the model has learned, it can then be used to predict and classify new data (VanderPlas, 2017).

Recently, machine learning has been the most used method. Machine learning is beneficial in that it is not subject to many of the draw backs common to analytical and statistical methods (Yilmaz, 2009). Previous methods are directly limited to the data that are available, which can be in different spatial resolutions and incomplete datasets (Korup & Strolle, 2014). Unlike machine learning, other methods are limited by the approach and strictly controlled by the user or expert opinion. Therefore, the parameters that factor in slope failures are weighted (measure of importance) and relationships between each are assigned by the expert. Machine learning has the ability to handle large, incomplete, and high dimensional datasets and can detect patterns and associations between the variables, without user or expert input.

According to Korup and Strolle (2014), there have been over 173 studies done using machine learning techniques implemented in landslide susceptibility models. The most common machine learning techniques according to that study are logistic regression (33%), artificial neural networks (31%), frequency ratio models (18%), weights of evidence (11%) and support vector machines (6%). Although not mentioned in the study, decision tree has also been used in a number of susceptibility studies. Though it is out of the scope of this study to describe in detail how each of the methods that have been used work, a short description of the most common methods and how they have been used in landslide study is provided.

Logistic Regression is a method that classifies data based on probability, using maximum-likelihood estimation. This method is often best suited for tasks that require a binary response, for example landslide (1) or no landslide (0). It has been mostly applied to landslide susceptibility constructing the relationship between the presences or absences of landslides based on the causative factors (Choi et al. 2012; Lin et al. 2017; Aditian et al., 2018). Artificial neural networks work by simulating biological brain function through multilayer perception networks and often use backpropagation for training (Tsangaratos & Benardos, 2014). A draw back of this method is the necessity for a classified set of training data that is also varied enough to be able to classify new unseen data, often used in landslide susceptibility modeling (Nefeslioglu et al., 2008; Choi et al. 2012; Aditian et al., 2018). Frequency ratio details and uses are detailed within the methodology section. Support vector machines aim to classify data by creating a decision boundary between a set of data to create two classes, the side of the decision boundary an new input falls, is the class it will be assigned to. Though, these methods have proved to be difficult when scaling to large datasets and changing input data conditions (Chollet, 2018). The binary nature can lead to difficulties in producing more detailed multi level landslide risk analysis (Yilmaz, 2010; Pradhan, 2013; Goetz et al., 2015; Pham et al., 2016). Decision trees are based on a hierarchical method composed of decision rules that recursively splits independent variables into homogeneous zones. The objective is to determine the best set of decision rules that can then be used to predict an outcome based on a set of input variables (Yeno et al. 2010; Bui et al. 2012; Pradhan, 2013). Issues can arise when dealing with problems that have a vary large number of variables, such as factors that cause a landslide to occur, that need to be accounted for when making decision rules.

Self organizing maps (SOM), however, do not have the same of the draw backs in the methods mentioned above. SOM can take data that has not been seen and classify it, but because it is an unsupervised soft clustering there can be any number of classifications determined through this method rather than a binary decision. This is important for classifying terrain for landslide risk, where there are more variance in conditions that cause landslides than to be classified by a binary risk or no risk. There are also no assumptions needed to be made, similar data will be clustered together without needing to tell the model how to cluster or what to cluster on. Because of this, it removes some of the biases that can be present in other methods based on the decisions made or the data that was chosen to be included (Chou et al., 2008; Friedel, 2011; Shaygan & Mokarram, 2017; Huang et al., 2017).

3. Objectives

The objective of this study is to create a functional landslide prediction program using SOM machine learning, that can identify future landslide locations based on the current conditions, a system that is affordable and robust enough to be applied in many locations. SOMs have been used in six previous landslide studies, each were focused on susceptibility and risk mapping (Chou et al., 2008; Fridel, 2011; Ahmed & Forte, 2016; Lin et al., 2017; Huang et al., 2017; Shaygan & Mokarram, 2017). Focusing on the prediction section of early warning systems, SOM neural network machine learning approach. Therefore, this is potentially the first time SOMs have been applied to landslide prediction.

In comparison to other machine learning methods that have been used, SOM is a more effective method because of the ability to scale to different sized locations (local and regional), able to use different sized datasets that have varying levels of dimensionality and it is a method that requires less experience to implement. Because of this, the SOM method can be used in any location, with limited data and resources, making it a favorable solution for landslide studies in locations where the implementation of other methods are not feasible. SOM is also less prone to some issues that can arise in most machine learning methods, such as overfitting, optimization, and computing times.

There is also the ability to bridge the gap between some of the landslide susceptibility and warning systems as well as those systems with machine learning. Also bridging the gap between regional and local methods, being able to scale up or down to the area that is needed without losing detail that is often present in local models and lost in regional. SOM have the ability to use expert knowledge and apply that information over larger regional sized areas than what would not be possible with an expert assessing a large site with the current conditions to produce warnings. Though a model may not have the same assessment accuracy or insight, being able to apply the knowledge over larger areas is a benefit of using this SOM method.

The main goal can be broken down into three objectives:

1. Develop a functioning self-organizing map program that can create an accurate landslide susceptibility map.
2. Assess a method of having new weather data continuously added to the model.
3. Assess a method self-organizing map that can predict landslides using the real time data.

To fulfil these objectives a number of sub-objectives must be accomplished:

1. Locate and acquire satellite imagery and digital elevation models for the study sites.
2. Generate and extract the necessary variables from satellite imagery and digital elevation models.
3. Develop several subsets of the study areas that can be used to train the model.
4. Develop a method of classifying and clustering the outputs of the self-organizing map based on risk and probability of landslide occurring.
5. Develop a process that can automate model runs with updated data and output to map of the study area.

4. Study Site

Costa Rica is a Central American nation with an isthmus position, having Nicaragua bordering to the north and Panama to the southeast. The total landmass covers 51,100 Km^2, formed by processes such as volcanism, tectonics, fluvial erosion, and weathering. The country is divided in half by a series of mountain chains that runs northwest to southeast (Herrera, 2016; Alvarado, et al., 2016). There is an average temperature of 26.8°C, with a thermal gradient of 5.4°C for every 1,000m altitude increase (Herrera, 2016). Precipitation is dominated by wet and dry seasons, with the wet season is from May to November. The amount of precipitation ranges from 1,300mm to 6,000mm depending on the region (Figure. 2). The geology and influence of both the Atlantic and Pacific oceans causes there to be a large number of climate and ecological zones from tropical precipitation forests to costal plains, each zone having a large number of varied plant and animal species (Alvarado, et al., 2016; Herrera, 2016).

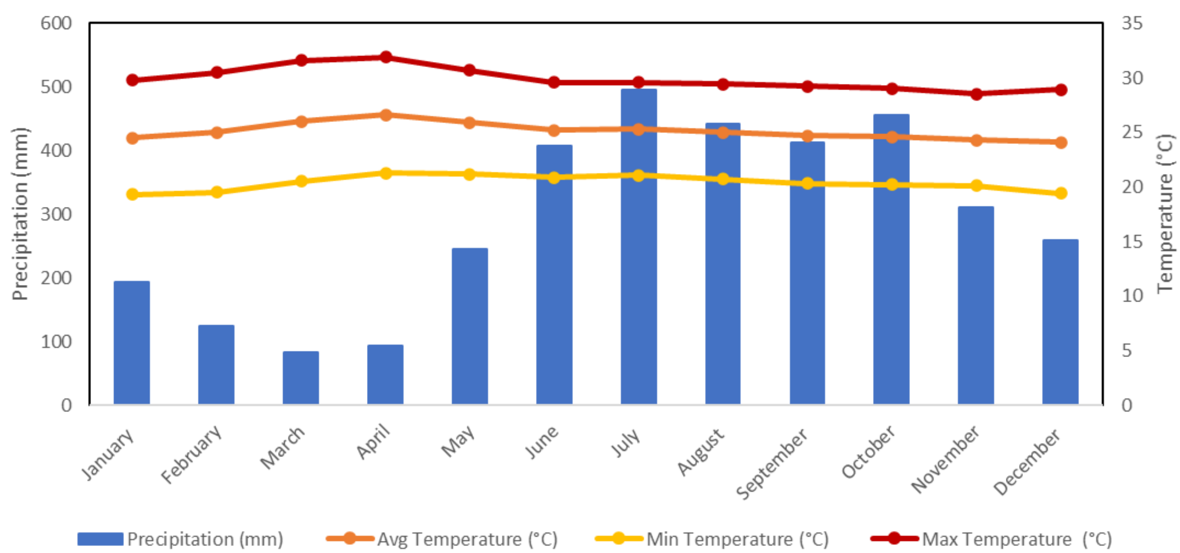


Figure 2. Climate for the primary study site recorded from a weather station in La Fortuna, showing precipitation and temperature levels annually.

The primary study site is located across the Provinces of Alajuela, Guancaste and Puntarenas, in Northwestern Costa Rica (Figure. 3). CERF was created by The Monteverde Conservation League, is the largest private reserve in Costa Rica, for the purpose of conservation, environmental education, reforestation, restoration of degraded land, sustainable development and eco-tourism (Burlingame, 2016). The site is comprised of CERF, Arenal Volcano National Park, Monteverde Cloud Forest Reserve, and Manuel A. Brenes Preserve, covering a total area of about 1,600 km^2. The nearest weather station is located just northeast of study site in La Fortuna, where there is an average temperature of 25.1°C and precipitation that ranges from 84mm in peak dry season to a high of 495mm in the precipitation season (Figure. 2). This site was chosen because of the large amount of data available and climate, geology, and topography favor the development of landslides. With data available at a 5m resolution, this site gives the best opportunity to build an effective model being able to identify conditions for all but very small movements. Additionally, allowing for a balance between high resolution, site size and, processing time. The secondary study area is located southeast of the capital city San Jose, within the province of Cartago, covering an area of about 760 km^2. Located within the study site is the city of Cartago, one of the larger city centers within the San Jose metropolitan area and Tapanti National Park that is located to

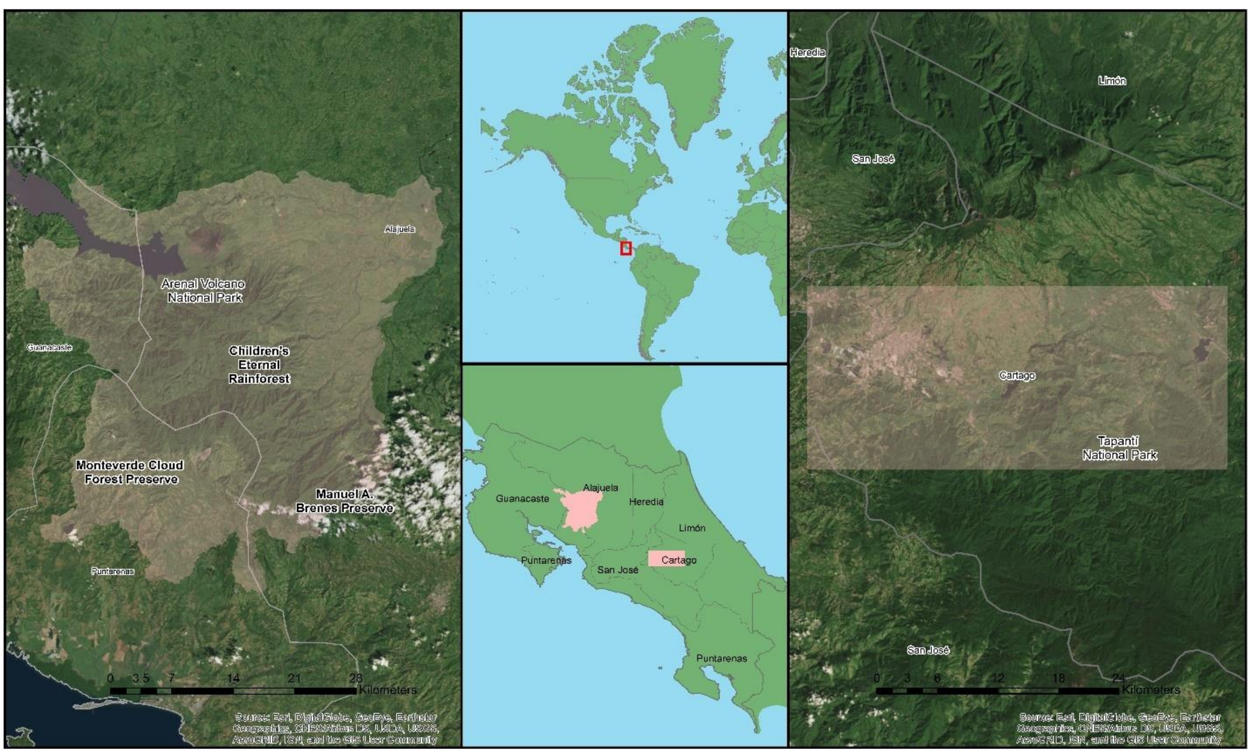


Figure 3. Map of study site locations, Study Site 1 on the left and Study Site 2 on the right.

the southeast of Cartago. This site will be used for validation and testing of the model.

4.1 Landslides in Costa Rica

Over half the world's landslides occur on the steepest 5% of earths surface; this small percentage is comprised of mountain belts, volcanic arcs and rocky coasts (Korup, 2012). This is the case in Costa Rica, where these environments make up about 60% of the landmass (Vasquez et al., 2017). In geologic terms, the country is a relatively young landmass, beginning to form about 25 Mya, under the Carrabin plate, this has also resulted in the high number of active volcanos located across Costa Rica

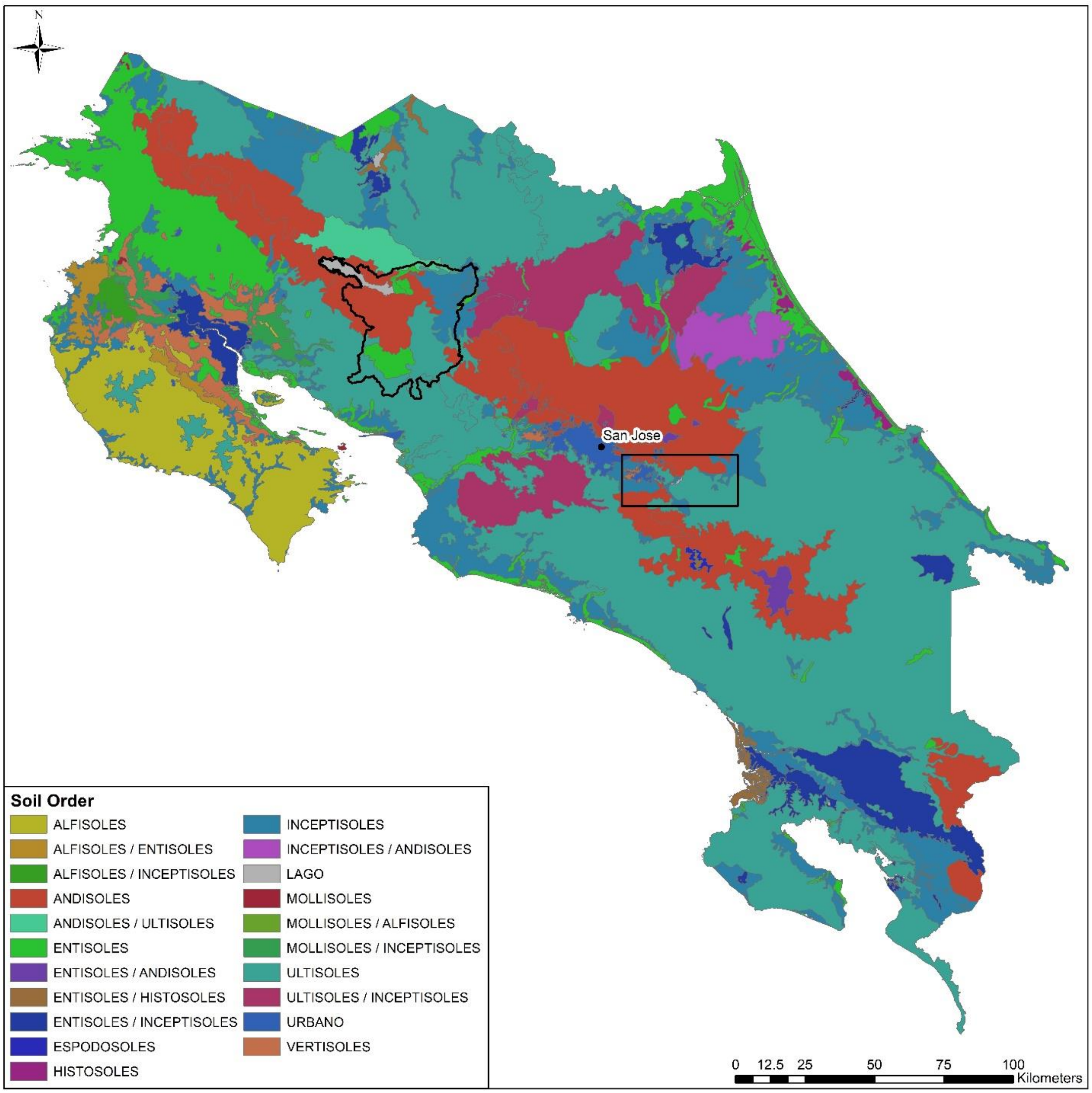


Figure 4. Map of Costa Rican Geology.

