Scientia Agropecuaria

Web page: http://revistas.unitru.edu.pe/index.php/scientiaagrop

Facultad de Ciencias Agropecuarias

Universidad Nacional de Trujillo

RESEARCH ARTICLE

Influence of high Andean grasslands on landslide reduction in Peru

Alberto Franco Cerna-Cueva[1,*]; Katherin Lourdes Uriarte-Barraza[1]; Grecia Isabel Lobatón-Tarazona[1]; Wensty Saenz-Corrales[1]; Casiano Aguirre-Escalante[2]; Peter Coaguila-Rodriguez[2]; Manuel Reategui-Inga[3]

[1] Escuela Profesional de Ingeniería Ambiental, Universidad Nacional Agraria de la Selva, 10131, Perú.
[2] Escuela Profesional de Ingeniería en Recursos Naturales Renovables, Universidad Nacional Agraria de la Selva, 10131, Perú.
[3] Escuela Profesional de Ingeniería Ambiental, Universidad Nacional Intercultural de la Selva Central Juan Santos Atahualpa, Chanchamayo 12855, Perú.

* Corresponding author: alberto.cerna@unas.edu.pe (A. F. Cerna-Cueva).

Received: 17 August 2023. Accepted: 18 May 2024. Published: 8 June 2024.

Abstract
Agricultural and urban expansion has caused considerable degradation of ecosystems. In the case of Peruvian high Andean grasslands, it was reported that between 2000 and 2009, this ecosystem was reduced by 7%. The limited or no protection they receive is partly due to the fact that the benefits of ecosystem services are not widely known. This research aims to establish and predict the influence of high Andean grasslands on the annual occurrence of landslides. To do so, we identified occurrences of landslides, falls, huaycos, avalanches, and alluviums in high Andean grasslands. We also examined urban areas and agricultural zones of Peru for the period from 2003 to 2016. Subsequently, we extracted data on precipitation, temperature, slopes, soil types, and geographical variables. This data was used to train a machine learning model. The results show that 96% of landslides occurred in human-intervened areas, and only 4% in high Andean grasslands. Precipitation and slope thresholds for landslide occurrence are higher in high Andean grasslands compared to agricultural and urban areas. The best-performing machine learning models were linear regression, Gaussian processes, random forest, and support vector machine. They had coefficients of determination of R^2 = 0.80, 0.80, 0.66, and 0.64, respectively. Predictions show that if agricultural or urban areas are established in wet or dry puna grasslands, the average number of occurrences multiplies. The multiplier factors are 2.1 and 7.08, the number of deaths by 2.8 and 10.49, the number of houses destroyed by 2.4 and 7.51, and the number of roads destroyed by 2.2 and 7.37, respectively. The study demonstrates that conserving high Andean grasslands significantly reduces landslides compared to urban or agricultural areas.

Keywords: High Andean grasslands, landslide; machine learning; ecosystem services; climate change.

DOI: https://doi.org/10.17268/sci.agropecu.2024.025

Cite this article:
Cerna-Cueva, A. F., Uriarte-Barraza, K. L., Lobatón-Tarazona, G. I., Saenz-Corrales, W., Aguirre-Escalante, C., Coaguila-Rodriguez, P., & Reategui-Inga, M. (2024). Influence of high Andean grasslands on landslide reduction in Peru. *Scientia Agropecuaria*, *15*(2), 333-348.

1. Introduction
High Andean grasslands provide essential ecosystem services, from water regulation and supply to biodiversity conservation. They function as natural reservoirs, ensuring a consistent supply of water for agricultural, domestic, and industrial use (Mosquera et al., 2023). Their rich biodiversity includes endemic species, highlighting their importance for conservation (Mills et al., 2023; Ríos-Touma et al., 2023). As carbon sumps, they are important in climate change mitigation, sequestering CO_2 (Alavi-Murillo et al., 2022). However, they face threats from agricultural and urban expansion, with a notable reduction of wet puna grasslands by up to 7% between 2000 and 2009 (Madrigal-Martínez et al., 2019; Zari et al., 2019).
Two types of grassland-dominated ecosystems have been identified in Peru: grasslands located in the wet puna and grasslands located in the dry puna. The dry puna grassland is a high Andean ecosystem with herbaceous vegetation that can occupy flat or undulating terrain, or hills with soft to moderate slopes. The soil has a sandy loam texture with low organic matter content, with a soil cover of less than 35%, and a maximum height generally not exceeding 1.5 meters. The climate in the dry puna grasslands is highly seasonal and is classified as subhumid according to the Holdridge bioclimatic classification. It is characterized by high temperatures and low precipitation during most of the year. The seasonality is pronounced, with a very intense dry season, especially in the south and west of the ecosystem, reflecting conditions typical of a subhumid climate where humidity fluctuations are significant and define the predominant herbaceous vegetation of the area. The vegetation is mainly composed of low grasses and grasslands with strong xeromorphic cacti with stiff, hard, sharp leaves. There

are also scattered resinous shrubs, along with saxicolous plants on rocky outcrops (usually with shrubs) and canllares (*Margyricarpus* sp. formations). The stands of Puya Raimondi form a remarkable community in these grasslands. The grasslands located in the dry puna cover an area of approximately 3.78% (4,887,186.88 ha) of the national territory, in the departments of Ayacucho, Apurímac, Arequipa, Cusco, Puno, Moquegua, and Tacna (MINAM, 2019b). The other type of high Andean grasslands are the grasslands located in the wet puna. They are characterized by herbaceous plants, mostly low grasses and herbs that grow in scattered clumps and have hard stems and leaves. There are also some scattered clumps of shrubs and saxicolous plants on rocky outcrops. According to the Holdridge bioclimatic classification, the climate of the wet puna grasslands is humid to super-humid, as shown in Figure 1. This zone is characterized by more constant humidity and higher rainfall than the dry puna. It can occupy flat, undulating, or hilly terrain with gentle to moderate slopes. It has a coverage of 35-50%, and its height does not usually exceed one and a half meters. Puya Raimondi stands also form a dominant community in this type of grassland. These grasslands cover an area of approximately 9.26% (11,981,914.03 ha) of the national territory, distributed in the departments of La Libertad, Ancash, Lima, Junín, Pasco, Huancavelica, and Ayacucho (MINAM, 2019b).

The reduction of high Andean grasslands leads to the loss of ecosystem services such as water regulation in the upper parts of the watersheds by capturing rainwater and water from the environment, passing through the filtration process, and subsequently supplying the lower parts of the watersheds. Some studies have shown that high Andean grassland ecosystems can provide better water quality in watersheds; in a study comparing two Peruvian micro-watersheds, Gocta and Chinata, it