(Bundchuh & Alvarado, 2007; Alvarado & Cardens, 2016). The topography together with a favorable geological environment, such as the inclination of slope, generate the conditions necessary for landslides and other natural hazards such as volcanic activity. The landmass has been subjected to rapid uplift from the subduction of the Cocos plate and earthquakes, and seasonal changes in precipitation contribute to landslides. The tropical climate found in Costa Rica also promotes increased levels of chemical and biological weathering of slope material. Large amount of annual precipitation help

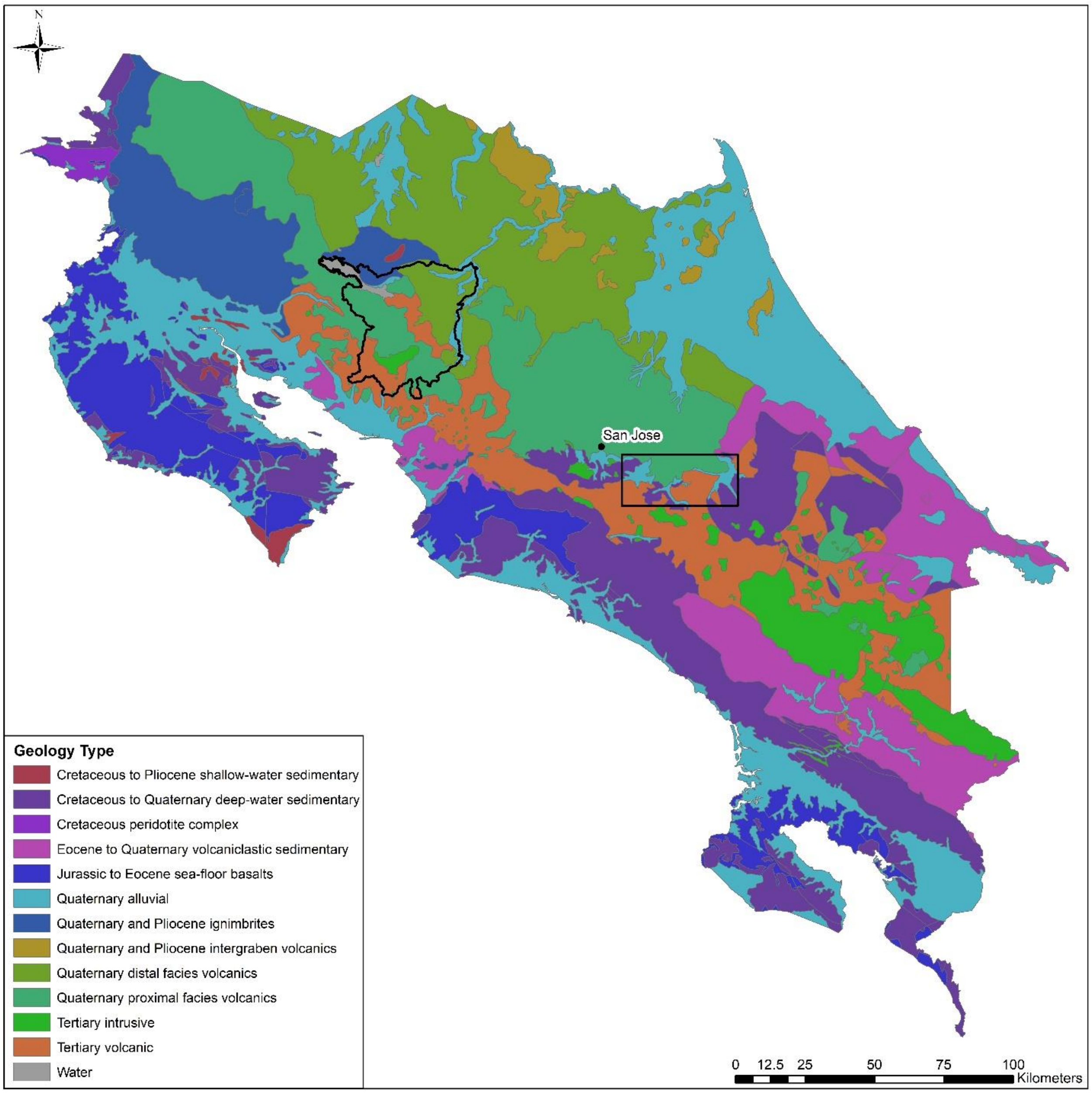


Figure 5. Map of Costa Rican soil orders.

increase chemical weathering and the topical temperatures with the precipitation allows for high rates of biological weathering, causing there to be very weak materials found on the slopes. Costa Rica is also subject to changing seasonal weather patterns, dominated by an extended rain season (September to May) and dry (May to September) season. It is the effects of the rain season that cause the majority of landslides to occur. November is the month that often has the largest number of slope failures, by this month the slopes have reached their saturation point where there cannot be any more water absorbed. Risk of landslides is further increased by poor agricultural practices, road and highway constructions with designs of inadequate slope, bad water management, unregulated developments and cuts on slopes without preventive measures (Anderson, et al., 2014; Vasquez et al., 2017).

Costa Rica's capital city and largest population centre, San Jose, is located within the Central Valley, surrounded by mountains and volcanic activity. As with many Central and South American cities, urban sprawl and population growth are causing unplanned poor housing developments. These developments are expanding up steep slopes and putting communities at risk. As recently as November 2019 a landslide killed an estimated 20 people in San Antonio de Escazu a suburb of San Jose. According to reports the affected area received 6.3 inches of rain within two hours the day of the incident, according to Costa Rica's Meteorological Institute (NBCNews, 2019). Events like these occur every year and can be expected to increase as Pujol-Mesalles and Molina (2013) have found that urban growth rate

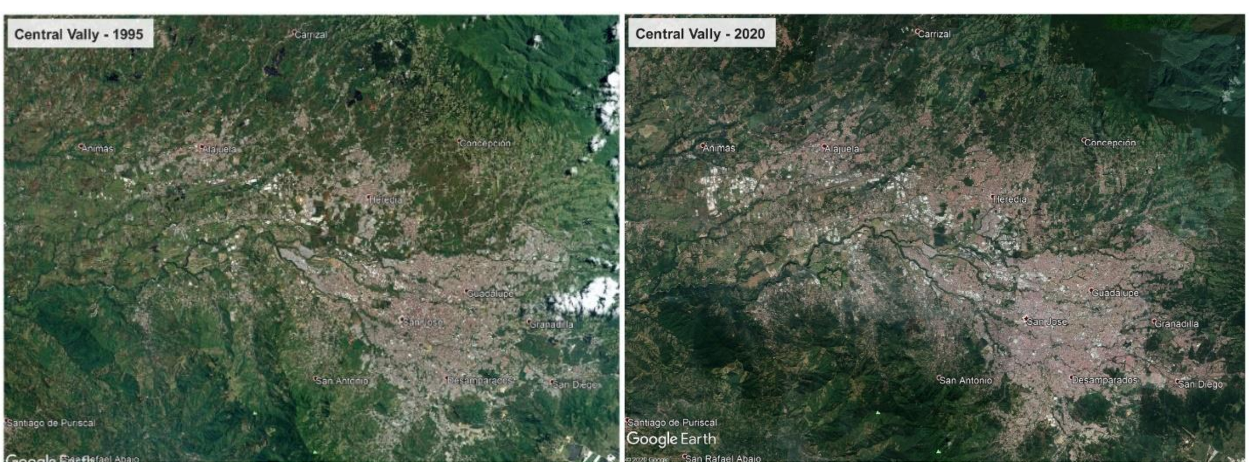


Figure 6. Urban sprawl of the Central Valley from 1995 to 2020.

has been increasing at a rate of 1.56% annually (growth rate of built-up area) and urban sprawl rates are 0.429% annually, The article also highlights that many of the cities in the San Jose Metropolitan Area are starting to reach the natural boundaries of the central valley causing more slopes to be developed. These rates show that there is an increasing portion of the population and infrastructure that are and will be exposed to the risk of landslides. This can be seen in Figure 6., where the difference of a 25-year period of urban growth can be seen in Figure 6.

Along with the population growth there is economic growth, which is drastically changing the land-use and further increasing the hazard of landslides. This issue is widespread to most Central and South America as documented by Sepulveda and Petley (2015). Costa Rica is especially vulnerable with the limited roadways that connect large portions of the country, these are frequently covered or damaged by landslide. In 2017 landslides blocked roads and damaged farms across Guanacaste (Tico Times, 2017), and in both 2018 and 2019 landslides caused a complete closure of a major highway Rute 32 each resulted from heavy precipitation fall (Q Costa Rica ,2018; Q Costa Rica ,2019). This limits access to essential supplies that communities rely on and depending on the size of the landslide and the damage done, these locations can be cut off for days or even weeks at a time. The economy heavily relies on agriculture, being a large producer of bananas and coffee. If these farms are built in the wrong location, they can be severely damaged by landslides severely impacting the companies and workers where their only source of income is lost.

5. Methodology and Principles

SOMs were originally proposed by Kohonen (1990), as a feedforward artificial neural network that uses an unsupervised machine learning algorithm. An Artificial Neural Network (ANN) is a machine learning method that attempts to mimic the functionality of biological brains. The aim of these models is not to directly replicate biological brains but rather to use the structure and functionality to solve complex real-world problems and processes. ANNs have become attractive to many because of their ability to fit nonlinear data, learning, and adapt to changing data and generalization (Basheer, et al., 2000). In SOMs, the high-dimensional inputs are projected nonlinearly to a low dimensional map of neurons, performing this transformation adaptively in a topologically ordered fashion (Chou, et al., 2008). It was developed for uses as clustering / pattern visualization of complex high dimensional data sets and data mining and processing (Chou, et al., 2008; Asan, et al., 2012; Shaygan, et al., 2017). SOMs have been used in many different applications such as, text mining, information management where the goal is to automate the annotation of electronic documents, data visualization, assisting in dimensionality reduction, visualizing relationships in data, clustering gene expressions, density modeling, and landslide susceptibility analysis (Yin, 2008).

Neural network architectures can be categorized into three groups supervised learning, unsupervised learning and competitive learning. SOMs fall under competitive learning, this is where neighboring cells within the network compete in their activities by means of mutual lateral interactions and develop adaptively into specific detectors of different signal patters (Kohonen, 1990). The neighborhood function that is unique to SOM is influenced by the localization of brain functions and local ordering within neurons, this highlights the first principle in self-organization, synaptic self-amplification (Kohonen, 1990; Haykin, 1999; Scholl, et al., 2017;). Stating that when two cells are within significant proximity enabling one to excite another persistently a growth process occurs, enhancing the firing cells ability to fire the surrounding cells. Meaning, the synaptic path between the cells to strengthen over time and respond to similar inputs (Kyan et al., 2014).

The main objective of SOM is to take complex high-dimensional input data and condensing it into a two-dimensional output space while preserving the relationships within the data. SOMs are similar in some respects to other dimension reduction techniques such as principle component analysis and multidimensional scaling but do not have the some of the disadvantages of those methods. Such as, not having to make assumptions on the distribution of the data and being able to handle noisy and missing data (Asan, et al., 2012). SOM can also be classified as an unsupervised learning method, which does not require labelled data for input classification and learning processes. Because there is no need of supervision there are advantages over using ANNs, SOMs are more adaptable to changing input environments, whereas each time there is a change with the input data for ANNs, training must occur again on the new data (Kyan, et al., 2014).

SOMs are a fully connected neural network therefore, every node within the network is connected to one another. The architecture is comprised of two layers, the input and output layer, often referred to as the competitive layer (Yin, 2008). The input layer that representing every input feature vector (x). The output layer is a collection of nodes (i) organized into a grid (Figure 7.). The two layers are connected by weight vectors (w_i), each vector is assigned a random weight between 0 and 1 upon initiating the SOM (Kyan, et al., 2014; Ahmed, et al., 2016).

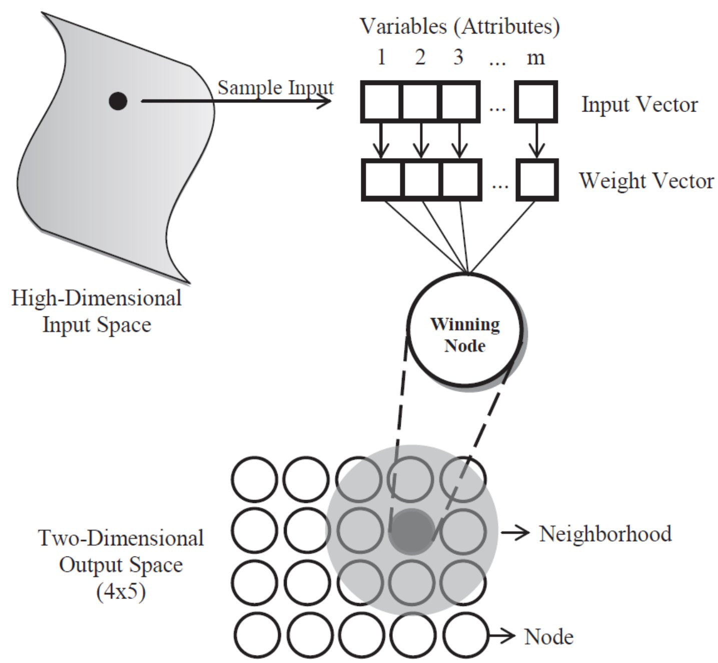


Figure 7. Example of the self-organizing map structure (from Asan, et al., 2012).

The algorithm is divided into two stages, competitive and cooperative. SOMs learn through competitive learning where each of the output neurons "compete" for the rights of each of the input vectors. The winning node is chosen by calculating the distance from the input to each of the output nodes, this is done using a Euclidian distance function:

$$d_i(t) = \|x(t) - w_i(t)\| = \sqrt{\sum_{j=1}^{m}(x_{tj} - w_{tji})^2} \quad i = 1,2,\dots,n \tag{4}$$

where $\|\cdot\|$ is the Euclidean norm. Once each distance is calculated a node "wins" by being the closest to the input vector, that output node is referred to as the best matching unit (BMU) and is calculated by using the minimum Euclidean criterion:

$$c(t) = arg_i min\{\|x(t) - w_i(t)\|\} \tag{5}$$

where *c* is the winning node at iteration *t*. The BMU now has that input vector assigned to it, the connecting weights are adjusted in order for the BMU to move closer to the input vector, adjusting the topology of the grid to fit around the data. Once the BMU is selected, the cooperative stage begins. SOMs have a neighborhood function; the neighborhood is the surrounding nodes determined by set radius distances away from the BMU. After each BMU is selected the neighborhood around the BMU is updated to move closer to the input vector. This is controlled by a neighborhood and a learning rate function:

$$w_i(t+1) = w_i(t) + \alpha(t)[x(t) - w_i(t)] \tag{6}$$

The neighborhood function finds the clustering that is within the data. Once the first BMU is selected and the neighborhood is updated, the nodes within the neighborhood are more likely to be the selected BMU of input vectors close to that of the first input, causing that group of outputs to have similar inputs and attributes, therefore, finding the clusters of similar data. The learning rate is a decreasing function of time, without it the neighborhood would continuously update the weights. The learning rate function controls how the amount of change for each iterations update. With increasing iterations, the rate at which weights are adjusted is decreased, therefore, the amount of change is much smaller in the last iterations than it is at the beginning.

The SOM have parameters that can be adjusted to better suit the data that is being classified. The neuron grid can be adjusted in both size and shape. The grid needs to be sufficiently large to classify the data, with a smaller grid the results are more generalized and the larger the grid the more detailed the classifications. The shape can be either rectangular or hexagonal which has an advantage of greater variance in neighborhood size (Figure 8.) (Asan & Ercan, 2012). The learning rate can be done in three different methods linear, inversely proportional to time, power series or exponential (Natita, et al., 2016). The number of iterations will have to be adjusted to the amount of data, increasing with increasing inputs. Having too few iterations will casue the SOM to not be sufficantly fitted to the data and having more will cause an unnessecary increase in model run time.

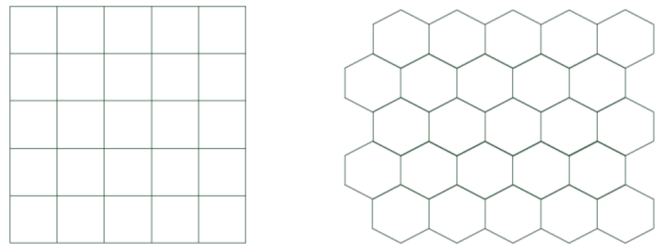


Figure 8. Example of rectangular and hexagonal topology (from Asan, et al., 2012).

There are two general rules when setting the number of output nodes, ten percent of the inputs or:

$$\text{Output map size:} \quad 5 \times \sqrt{N} \tag{7}$$

where N is the number of inputs. This can be done through either manual adjustment or an automated updating approach. The learning rate and neighborhood size will also having to be adjusted to find the optimal model parameters, also done through manual adjustment.

The SOM that will be used is the python library Minisom, which is a numpy based implementation of the Self Organizing Maps. Minisom is built to be easy to use and implement without a computer science and machine learning background while still being able to control and adjust the parameters to suit the data to be used. Minisom allows for control over the map size, number of inputs, learning rate, neighborhood function, decay function and number of iterations. Other features include being able to extract which inputs are assigned to each node and extracting the M.I.N.D values. These features enable the ability to put the coordinates of the winning node and M.I.N.D values into the input table for an easier process of clustering and visualizing the results within a GIS environment.

5.1 Spectral Clustering

One of the drawbacks of SOMs is that although it can classify complex data well, this classification is an example of fuzzy or soft clustering. It cannot for example, create distinct classes of 1 to 10, the SOM needs to be paired with another clustering technique, for this project the technique that was chosen is Spectral Clustering. Spectral Clustering is a relatively simple unsupervised clustering method but has proven to work well with complex datasets where distinct clusters are more difficult to determine. Spectral Clustering has its roots in graph theory, using eigenvalues and eigenvectors which clusters data to optimize intra-cluster similarity and limit inter-cluster similarity (Bach & Jordan, 2003; Law et al., 2017).

The clustering is done using a table of the X and Y coordinates and M.I.N.D values for each node. This preserves the variation in relationships that were created by the SOM while allowing clustering to be done. Because of the 3 – dimensional nature of this data some more common and simple clustering methods, such as K-means, are not suited for this data. It is important to have a method that can properly handle and use 3-D data as to not lose the information from the SOM. Grouping the results into 10 clusters was chosen to allow details in the results to be shown. There needed to be balance between the amount of detail shown and ease of distinction between risk levels. Having only 5 risk levels will group too many areas together and reduce the significance of the results. Having over 10 risk levels will make it increasingly difficult for the expert to distinguish between each of the levels.

5.2 Frequency Ratio

Frequency ratio is an approach based on a variation of the probabilistic method and has often used in landslide susceptibility analysis for its ease of identifying the effects of each of the variables has on landslide occurrence (Mondal & Maiti, 2013; Chen et al. 2013; Tay et al. 2014; Khan, et al. 2018;). Though it can be used as a method of determining susceptibility in and of itself, in this study it is used as a representation of relationships between the landslides and variables that the clusters of the SOM would be expected to find. It is done by assessing the quantified association between each of the variables that influence landslide occurrence and the landslide inventory, this will be done in this study to assess the variables that should be used as input for the SOM (Khan, et al. 2018). The primary reason this technique is used is to assess the associations there are between the landslide inventory and the found risk levels, as a method to test the results:

$$Fr = \frac{Npix(1)/Npix(2)}{\sum Npix(3) \,/ \sum Npix(4)} \tag{8}$$

where N pix (1) is the number of pixels for each risk level found within landslide area, N pix (2) it the number of pixels for each risk level for the total area, ∑ N pix(3) is the total number of pixels within the landslide areas and, ∑ N pix(4) is the total number of pixels in the study site (Khan, et al. 2018). An Fr value over 1 represents a positive relationship and under 1 represents a negative relationship. The results will show which risk levels have the highest association with landslides, the higher risk levels would be expected to have the greatest association and the lowest risk to have neutral or negative association.

5.2 Model Implementation - Multi Scale and Location Prediction

Most susceptibility and prediction studies undertaken are done over a single area at a single scale, this program is designed to handle various locations of differing size. The reasoning for this is with most methods focused on a single location are limited to what works optimally for that study site. Which means that each of those methods may lack the capability to be easily implemented else where. However, one of the strengths of using an SOM and this method in particular is its versatility to be used not only a single site at multiple scales but also in different locations. The second site of this study is used to show the SOM method can be used on various sites. Using the same settings and verification methods used for the primary site will be used on this secondary site. There will also be three scales that the program will be implemented at the primary study site. These scales are differing temporally, spatially and, based on risk levels (Figure 9.). Larger areas with a higher number of inputs results in the more time it takes for the program to work and therefore, fails for close to real time results, whereas focusing on smaller higher risk locations allows for the program to work much quicker and is able to produce predictions in a much shorter time. The largest area, such as the full study site (~1,600 km^2), will be done a month to season long time scale, using the cumulative precipitation data and is able to predict slower deep-seated slides. At the medium (~274 km^2) time scale of a day to a week which can be focused on deeper fast-moving slides where cumulative precipitation over a period of days is a strong influence. The final and smallest site (~60 km^2) will have the shortest time scale will be close to real time and focused on the highest risk areas. At the smaller spatial scales allows for the program to run hourly and have up to date results. Including real time precipitation amounts and intensity will focus on shallow fast-moving slides/flows that can be triggered by the shorter and high intensity storm events.

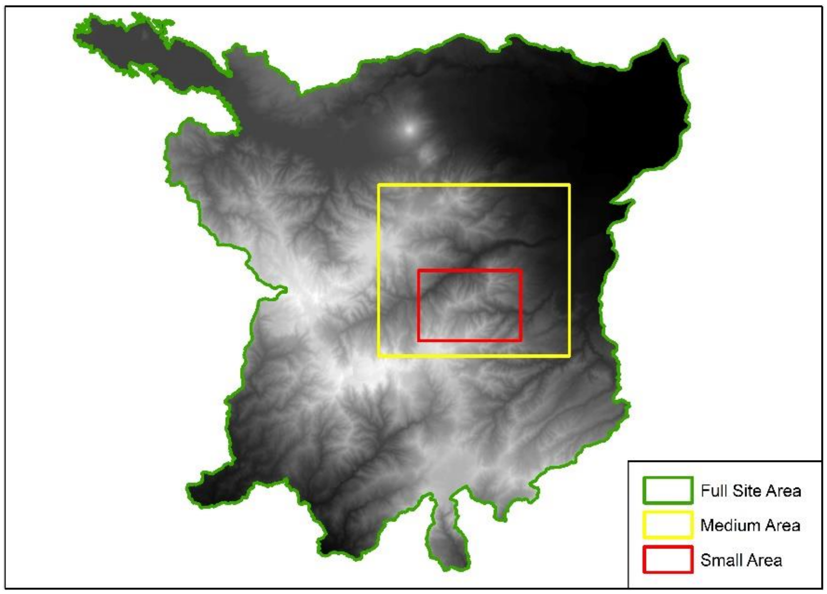


Figure 9. Image of the multiscale locations that are used in this study.

5.3 Model Implementation - Landslide Type

There are two methods that are able to produce results based on a specific landslide type. The first being, the program can be adjusted to focus to one specific type of landslide based on the conditions that the type of movement occurs in. Though there are many factors that cause a landslide to occur, for each type there are common factors and conditions that result in that specific type occurring. This can be shown in Sidle & Ochiai (2006) where it was found that general categories of mass movements from around the globe fall within a slope range. The study used three categories, creeps, flows and earth flows, creeps generally occur on less extreme slopes (4° to 18°) whereas faster flows on more extreme slopes (23° to 70°) and earthflows on slopes of (5° to 25°). These values can and will vary across different locations, environmental conditions, and prominent movement type, and this is where local expert knowledge can and needs to be implemented in the program. . Although these values are not meant to be representative of what the conditions or movements found in Costa Rica, but rather using these values are meant to show if the SOM can handle being focused on specific conditions, for each location this method is used in will have different ranges or conditions that will be particular for that location. If this method is found to be effective, in the future the conditions that cause certain movements can be used.

There are four landslide types that are going to be looked at, although there are more types these are the four categories that most landslides that occur on soils fall into, flow, slump, earthflow, and creep. Using flows as an example, this class of movement are mainly found on slopes with angles between 20° and 70° according to Sidle & Ochiai (2006), therefore, locations which have these gradients are included and all other slope angles will be discarded. This theory can also be applied to more than the four types and be specified for each type in each location. Resulting in the program predicting risk levels based only on the conditions that flows will occur and not the conditions where for example creeps are likely.

The second is by using the weather in conjunction with the multi scale prediction. As mentioned in the introduction certain weather patterns impact the type of landslide that can occur. Shallower and fast-moving landslide are results from high intensity precipitation events, where a large amount of precipitation is introduced within a short time period. Deeper fast-moving slides are results of longer duration storms, where a high amount of precipitation is introduced over days or weeks. Finally, deep slow-moving slides are results of large amount of precipitation occurring of the course of months or a full rain season. Each of these types of movements has an identifiable triggering mechanism that can be used to assign risk. When used in conjunction with the multiscale prediction each slide will have a model that is designed to assign risk based on those triggering factors. The smallest scale can be trained to use near real time or forecasted radar data to focus on rapid shallow movements in the highest risk locations such as populated areas or important roadways. The medium scale can be trained to focus on using cumulated radar data for each day assigning risk over a larger area. Lastly, with the largest area cumulative precipitation data over each month or season can be used to assign risk for large slow-moving landslides.

5.4 Model Testing Using Landslide Inventory

In typical machine learning approaches testing and training are done using a landslide inventory which is divided into training and testing sets. Where the training set is used for the model to learn on and the testing used to test model performance on new data. However, when using an SOM there is no training on landslide location necessary. In most methods the process would require a program to train or learn the classifications it is intended to determine. The SOM program rather finds similar features in the data and groups them together. The idea is that landslides occur under similar conditions and circumstances and the features that cause a landslide will be able to be found by the SOM within the data provided. This also reduces some overfitting issues that can be found using other training methods. Because SOM do not require training or testing data in order to be implemented, there lacks a simple built-in method to test how well the model is working.

One method that was developed is using the landslide inventory built and comparing the level of risk that the model produced within the boundary of each landslide. This method may not be perfect representation of the quality of the model and would still need to be examined by an expert, but it gives a numerical value to the quality. Being able to test the results become important when changing the variables used and settings of the SOM to find the model that works the best.

The landslide inventory that was built used from images taken from Google Earth. Each landslide that was found then had a boundary line created to be imported to a GIS environment. Each boundary line is then used to identify landslide areas of the SOM result. Only images from between 2016 and 2020 were used, this is to keep the images and therefore the landslide current and without the conditions changing. Using images that go further back would increase the likelihood of the conditions that caused those landslides to have changed, therefore, any analysis done with more recent landslides with older ones would decrease the validity of any model trained and tested on the dataset. Though movements and their locations can be identified, it is unreasonable to classify each movement to a specific type through these satellite images. In doing so without in field research for conformation would require major assumptions to be made. Using these unvalidated assumptions would likely bias the results to make them invalid for use. It may be possible to classify some of the movements, but for this information to be applied within the model the information would need to be accurate and validated which was unable to be done for this study.

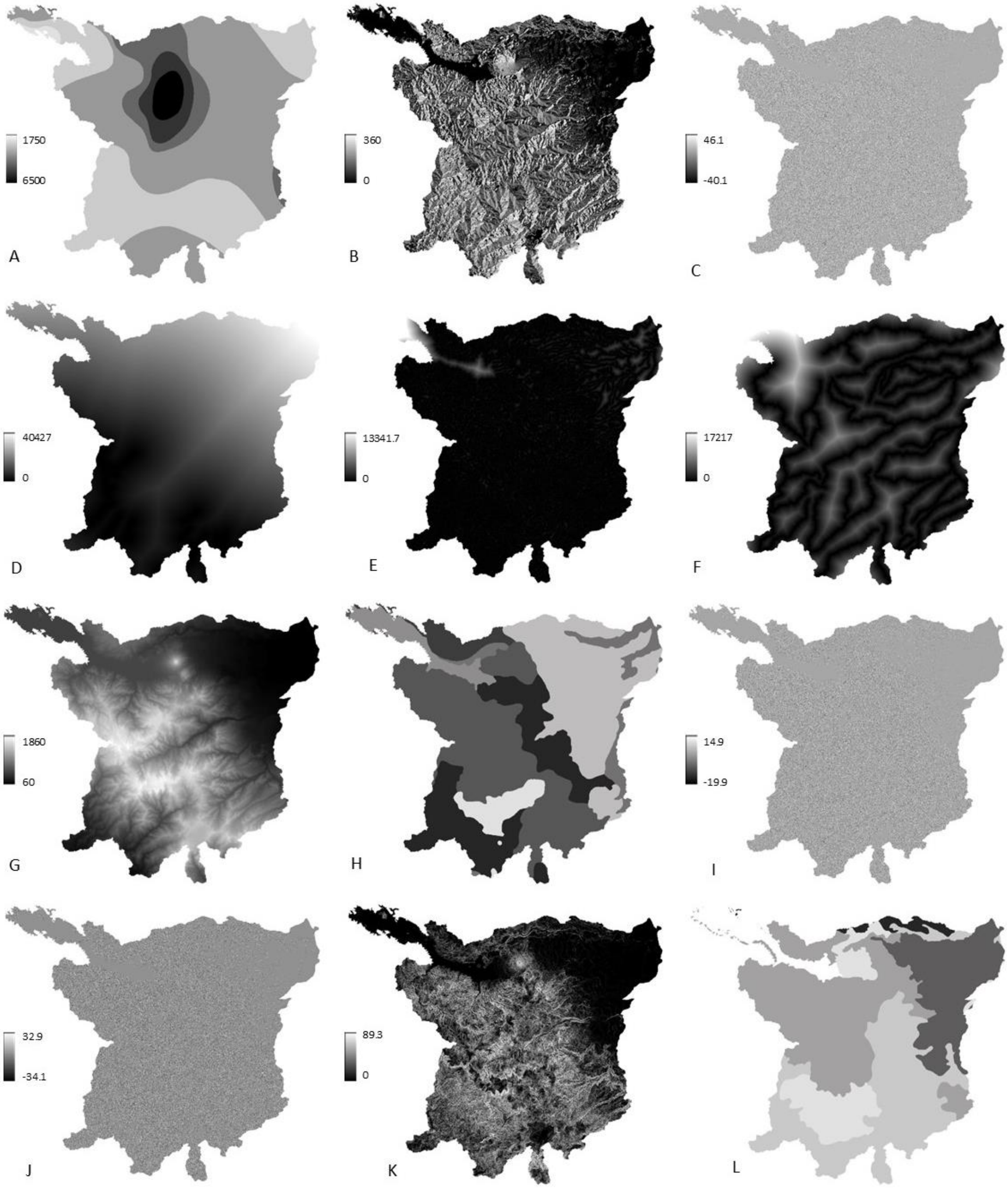
The technique compares the mean risk level for the full site to the areas that are within the landslide boundaries. If the model is working correctly, it would be expected that the mean value from within the landslide areas are higher that of the full site. The results will then be examined using the Mann-Whitney U test to see if these distributions are statistically significant. The Mann-Whitney test has been chosen because the results are a non-normal distribution. It is important to see if there is a statistical significance between the values because it could be the model is over calculating the high-risk areas to the point of assigning the full site to high risk. This may show that within the landslide areas there is high risk, but it is not meaningful when the full site is also classified as high risk.

A secondary method is using frequency ratio, though less exact and statistical than using the mean values mentioned above, it will show what exactly are the risk classes within each of the landslides for the results. It would be expected that the higher risk groups would have the highest association and the low risked having less. This gives the results a secondary measure of how well each result is performing. It can be assumed that a result that with favorable mean values and as expect frequency ratio is a better performing model than if only one of the measures were positive.

The method of assigning risk to the created clusters based on the static variables, and then testing the averages both in an out of landslide areas, is not a viable method when precipitation data is introduced. The precipitation data will change where the high-risk areas are, the higher precipitation amount areas will have higher risk and areas with lower precipitation amounts will have lower risk. Since it is likely that some landslides, and therefore, high risk conditions, will be located within lower precipitation areas using the average risk will skew the results to show lower risk, because of this a different method will be needed. Another factor that needs to be considered is that although some landslides will be in the lower precipitation areas does not automatically result in that area being low risk. The topography may still have conditions that will have a high risk of landslides even with lower precipitation amounts, especially in highly varied topography with steep slopes for example. The risk levels will be determined the same as will the average risk only with the precipitation levels now accounted for. It is expected that the locations with the highest levels of precipitation will have higher risk, so these locations will be assigned at higher levels. By comparing the average amount of precipitation and assigned risk level within each landslide area a correlation can be determined. A positive result using this method would show a correlation that has higher risk levels associated with higher precipitation.

5.5 Input Data

Where and when landslides occur are dependent on a large number of factors. Unlike a majority of systems currently employed that use a limited number of variables in susceptibility or predicting, the percentage of studies using each variable are shown, slope (71%), slope aspect (57%), geology (54%), curvature (43%), hydrology (43%), elevation (32%), soil (28%) and, NDVI (23%), this project will use all possible variables that can be effectively implemented (Korup & Stolle, 2014). The variables used are shown in Figure 10 and listed and described within Table 1. These variables may also be used as proxies or proxy variables, serving in place of variables that have not been studied and recorded or are immeasurable. A database of previous landslides will be used for validating and assessing the results of the susceptibility model. Realtime weather data will be implemented into the model, showing the intensity and quantity of precipitation. For the primary study site, a majority of the data such as elevation model and hydrography, was gathered and sent by the Texas A&M Soltis Center, a research facility located within the study site. Similarly, for the secondary study site, data was acquired from Instituto Costarricense de Electricidad (ICE) a telecommunications and geology maps acquired through the website of the U.S Department of the Interior. There are two main types of data that will be used, categorical and ordinal. Categorical data is data that is partitioned into groups. Color is an example, there is no order to color data rather something is one color and not organization in Costa Rica. Other the data and each input can be ordered from highest elevation to the lowest. This is important to define data such as satellite images were acquired form EarthExplorer, soil the others. Ordinal, is data that has a clear order to it, such as elevation, where there is a clear order to because of the type of data that will be used in the SOM. Most of the data can be classified as ordinal, slope, elevation, slope curvature and topographic wetness index, are some examples. Categorical data are needed because of how the data is read by the SOM, where variables cannot be ordered. Soils, geology and slope aspect are some of the variables that need to be categorical when used in the SOM. For soil type, where there are multiple types and subtypes, where the input data needs to be numerical, each type will be assigned a representative number or ID. The issue arises when the SOM will read this similar to a ranking where that is not intended, rather need to be seen as a true/false in order to make this work, each soil type would have its own column with a 1 indicating that specific location has that soil type, the remaining types would each have 0. This is the case with geology and slope aspect as well.


1750
6500
A
360
0
B
46.1
-40.1
C
40427
0
D
13341.7
0
E
17217
0
F
1860
60
G
H
14.9
-19.9
I
32.9
-34.1
J
89.3
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K
L

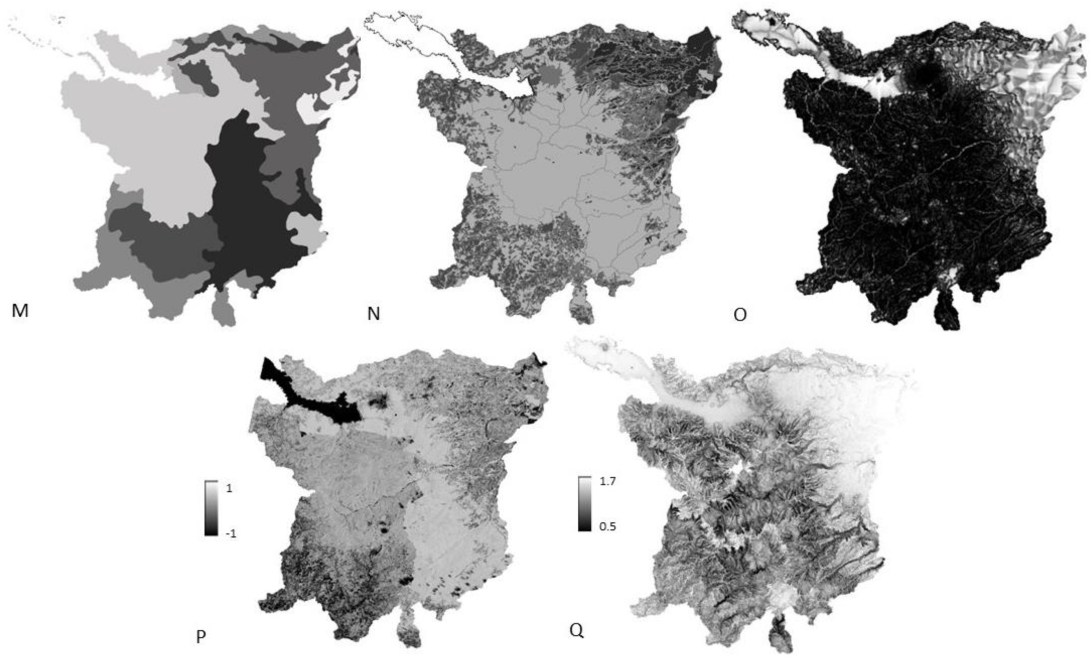


Figure 10: Variables that will be used for the mode: A.) Annual Average Precipitation B.) Aspect C.) Curvature D.) Distance from Faults E.) Distance from Stream F.) Distance from River G.) Elevation H.) Geology I.) Plane Curvature J.) Profile Curvature K.) Slope L.) Soil Order M.) Soil Sub Order N.) Land use O.) TWI P.) NDVI Q.) Openness

Table 4. List and description of the variables that will be used.

Variable	Description
Elevation	Elevation is an important and useful variable to studying landslides. From elevation data, many variables can be extracted such as, slope, aspect, plane and profile curvature.
Slope	Landslides are largely dependent on the slope gradient that is present. In most situations a larger slope gradient signifies a greater chance of landslides occurring. Though, the exact gradient that is needed for landslides to occur is affected by the material that makes up the slope among other variables.
Aspect	Aspect does not have a major direct impact on slope stability but is a controller of many small but important impacts. Influencing evapotranspiration, weathering processes, vegetation and root development Aspect is used as proxy for how multiple weather and climate variables are influenced by the topography of the study site. Including factors such as prevailing winds, precipitation patterns, and which slopes receive the most sunlight.
NDVI	Vegetation has a major controlling factor of landslides, both in how much vegetation and the type of vegetation is present on a slope. Vegetation and corresponding root systems help strengthen slopes and influence soil erosion and infiltration rates.
Soil type	The ability of a slope to resist the forces acting on it largely depend on the materials that make the slope, different soils have unique properties that affect the strength of the slopes. Using the recorded soil is a proxy for the characteristics that define and differentiate soil types. Factors such as specific gravity, internal friction angle, porosity and pore pressure all influence the occurrence of landslides in different soils.
Geology	The geology is a measure of the material that in underlying the slope and is the main source of the slope material and soil. Giving further insight to the material of the slope and its ability to resist failure. This also acts as a proxy for the underlying structure and weathering and erosion rates.
Annual Average Rain	Water is the leading trigger of landslides. Erosion, weathering, increasing weight and pour pressures of the slope are all caused by precipitation. This is the second proxy that will be used for how weather patterns are influenced the topography.
Land Use	The removal of vegetation, developments undercutting and adding weight to slopes are all factors from land use heavily influences the stability of slopes.
Distance to Faults, Streams and, Rivers	The distance from different features will have effects on a slope. Streams and rivers (main outlet from each watershed) will erode the bottom of slopes and are also an indication on which direction the water flows through the system and acting as a proxy of where the concentration of water will be thoughout the slope system. Further an area is from a stream/river the less water there is likely to be. Distance from Faults increases the likelihood of there being earthquakes in that location, increasing the chances of landslides occurring.
Topographic Wetness Index (TWI)	TWI is a measure assessing the topographical impacts on hydrological processes, showing upstream contribution and flow direction within a slope system. The distribution of water throughout a slope system impact where and when landslides are likely to occur.
Slope Length	The size of the slope changes many of the characteristics that influence landslides. Longer slopes have more weight and more water accumulation down slope.
Profile and Plane Curvature	The shape of the slope has a major influence on the stresses of the slope. Divergent slopes are generally more stable than planer or convergent because is has the ability to disperse the loads and water. Whereas a convergent slope shape concentrates the stresses toward a central valley, with watering rapidly increasing the pour pressures.

5.6 Precipitation Data

Precipitation data that is used in the model are simulated radar images. The program is designed to be able to implement live radar images at equal time intervals, gathering both precipitation amount and intensity from each image. Radar images measure the relative amount of precipitation that is falling, in most cases represented as light precipitation as light green and storm conditions as dark red or purple, an image with these colors can be analysed, with the color range being broken into classes based on amount or intensity levels. These groups can then be used to get an estimated amount and duration of each intensity level for each cell over a given location. It is important to have both amount and intensity for each has a different impact on triggering landslides. Amount is taken by estimations from each intensity group, this can then be more accurately calibrated through a network of precipitation gauges. For each cell with have the cumulative amount for each hour. Where it is important to differentiate between amount and intensity is when there is an uneven distribution of precipitation fall/intensity across the study site. One area may have a short duration high intensity storm, and another may have low intensity long duration event. Both areas may receive the same amount of precipitation fall within an hour but will have very different impacts on influencing landslides, for situations such as these, the use of different time scales and using both precipitation intensity and amounts are important to be used and are accounted for.

The precipitation data used are simulated based on the weather patterns of September 2019. September was chosen because it is the start of the heavy landslide season in Costa Rica. October and November have the largest number of landslides each year. Weather patterns were studied, looking at both size and directionality of precipitation events that occurred over the study site. This ensures that the created dataset can more accurately depict the storm events, for each day the duration, storm type, start, and end time are recorded for the full month. Each precipitation event has each hour classified into light, thunderstorm and, heavy thunderstorm, then the created data set mimics each day, matching the amount and intensity (Table 5.). If using the radar imaging is proven effective, then the model can then be used with weather forecasts. Though this may reduce accuracy of the program, having the

Table 5. The month of September 2019 broken down by day, start time, end time and precipitation intensity. L = Light Rain, Ts = Thunderstorm and, Hts = Heavy Thunderstorm.

Day	Time Start	Time End	Duration	1	2	3	4	5	6	7	8
1	12(PM)	2(PM)	2	L	Ts						
2	3 (PM)	8(PM)	5	Ts	Ts	L	L	Ts			
3	2(PM)	3(PM)	1	L							
4	2(PM)	6(PM)	4	Ts	Ts	Hts	Ts				
5	1(PM)	5(PM)	3	L	L	L					
6	11(PM)	12(PM)	1	L							
7	2(PM)	10(PM)	8	Ts	Hts	Ts	Hts	Ts	L	L	L
8	12(PM)	1(PM)	1	L							
9	3(PM)	5(PM)	2	Ts	L						
10			0								
11			0								
12			0								
13	6(AM)	2(PM)	8	L	L	L	L	L	L	L	L
14	6(PM)	7(PM)	1	L							
15	1(PM)	9(PM)	7	Ts	Ts	Ts	Ts	L	L		
16			0								
17	1(PM)	6(PM)	5	Ts	Ts	L	L	L			
18	3(PM)	9(PM)	6	L	Ts	L	Ts	L	L		
19	3(PM)	7(PM)	4	L	Ts	L	L				
20	3(PM)	7(PM)	6	L	L	L	L	L	L		
	10(PM)	1(AM)	3	Ts	Ts	Ts					
21	2(PM)	9(PM)	7	L	L	L	L	L	L		
22	9(PM)	11(PM)	2	L	L						
23	1(PM)	2(PM)	1	Ts							
	3(PM)	7(PM)	4	L	L	L	L				
24			0								
25	11(PM)	12(AM)	1	L							
	1(PM)	4(PM)	3	L	L	L					
26	5(PM)	9(PM)	4	L	L	L	L				
27	2(PM)	5(PM)	3	L	L	L					
	9(PM)	6(AM)	7	L	L	L	L	L	L	L	
28	12(PM)	8(PM)	8	L	L	L	L	L	Ts	L	L
29			0								
30			0								
31	1(PM)	2(PM)	1	L							
	5(PM)	1(AM)	8	L	L	L	L	L	L	L	L

ability to produce landslide predictions before the storm occurs then it will significantly increase the impact it can have in landslide effected locations.

6.Results

Within the primary study site, a total of 76 landslides were located and mapped that occurred between 2016 and summer of 2020, varying in size, type, and location (Figure 11.). It is important to note that though the expected would have full site means much lower than what would be found within

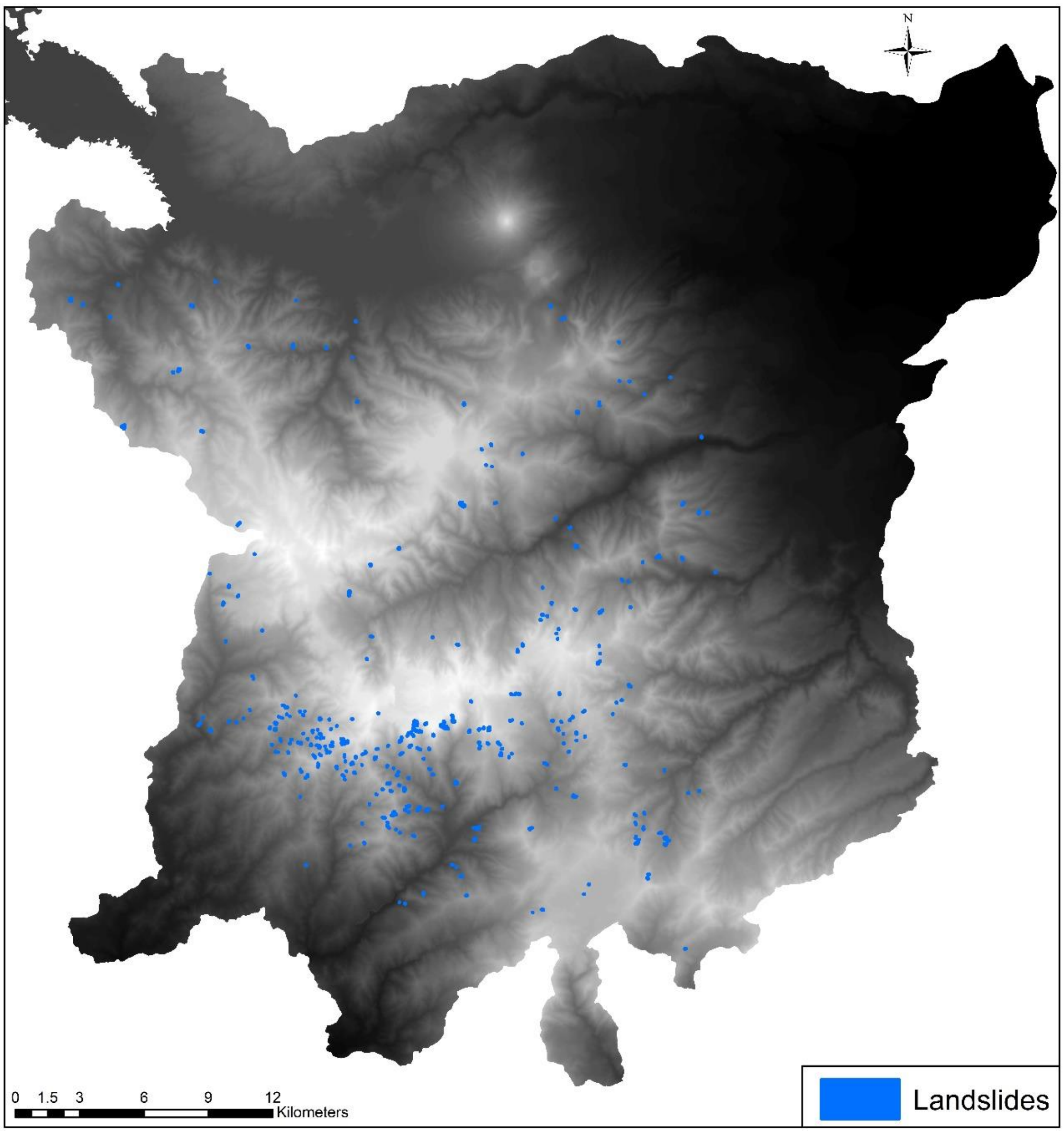


Figure 11. Image of the 76 landslides located within the primary study site between 2016 and 2020. Each blue area is a located landslide.

landslide areas, the amount of steep slope conditions within each of the sites should be taken in consideration. When an area has a significant area with steep slopes this will likely cause higher risk levels. The full site has 62%, medium site has 44%, and the small site has 66% coverage of slope greater than 20° which is the minimum requirement of most fast movements to occur. It can be assumed with increased coverage of steeper slopes those areas will produce on average higher risk values, whereas areas with less overage will produce lower risk values.

Once the landslide inventory was complete and the variables prepared, the first tests where to confirm that SOM could perform as intended. Requiring the SOM to cluster areas of similar characteristics by identifying areas of similar topography making sure they are clustered together. It became clear with these early results that the categorical data was having a major influence on the results. Whether it is because of this implementation of SOM or the settings used is unclear. When a categorical variable was used, especially when there is a distinct transition line occurring across the test area it would dominate the clustering, which a clear line in which the two classes of the variable meet is visible in the results. The issue caused by this is when determining the risk level for each cluster it is no longer looking at each of the variables used but dominated by if an input within one of the sections of that particular categorical variable. The same issue occurs with more than two categories within single variable and multiple categorical variables.

Table 6. Table shows the correlations between the variables used.

Layer	Elevation	Distance from Stream	Slope	TWI	Curvature	NDVI	Plan Curve	Profile Curve	Positve Openness
Elevation	1								
Distance from Stream	-0.10487	1							
Slope	0.48098	-0.18584	1						
TWI	-0.57151	0.31267	-0.62644	1					
Curvature	0.04124	0.0107	0.00467	-0.02527	1				
NDVI	0.31263	-0.08636	0.29091	-0.43699	-0.01697	1			
Plan Curve	0.01838	0.01205	0.00164	-0.01832	0.73588	-0.02123	1		
Profile Curve	-0.0446	-0.00661	-0.00521	0.02249	-0.88485	0.00904	-0.33591	1	
Positve Openness	-0.47658	0.22166	-0.80937	0.6248	0.26189	-0.29302	0.18581	-0.23659	1

Once it was determined that categorical variables were no longer able to be used the remain variables were then tested for correlations to make sure that each of the variables are independent (Table 6.). If a variable was found to have a high correlation to another it would be removed to prevent unnecessary redundancies, also reducing the amount of data needed saving storage space and processing time. With exceptions made to Curvature, Plane Curvature and, Profile Curvature, it is expected that these will have a strong correlation as curvature is a combination of both Plane and Profile curvature and therefore, these variables are not run together. As shown in (Table 6.), each of the remining variables do not have strong correlation to each other with one exception being the correlation between slope and positive openness being negatively correlated at -0.81. Looking at the remaining variables that are going to be used a frequency ratio table was created, giving a representation of the conditions that the landslides occurring and the conditions that the SOM will be clustering together for optimal results. Table (6) also shows which variables have more importance in landslide occurrence, class 2 of openness (9.81), class 6 of slope (10.28), and class 2 from plan curvature (5.61) should be noted for having the highest FR values (Table 7.).

Table 7. Table shows the variables that were used for the corresponding run. Each variable is broken down in even classes, the numbers under Landslide and Fullsite are the total number of cells found within each class across the study site and, the FR value is the frequency ratio.

Slope Class	Landslide	Fullsite	FR
10	634	22788366	0.14
20	1446	14750620	0.50
30	3430	13356989	1.32
40	3568	6987934	2.62
50	1945	1884402	5.30
60	626	313073	10.28
70	57	63704	4.60
80	0	11684	0.00
90	0	7960	0.00

Distance to Stream	Landslide	Fullsite	FR
0 - 313	4526	19604323	1.19
313 - 1046	3763	18256069	1.06
1046 - 2354	2136	12850112	0.86
2354 - 3924	1036	5359461	1.00
3924- 5493	221	2061385	0.55
5493 - 7010	0	999426	0.00
7010 - 8423	0	518643	0.00
8423 - 9836	0	309444	0.00
9836 - 11301	0	156426	0.00
11301 - 13341	0	50774	0.00

NDVI	Landslide	Fullsite	FR
(-1) - (-0.7)	0	1653	0.00
(-0.7) - (-0.5)	0	1636	0.00
(-0.5) - (-0.25)	0	1730	0.00
(-0.25) - 0.0274	0	260726	0.00
0.0274 - 0.0278	146	792483	0.95
0.0278 - 0.44	1786	2976808	3.08
0.44 - 0.56	2233	5840576	1.96
0.56 - 0.64	2031	9147085	1.14
0.64 - 0.72	2173	12783253	0.87
0.72 - 1	3337	28260387	0.61

Curvature	Landslide	Fullsite	FR
(-40) - (-4.9)	0	25736	0.00
(-4.9) - (-2.5)	305	428559	3.66
(-2.5) - (-1.3)	1388	3401497	2.10
(-1.3) - (-0.5)	1725	5863711	1.51
(-0.5) - 0.1	3737	28835413	0.67
0.1 - 0.7	2981	14847328	1.03
0.7 - 1.8	1011	4663386	1.11
1.8 - 3.8	536	1922177	1.43
3.8 - 8.5	21	178201	0.61
8.5 - 46	0	5879	0.00

Elevation	Landslide	Fullsite	FR
60 -209	0	9445476	0.00
209 - 414	69	6635574	0.05
414 - 603	125	6348746	0.10
603 - 754	140	7010553	0.10
754 - 902	1175	7089220	0.85
902 - 1054	1815	6576068	1.42
1054 - 1211	1455	6224658	1.20
1211 - 1369	2845	4993424	2.93
1369 - 1541	2050	3525703	2.99
1541 - 1860	2040	2321641	4.51

Openness	Landslide	Fullsite	FR
0.36 - 1.03	139	125429	5.69
1.03 - 1.11	1233	644843	9.81
1.11- 1.17	1598	1525775	5.38
1.17 - 1.22	1582	3145644	2.58
1.22 - 1.27	1696	4919820	1.77
1.27 - 1.32	2174	6770820	1.65
1.32 - 1.37	1998	9000452	1.14
1.37 - 1.43	1186	10717268	0.57
1.43 - 1.5	59	10461331	0.03
1.5 - 167	49	12806892	0.02

Plancurve	Landslide	Fullsite	FR
(-19) - (-3.5)		4384	0.00
(-3.5) - (-1.9)	117	107088	5.61
(-1.9) - (-1.2)	486	640311	3.90
(-1.2) - (-0.6)	1054	2245677	2.41
(-0.6) - (-0.2)	1818	5398786	1.73
(-0.2) - (-0.0)	2860	14156027	1.04
(-0.0) - 0.2	3301	27375945	0.62
0.2 - 0.8	1797	8515786	1.08
0.8 - 1.6	239	1545826	0.79
1.6 - 14.8	42	182057	1.19

Procurve	Landslide	Fullsite	FR
(-34) - (-7.1)	0	4225	0.00
(-7.1) - (-3.2)	13	39922	1.67
(-3.2) - (-1.6)	152	354673	2.20
(-1.6) - (-0.8)	678	1924345	1.81
(-0.8) - (-0.3)	1498	5388919	1.43
(-0.3) - (-0.1)	3663	28891080	0.65
(-0.1) - 0.7	4226	19487939	1.11
0.7 - 1.4	1294	3784077	1.76
1.4 - 3.8	190	282409	3.46
3.8 - 32.5	0	14298	0.00

TWI	Landslide	Fullsite	FR
42 - 357	8727	22539012	2.00
357 - 787	2283	13512044	0.87
787 - 1302	462	7736940	0.31
1302 - 1875	39	4359369	0.05
1875 - 2476	34	3041177	0.06
2476 - 3077	33	2438582	0.07
3077 - 3707	39	2264225	0.09
3707 - 4337	89	1683312	0.27
4337 - 4910	0	1690736	0.00
4910 - 7343	0	1105274	0.00

The next stages of testing started by using three variables, slope, topographic wetness index, and curvature. These were chosen as the starting variables as they represent the major factors in causing landslides either directly or by proxy, while also giving a baseline of results before adding more variables and complexity. The results show that within each of the site tested there the difference of different variables as an attempt to find the optimal combination of variables, the results of these runs are located in Table (8). means are significant at the 5% confidence level. Once this was found each test following added or use of different variables as an attempt to find the optimal combination of variables, the results of these runs are located in Table (8).

Table 8. Table breaks down each test run and which variables were used.

Run	Variables Used
1	Slope, TWI, Curvature
2	Slope, TWI, Curvature, Elevation
3	Slope, TWI, Curvature, NDVI
4	Slope, TWI, Curvature, Distance to Stream
5	Slope, TWI, Curvature, NDVI, Distance to Stream
6	Slope, TWI, Profile Curvature, Plane Curvature
7	Slope, TWI, Profile Curvature, Plane Curvature, Positive Openness
8	Slope, TWI, Profile Curvature, Plane Curvature, Positive Openness, Distance to Stream
9	Slope, TWI, Profile Curvature, Plane Curvature, Positive Openness, Distiance to Stream, NDVI
10	Slope, TWI, Profile Curvature, Plane Curvature, Positive Openness, Distiance to Stream, NDVI, Elevation

Table 9. Table shows the results from each corresponding run. Divided by each run, average for full site, average within landslide areas and if the results are significant.

Run	Full Site Average Risk Level	Landslide Average Risk level	Sigificant (5%)	Mid Size Site Average Risk Level	Landslide Average Risk level	Sigificant (5%)	Small Size Site Average Risk Level	Landslide Average Risk level	Sigificant (5%)
1	3.86	1.89	Yes	5.31	3.47	Yes	5.88	4.86	Yes
2	6.40	5.31	Yes	5.52	7.19	Yes	5.41	5.05	Yes
3	4.83	2.22	Yes	4.54	2.37	Yes	4.21	3.22	Yes
4	4.87	2.37	Yes	5.52	3.36	Yes	5.15	4.35	Yes
5	4.80	2.64	Yes	4.22	3.02	Yes	4.98	4.71	Yes
6	5.71	3.27	Yes	6.00	4.03	Yes	4.75	3.90	Yes
7	4.30	2.39	Yes	6.35	4.11	Yes	5.61	4.97	Yes
8	5.42	3.74	Yes	5.29	2.73	Yes	5.73	5.40	Yes
9	4.71	2.58	Yes	5.38	4.71	Yes	5.13	5.86	Yes
10	5.86	3.28	Yes	4.70	3.02	Yes	4.60	4.44	Yes

The results show that differing variables or combination of variables an SOM can still extract the features that will have the highest likelihood of a landslide occurring (Table 9.). The results are on a scale of 1 to 10, with 1 being the highest landslide risk, therefore, the lower the mean values the higher the average risk. Each of the runs produced results that had landslide area at higher risk than other areas, with the exception of one outlier of run 2 on the medium site having the worst results with 7.2 average risk in landslide areas and only 5.3 for outside landslide locations. The average risk value for all tests ranges from 6.4 to 3.8 with an average of 5.2, while the average landslide risk ranges from 7.2 to 1.9

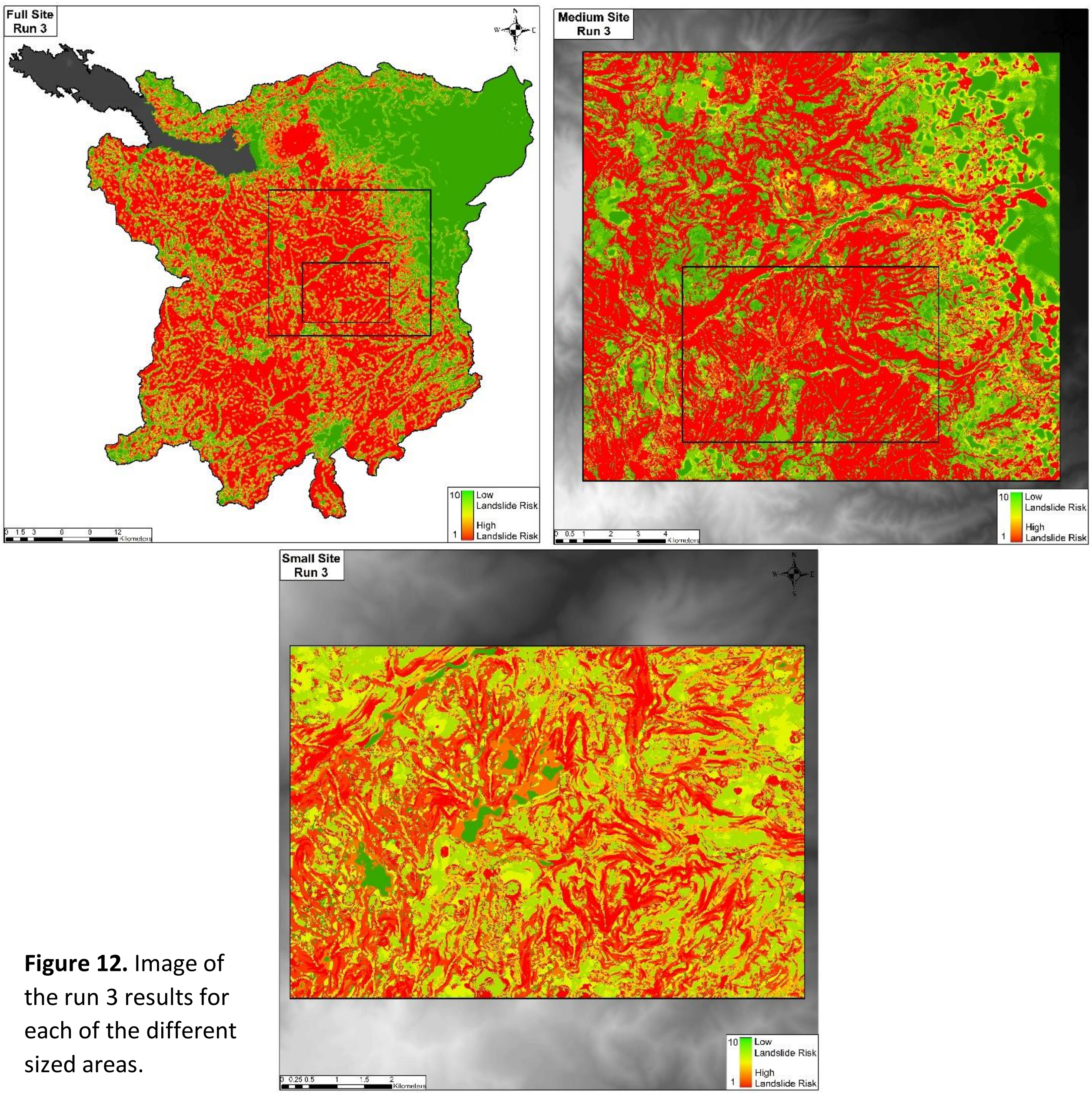


Figure 12. Image of the run 3 results for each of the different sized areas.

with an average of 3.5. The third run is the one that performed the best, across each of the sites it is consistent in having the highest difference between the risk inside landslide area and the full site, averaging a difference of 2.1. This shows that this combination of variables more often produced lower values for non landslide areas and higher in landslide areas, not only in one location or scale but in all three tested (Figure 12.). Though there are other combinations that produced promising results such as run 1 on the full site which produced the highest risk levels for the landslide areas (1.9) or run 8 on the medium scale which produced the largest difference between the mean values (2.6). Overall, with the exception of run 2, each of the runs produced positive results in assigning high risk to the landslide locations, each of the variable combinations and locations have done so.

The results represent the ability of the SOM to take any data, number of variables, and different locations and produce positive results. This is also shown in the results from the second study site which when run with slope, TWI, curvature and, NDVI also produced statistically significant results using the same SOM size and settings. The run on the second site produced a mean of 4.03 for the site average and 2.01 for the landslide average, the results can be seen in Figure 13.

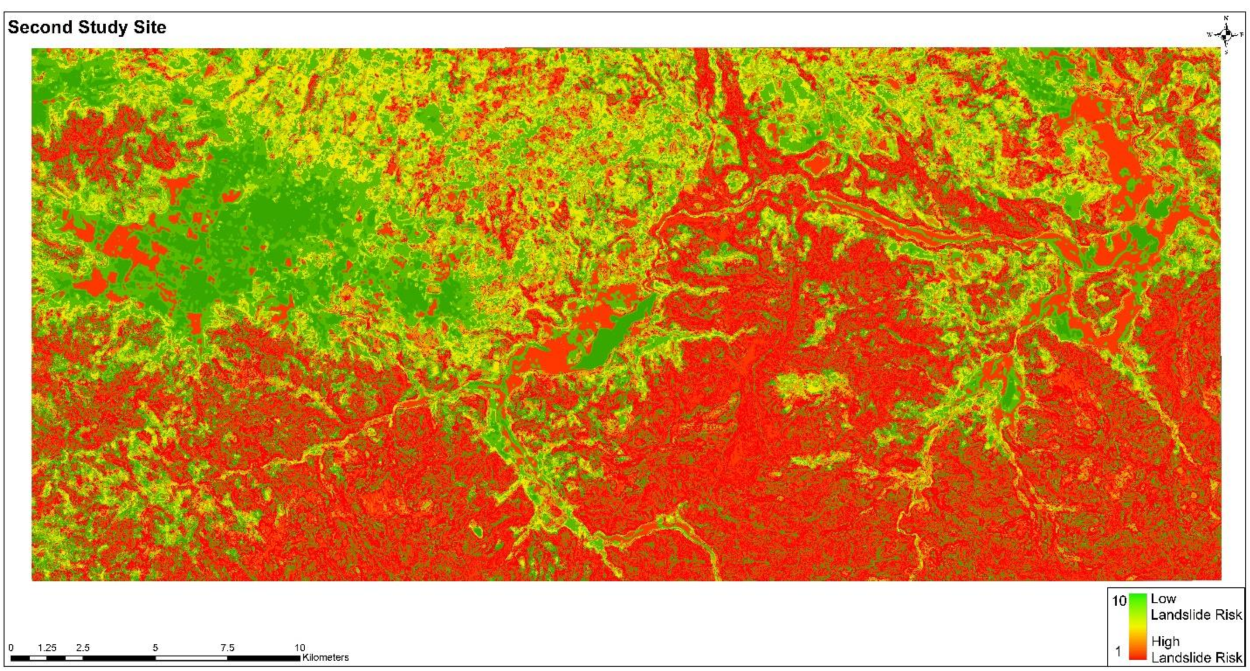


Figure 13. Image showing the results from the secondary study site.

The results found (Figure 12.) can also confirmed with the FR values. Not only are there strong relationships with the high-risk levels, but there are also negative relationships with the low risk levels. Though it is not a perfect measure of the quality of the results, it seems able to be skewed when there is a significantly small number of pixels that fall within that specific risk level. This can be seen within the results of medium site test 5 FR value for risk level 7 where only 17 pixels (0.004%) of the landslide areas and 17,737 (0.001%) produces a FR value of 2.65, the second highest of the test. When each of the tests and site size are assessed with the FR values, 87% (n=26) of the tests had the highest frequencies within the high-risk levels. Therefore, showing that the tests produced results that were clustering the high-risk locations together.

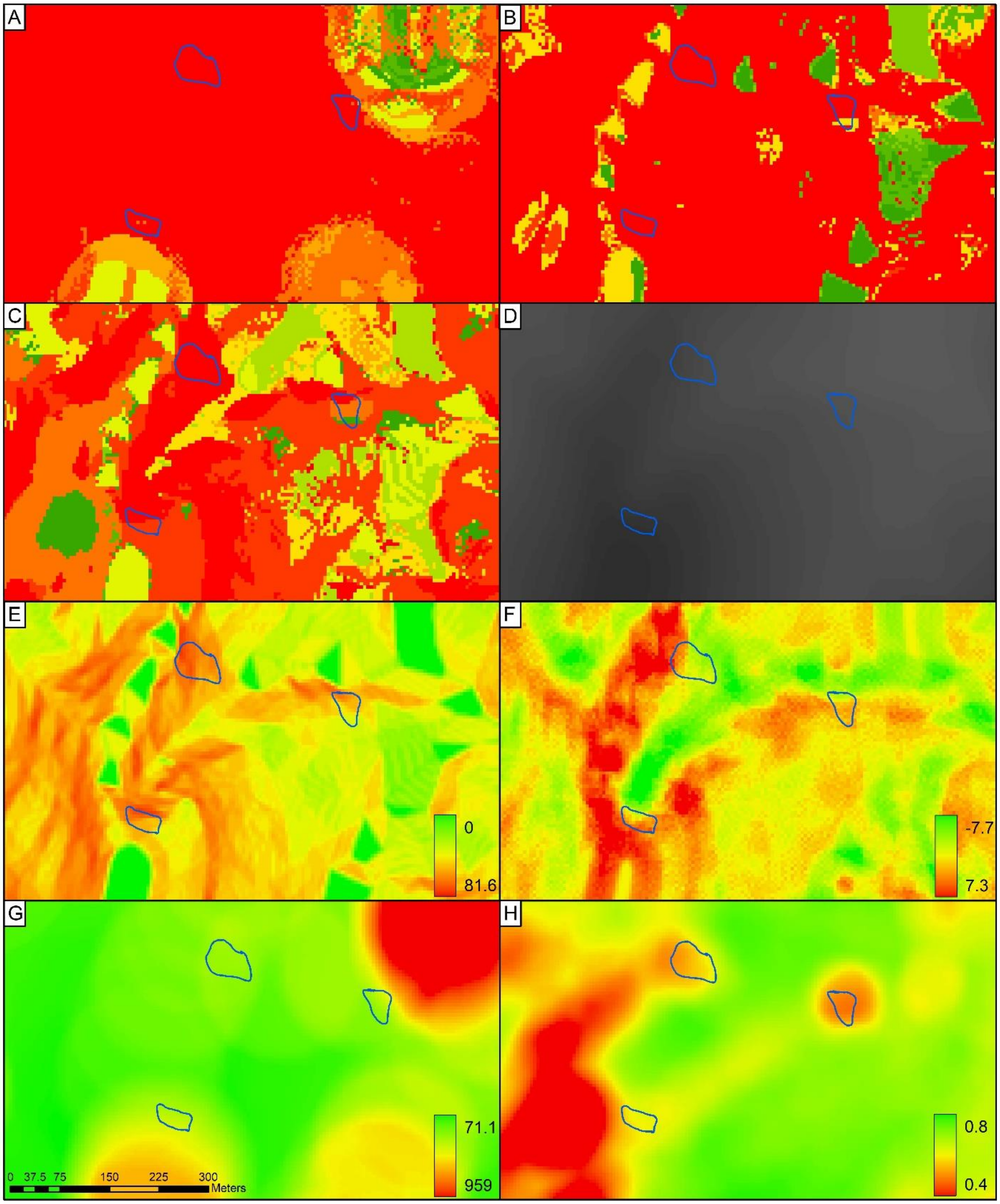
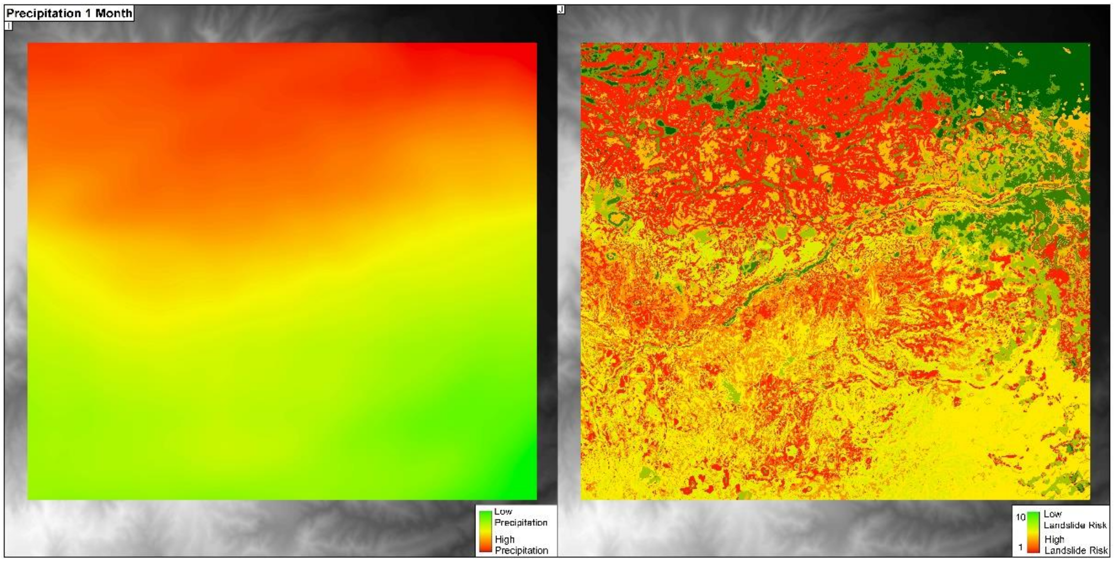


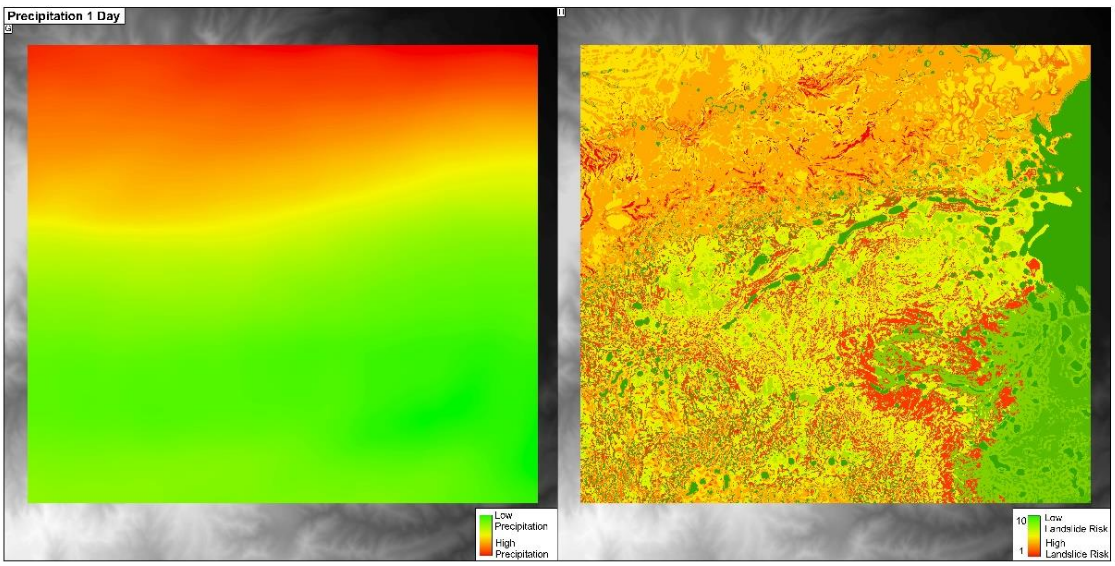
Figure 14. Image showing a close up of three landslide locations, the results from each scale level and variables use for run 3. A.) Full Site Run 3 B.) Medium Site Run 3 C.) Small Site Run 3 D.) Local Elevation E.) Slope F.) Curvature G.) TWI H.) NDVI

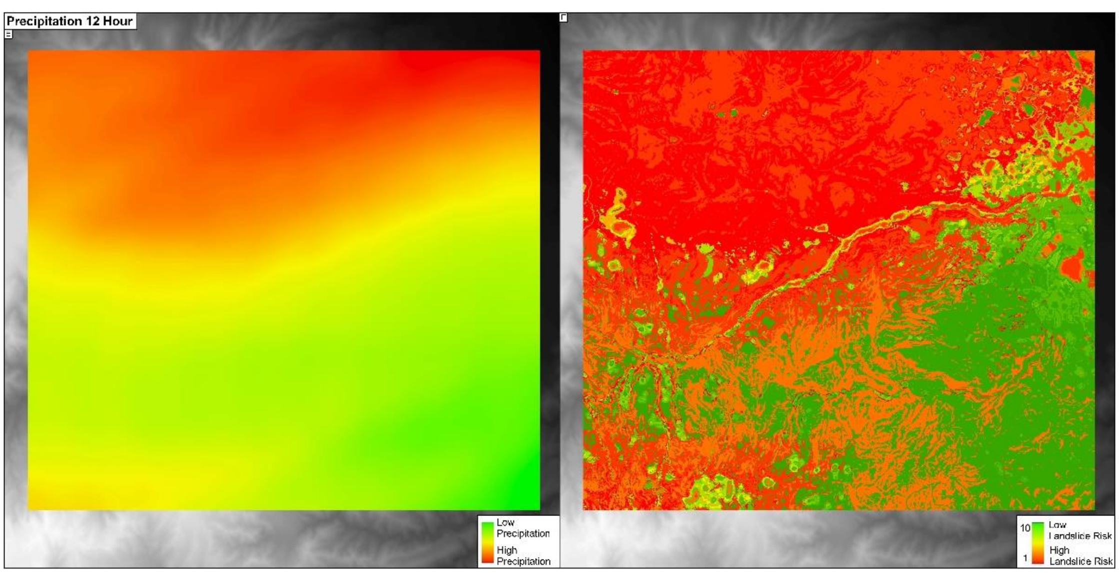
In Figure (14), shows the differences of each result done on run three, showing three landslides that fall within all three areas. Within this figure it is shown the differences that are present between each of the areas while each used the same variables and SOM settings. As expected, the full site is more generalized and grouping more area together under a single risk value, and more detail is found within the two smaller areas. The variables used for run three are also shown, based on these images, it is more clear where the SOM was grouping together in order to form the risk levels. The TWI in this area shows that it is the combination of variables that causes the clusters and not a single one, as here if there was an increased influence by the TWI there may be a lower risk level here. However, due to the combination of the variables, such as the higher slope and curvature, the higher risk is found.

6.1 Precipitation Tests

With the susceptibility tests completed, a baseline of results and, the optimal variables found, the model can be tested with precipitation data. There are five tests that were run, to show how the model could perform at different time scales, 1 month, 1 day, 12 hours, 6 hours and, 1 hour. These were chosen to represent the different time scales that would be used in conjunction with the multi scale prediction. The small sized site can use 1-6 hour, medium 12 hours to 1 day and the full site at scales over 1 day. All tests are done on the medium scale site in order to better determine the differences between the time scales and have consistent testing. The day of September 28th was chosen to use for the test because of the number of hours of precipitation that occurred within the previous 72 hours, giving the test period enough hours to have variations between each of the time scales tested. With the exception of the 1 hour test, each of the results show a negative correlation between the risk level and total precipitation within each of the landslide areas: 1 month with $r^2 = 0.33$, 1 day $r^2 = 0.24$, 12 hours $r^2 = 0.36$, 6 hours $r^2 = 0.38$ and, 1 hour $r^2 = 0.0006$. Figure 13 shows how the SOM is picking up on the areas of increase amounts of precipitation and then therefore be assigned higher risk, they also


Precipitation 1 Month
Low
Precipitation
High
Precipitation
10
Low
Landslide Risk
1
High
Landslide Risk


Precipitation 1 Day
Low
Precipitation
High
Precipitation
10
Low
Landslide Risk
1
High
Landslide Risk


Precipitation 12 Hour
Low
Precipitation
High
Precipitation
10
Low
Landslide Risk
1
High
Landslide Risk

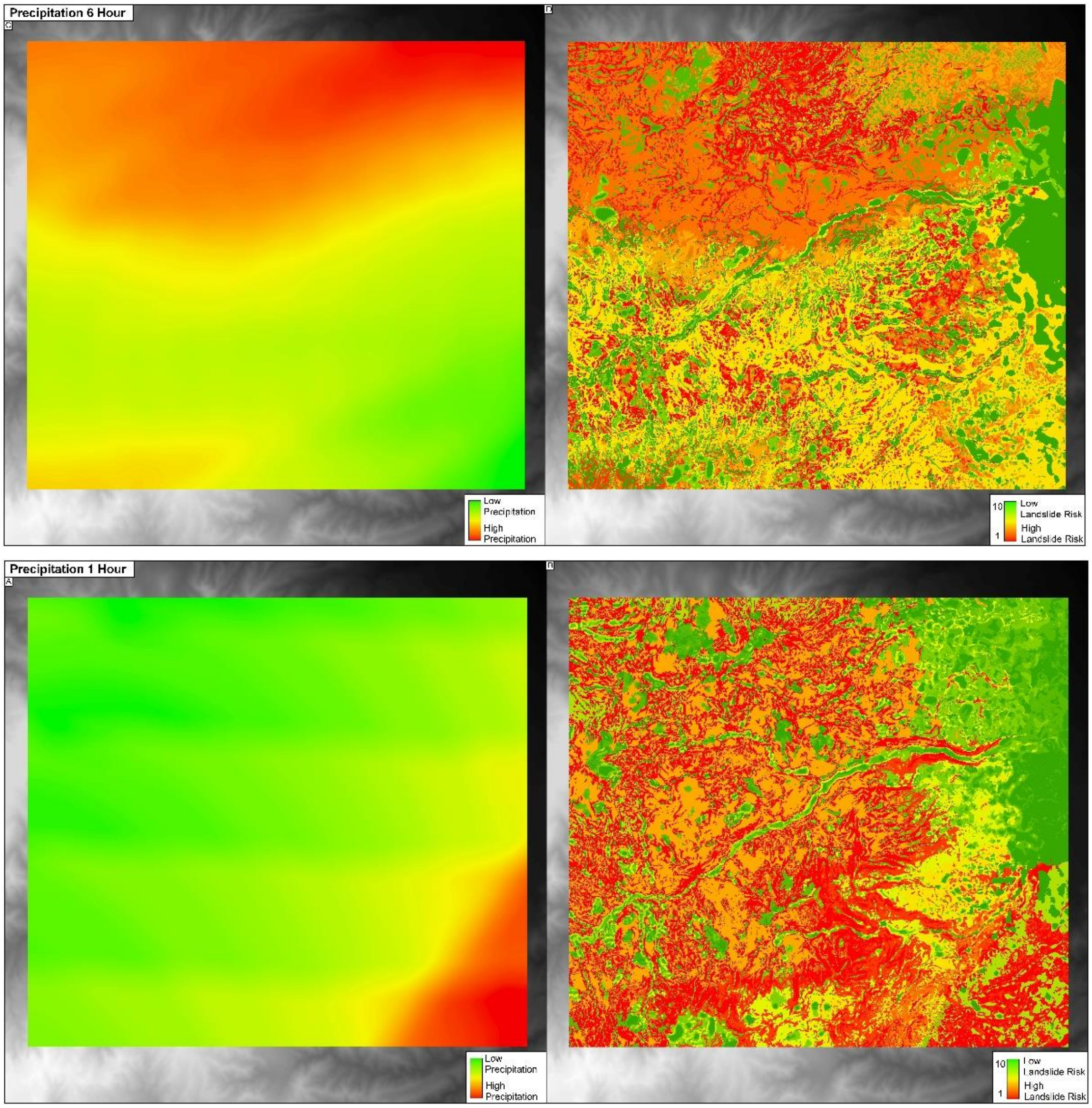


Figure 15. Images of each of the precipitation tests, showing precipitation amount and results for 1 month, 1 day, 12 hour, 6 hour and 1 hour.

show how it is not only the precipitations amounts that are being accounted for. The areas that fall within the locations with the least amount of precipitation can also have areas that are higher risk, based on the topography which would be high risk without the introduction of precipitation to the system. These results show that with changing weather conditions the SOM method can adapt and cluster the input data based on not only the static topography but also more dynamic weather conditions. The result for the 1-hour test and the comparison to the other test can show a number of observations. The first being that the SOM, as found with previous tests, performs better with more varied data, this means that if the amount of precipitation that occurs over the study site within an hour is relatively consistent then there will be little difference in the results as there are no specific areas that have increased amounts to pick up on. Though it is likely that more variation will be present within an hour when using live radar images. Furthermore, when accounting for more than a single hour there is an increased likelihood that the amount of variation will increase as seen in the results that account for more than a single hour.

6.2 Landslide Type Tests

Unfortunately, the results for the tests that were focused on specific conditions for a landslide type did not produce meaningful results that could predict where a specific landslide type is likely to occur. One issue that arose was the ability to assign risk to the clusters that were made. The data sets that were created focus on a specific landslide type, eliminating areas where that landslide is highly unlikely to occur, for example areas where slope is below where a specific movement type would occur at. Therefore, depending on the movement type, this can remove a significant portion of the full site data set. This resulted in having a reduced area that can be assessed and assigned risk levels, increasing the difficulty in assigning the risk. This caused the method that is used to assign risk when the full data set to not be viable. Another method was attempted by using the cluster that is most represented in the landslide areas, those that fall within that specific range, and assign the risk levels by the cluster that is most represented within those landslide areas. Either method created issues in verification of the results, seemingly unable to develop a method that can eliminate biases and be able to compare to multiple results. These test where also found to be redundant with other tests done within this study. When using precipitation data within the model and depending on the time scale that is used, landslide type is already being assessed. When using the month or longer time scale this helps assign risk to deep slower moving slides, where the amount of precipitation over long periods is an important determining factor. The same situation arises with fast shallow sides with 1 to 6-hour precipitation and fast deep slides with 12-to-24-hour precipitation. Although not limiting the data to the locations that a specific landslide is likely to occur, accounting for the conditions that will likely cause those slides to develop will result in the same desired results.

7. Discussion

The foundation of this study is based on the idea that landslides are more likely to occur under similar conditions to where landslides have previously occurred. Therefore, if those conditions can be determined and found elsewhere a risk value can then be assigned to those areas. As there are many variables and conditions that can contribute to where and when a landslide can occur, determining these relationships for a given area is difficult. Though it is unlikely that a model can out preform an expert's knowledge on a small specific site, using high resolution data (5m), a model can be created to apply that expert knowledge persistently over a large area using current conditions, which an expert would be unable to assess on such a large scale and short time frame.

The SOM method has shown that it can take the more important factors in landslide occurrence over a given location and cluster them together based on the likelihood of a landslide occurring. In other terms, it is identifying the locations within the study site that would have the lowest Factor of Safety values, it does this by graphing the input variables and grouping them based on the similarities found that would lower the safety and therefore, the stability of the slopes. For example, areas of no slope compared to areas of high slopes, steeper slopes would be likely to have lower stability with more landslides, and the low slopes are stable and without landslides. Therefore, it can find the conditions where previous landslides occurred and group those areas together and then the user is able to assign risk. The results show that the model performs better with larger datasets when the tests are run using the same SOM settings. The large and medium sized sites tended to have a larger difference between the full scale and landslide means, while also having the lowest risk average of the three scales (Figure 16 and Figure 17). The location of the small-scale site may be the reasoning for there being a lower risk average, though this does not mean that the average risk level for the landslides should be lower. This would mean that the model preformed worst on this scale, as it would be expected that the landslide average would produce higher risk values no matter where the site is located. While it is possible that different settings (SOM size, neighborhood size, learning rate, variables used, etc.) or a different location could produce better results, that is not what was found in this study. This may also be a result of less variance within the data of the smaller site, a smaller variance may result in the model finding it increasingly difficult to find the clusters when the variances are reduced.

One of the goals of this study was to use more variables than previous studies have used to create a model that could potentially produce more detailed results. The results show that the model

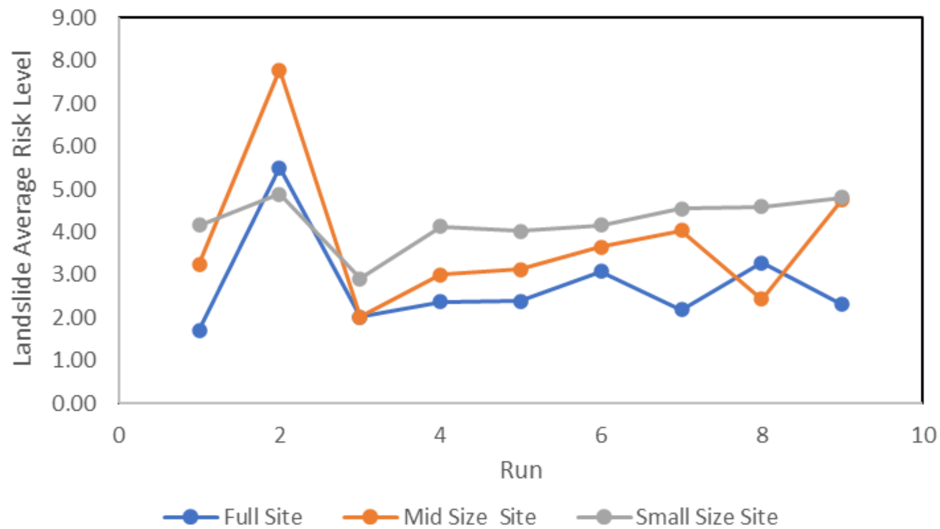


Figure 16. Chart showing the difference of site mean risk value and landslide mean risk value.

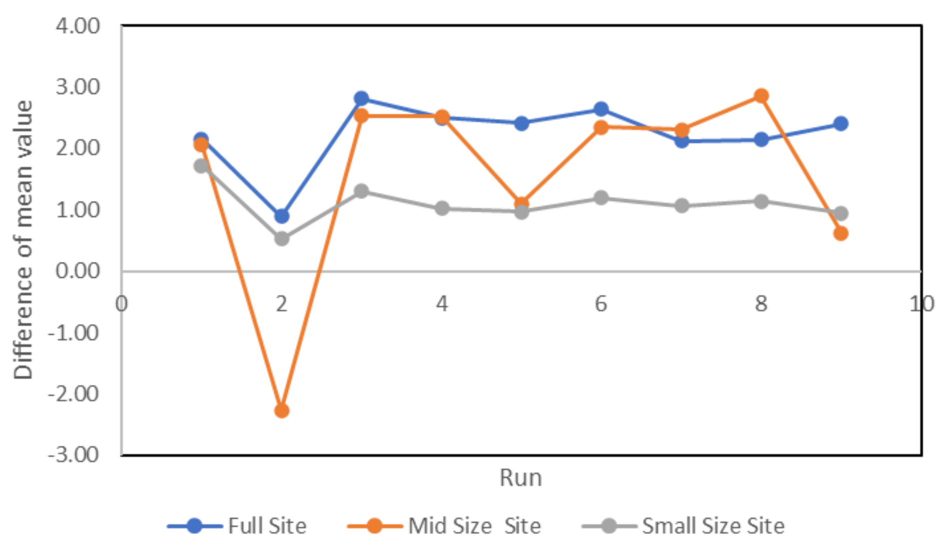


Figure 17. Chart showing the average landslide risk values for each run on each site.

can still produce positive results with a larger number of variables, even though the optimal test only used four. While these were not the expected results, this is not a negative nor does it prove the model ineffective. The model showed that with any number of variables it can produce positive results, which by any standard is a positive outcome. It should be noted, as with all the results produced, that it is possible that there can be better results produced with this method but was not found within the time frame of this study.

The precipitation results show a correlation between higher risk and higher precipitation was found. As discussed in the methods, when using precipitation data in conjunction with static variables, this creates a situation that makes it highly unlikely that there will be a significantly strong correlation (0.7 or higher). Though the higher precipitation is likely to cause landslides there are also locations that will be high risk based on topography without the introduction of water to the system. Therefore, there will likely always be landslides or high-risk areas where landslides are likely to occur even with that area having the lowest amount of precipitation of within the study site. Because of this, the results that were found show that the SOM method can adapt to changing precipitation amounts and is able to group the areas that are high risk based on those levels. The results may vary if the model was run with live radar images, especially if the resolution of the images is significantly larger than the 5m resolution that is used in this study. As long as the radar images are detailed, and the natural variations are maintained in the images then the SOM method will be able to produce positive and possibly better results than what was found in this study.

7.1 Program Versatility and Ease of Use

The methods used in this study are not revolutionary, SOM have been used in previous landslide susceptibility studies but the way in which SOM is used and implemented here, is what makes this study effective and unique (Chou et al., 2007; Friedel, 2011; Ahmed & Forte, 2016; Huang et al., 2017; Lin et al., 2017; Shaygan & Mokarram, 2017). By reducing some of the issues that are common in machine learning such as overfitting, underfitting and, biases, and the advantages mentioned below, SOM can be a simple and effective method for landslide prediction that is worth further investigation.

One of the strengths that became quickly apparent when using the SOM was the easy of use. Once the initial setup was complete, the program could handle data varying number of inputs and dimensions. This versatility allows the program to be used in any way that a specific location requires, ranging from different number of inputs, scale of inputs or number of variables available. The intrinsic adaptability of an SOM along with the program designed to be used by experts that do not have a substantial background in computer science or programming makes this optimal method to be used in locations that lack any landslide warning system. With minor changes to the parameters in the program, it will be able to produce results with any number of variables and inputs. Though it is important to note, the quality of the data is still important to the results. Using data that is at a scale much larger than the size of a landslide may be good for larger area susceptibility mapping may not be appropriate for producing more detailed prediction results. It is nearly impossible to determine how other methods may have performed using similar techniques and data, it is reasonable to say that for many of the methods may have difficultly adapting to the changing scales and implementation of live radar images. As many of those methods rely on a training method that requires the data to always be consistent to produce results, the addition of radar images that will tend to be highly varied from one another may provide significant challenges for these methods to replicate.

This study uses a second site as an example of how it can be applied to another site with different data and characteristics. Using the same settings and variables this method was able to take data that it was not developed around and was able to produce significant results. This strength comes from the SOM grouping data that is similar and not based on any supervised inputs but rather the patterns within the data. This versatility also extends to includes landslide type and type of variables. The results also show the possibility of changing the focus of the program, using a single SOM used over multiple sites and another focusing on a single area or landslide type. Therefore, can also be used in a way that best suits the needs of a specific location.

The multi scale method is intended to not only cover sites based on risk levels and processing time but also landslide types by using different time scales. Certain types of movements occur under different conditions, these conditions can then be used to assess the risk of those types of movements. Larger deep-seated slides are more likely to occur with higher precipitation levels over longer durations, as can be seen in the results for the one month. As with the shallow fast movements, which are caused by high precipitation levels over shorter durations, which can be represented by the shorter time scales in the one hour and six-hour tests. Though this may not assess the movements found in the inventory, this is a method which can be used to assess future movement events.

It is difficult to compare the results found with this study to other machine learning methods without implementing each on the same site and data, especially since the method used in this study (multi-scale, live radar images, etc.) has not been implemented in similar studies. Though the lack of consensus across landslide researchers about which, or if, machine learning method is the best when it comes to landslide assessment. There have been a number of studies done that have compared multiple methods to one another on the same location and there has not be a consistent best performing method determined. These studies have found different methods to be the best performing or the results show little difference between the methods (Brenning, 2005; Yilmaz, 2008; ; Yilmaz, 2009; Choi et al., 2011; Pradhan, 2012; Korup & Stolle, 2014; Goetz et al., 2015; Pham et al., 2016; Nguyen et al., 2019). This could potentially mean that there is not a single best method, and the importance falls to what method works good for a given location or a method that the expert can implement effectively.

7.2 Selecting SOM Parameters

The size of the SOMs that were used are significantly smaller than was recommended by the creator of the MiniSOM library. When setting the SOM size, a balance needed to be found between the number of inputs and processing time. The MiniSOM program suggested using 5 x √N as a rule to set the SOM size. This would require 7,056 nodes or a map of 84 by 84 would be required for an area of 2 million inputs. When this rule was first put into practice, it became clear that with the number of inputs (N) that are being used that the processing time would be too great to have any meaningful use with real time data. One example, an area of 274 km^2 has about 10,500,000 input points, by the rule it should require an SOM of 16,129 nodes or a map size of 127 by 127. With a map that size it would be estimated to take between 48 and 72 hours, and for the purposes of this study a location this size would be expected to produce results every 24 hours when focusing on faster deeper slides. It was found that using a smaller SOM size can produce good results and remain well within processing time requirements. It was also found that the size of the SOM it not always the primary factor that leads to more detailed and better results rather the variables used are more important to producing better quality results. When the full site was run (~60,500,000 input points) using a 2025 node SOM compared to a 11,025 node SOM there was much more apparent detail along slopes rather than grouping large portions of slopes together. Whereas, when the 2025 node SOM was run on a smaller site (~10,000,000 input points) much of the variation present within the system can be seen in the results and little difference was found when compared to runs with the 11,025-map size. Though when run on even smaller locations (under 3,000,000) the input variables had a greater impact on the amount of detail found in the results. When run with 2,025 nodes and then with 7,744 nodes (5 x √N map size for the numbers of inputs) there was little difference between the two in terms results produced. These results show how depending on the size of the input data the results may be more sensitive to certain changes in data or SOM parameters.

7.3 Issues with Categorical Data and Highly Detailed Data

Any model that is developed is limited by the data that is used, data may not be available or the data that is, has low resolution. Limited number of variables may decrease accuracy and effectiveness and a low resolution will lack necessary detail and information in the results. The study site was chosen because of the data available, with a large number of variables and at a high resolution. One of the aims of the study was to implement as many of these variables into the model as possible, with the goal of producing a production program that uses more landslide effecting factors than a majority of current methods. It became clear in early testing that the variables that can be classified as categorical decreases the performance of the SOM, especially data that has hard line distinctions between each value/category. One example is soil, when implementing soil into the SOM it needs to be categorized, as mentioned in the methods section. With hard divisions the SOM seems to pick up on these add divide the results into each of the soil categories that are within the study site. Because of this any variable that needed to categorized is not included the model. Although there may be different parameters for the SOM that can produce usable results with these variables, they were not found within the timeframe of the study. The model seemed to work much better with datasets that were more variable and highly detailed, such examples would be slope, TWI and, curvature. These variables tended to provide better results and classify more similar landscape features together which is what is important for the viability of the program. It may be more appropriate to implement the categorical variables with proper characteristic values and or properties, one example being have soil shear strength values determined from field testing for each soil type, though this would require much more field work and on-site evaluation.

7.4 Using Expert Knowledge

One advantage of this program is how it implements expert knowledge. The knowledge of an expert that has worked and studied a site for years will know that site better than the results any model can produce. However, an expert cannot assess a large study site on consistent basis, this is where the model is used. Using the expert knowledge about the relationships between landslides and the variables a model can be made to assess the potential risk of a movement occurring based on current conditions, which an expert can not do on that scale or timeframe. Many machine learning methods rely on the program and the variables that can impact the likelihood of landslides without extensive input from experts, these systems take the inputs and output the susceptibility without the user. Where this SOM method can continuously have that expert input throughout the process. The program is currently designed to have an expert needed to assign the risk level to each of the cluster outputs, this way there is oversight and expert knowledge always being utilized throughout the process and in the results. This is important to keep the program consistent and functioning correctly, though there is opportunity for the program to have more automation applied with new data input and timed executions. With an expert having overview and assessment of how well the model is performing allows for each of the risk levels/clusters to be analyzed with each new result output, the longer the program is in place the more tuned and accurate it can become for that location.

7.5 Consistency

One thing that became apparent early in testing was that although the SOM can produce significant results, it is difficult for a SOM to reproduce the same and consistent results. When an untrained SOM is run, the results will group data of similar characteristics, but when the same SOM is initialized again, and due to the randomized nature of the SOM training, the results will have the same similar characteristics clustered, but the results will not be a pixel for pixel match. This is also the case when using subset of the full study site, the full site and the subset can be run using the same trained SOM but the clusters produced will be similar but will not be a complete match. The number of inputs and the different ranges of values for each variable are the likely causes of this lack of consistency. Although each have slightly different clusters the main characteristics are still clustered together and can produce significant results, but it cannot be expected that there will be identical groupings between the two different areas. Thus far, the only method in which to have exact results be reproducible is to have a trained SOM run on the same set of input data. It was also found that using the built-in training and import of a trained SOM the MiniSOM has showed little difference between results that were self trained. The training was done using 30% of random selection from the full site. The lack of a difference may be due to the settings used and there may be a way to better utilized the trained SOM but are still able to produce results without any previous training necessary.

7.6 Error

It is important to note that without being able to go into the field to verify the results found there may be error within the results that are unable to be corrected for. To properly assess the quality of the model it is necessary to do in field study, such as going to landslide sites, determining if the conditions are the same as the data used and then finding areas without a landslide and assessing the risk level found within the model to those conditions found. Without any in field information or verification on the conditions, the model works on the assumption that the data is correct and matches what would be found in the field. If there are inconsistencies found, the results would likely be incorrect and therefore, the model and/or the data would need to be adjusted to best represent the real world for the most accurate results. There may also be more landslides that are within the study sites that would increase the number of landslides to test the results against. The only true way to verify the results is to be in the field mapping these landslides right after they occur and comparing to the model, unfortunately due to current circumstances this is not possible.

Another source of error that may be present is the location differences between the different datasets. Many of the datasets used are taken from different sources, though through the GIS software used these are matched as best as possible there still presents the possibility of some layers being offset of one another. This becomes an issue when testing the results with the landslide inventory. If the landslides are not correctly located then it will change the results in either positive or negative ways. The same issue can arise with any dataset used that is not derived from on another such as all features extracted from the original DEM used. Until such a time where these results can be field verified there may be error present within the model and results.

The images that were used to build the landslide inventory can also be a source of error, especially in cases when assessing the landslide distribution with respect to the categorical variables. Though it would be important to account for the variations of the soil types, vegetation types and the underlying geology that is within the study site, any assessment made would likely be skewed and incorrect, due to the images used to build the landslide inventory. The imagery that is present within the study site is inconsistent, with the centre of the site largely having older images from 2016 and the remaining area having more recent images. With some areas having older images it is likely that there have been landslides that have occurred since those images were taken in mid 2016. Areas in which have more recent images are likely to have more landslides identified and therefore, skew that assessment towards those more recent image locations. This would likely not be representative of the direct associations between landslides, soil type, vegetation type and, geology. Though NDVI can still be used within the program and results, the program is not identifying specific vegetation types but rather the amount of vegetation across the site. Geology, as well as soil types, were also variables that were required to be categorical and therefore, could not be used for the tests.

7.7 Model Impact in Costa Rica

This research aims to bridge the gap between regional and local methods by using real time and detailed data to prediction potential landslides both spatially and temporally. An SOM machine learning method using a large number of variables (or a specific combination of variables) will potentially give the most complete and robust machine learning approach to date. With landslides being a major natural hazard in Costa Rica and with an increasing population that are unknowingly putting themselves at risk, there needs to be a system in place that can reduce the risk. This study has provided a method for landslide risk assessment that can be used in Costa Rica. When compared to the landslide risk maps that are created by the Costa Rican government which assigns risk by province with little information. The model used in this study can be used on a consistent basis to provide information to the population of Costa Rica. Not only providing information for land use planning but having that information provided directly to the population. Having a consistent source of risk assessment which is in place over a long period of time can inform the government and people of Costa Rica on where the highest risk areas are and potentially make decisions based on reducing the hazard. However, it is completely up to the people and government of Costa Rica to choose what is done with this information and how it is used. This research can only provide information, results and evidence for the results, it is up to people to chose how it is used.

7.8 Assessing Past and Future Movements

Once a movement has occurred the condition that are found in that location have changed, either increasing or decreasing the Factor of Safety in those locations. Therefore, for the model to account for previous movement occurrences this would need to be represented in the data used. Depending on the movement and the conditions of which it occurred in will have an impact on if another movement is likely to occur in the same location. If there is a movement that has caused an increase in slope angle up slope there is an increased chance of another movement occurring. However, if a movement has reduced slope angle or has removed all material down to the source material another movement is unlikely to occur. There are two factors that would be required for the model to account for these changes. First, the data would need to be at a resolution that can account for changing conditions, a resolution too low either no changes will be made or only the very large movements are accounted for. A high resolution (<1m) will be able to account for small changes in the environment, but it would be likely that the site size is decreases and the processing time it greatly increased. Second, would require data to be updated on a regular basis, without new data the new information will not be accounted for, though, the issue of how often new data is required would need to be determined. In the model's current form, if was run using high resolution data on current conditions, the effects of a previous movement would need to be broken down by the impacts on the variables used. Using the variables from run 3 as an example, if there is a decrease in slope angle or a flattening of slope shape will decrease the risk assigned to those areas. However, there will likely be a decrease in vegetation which may increase the risk levels. Although these changes could potentially change the results and how the model assigned risk to those areas, this would only be an important factor if there is the resources to consistently update and re survey the study sites.

Although, this model can work under current conditions there maybe changes that are necessary in the future due to changes in climate due to climate change. Variations in both temperature and precipitation levels are likely to alter the environment. These variations will change the vegetation patterns currently found, possibly increasing the landslide risk to some areas or increase vegetation amounts in areas increasing slope stability. An increase of precipitation levels can cause more landslides in Costa Rica, a location that is already dominated by precipitation triggered movements. These changes in the climate and environment would need to be reflected in the model for it to keep identifying the areas with the lowest Factor of safety.

8. Conclusion

The results of this study has shown that the SOM method can be used to predict landslides in Costa Rica. The SOM machine learning method has shown that it can be an effective in predicting landslides, being able to assess the factors that influence landslide occurrence as well as using radar images to use up to date precipitation data in landslide prediction. SOM benefit from not having some of the limitations of other machine learning methods and has used more variables than what is commonly found in most landslide studies. Costa Rica, with an increasing population that are unknowingly putting themselves at risk, would benefit from a system such as what was found in this study, that can reduce the risk from landslides. With the amount of mountainous terrain there is a limited number of roadways accessing large portions of the country, landslides can cover and damage these roads. Knowing where and when a landslide is likely to occur can help government officials to either evacuate communities or put in place mitigation measures to reduce and lower the loss and risk. Landslide risk assessments are often susceptibility maps determined with a few limited variables, this tells managers and local officials' where landslides are likely to occur over large areas but little about when and what conditions are likely to cause a landslide. Alternatively, local prediction methods that are focused on single slopes and measuring movement of the slope and infiltrations rates to produce warnings. These prediction methods are restricted by the limited area assessed and by high costs to implement. The methods used in this study combine the benefits from both methods using SOM machine learning to produce a model that can be used in any location and conditions.

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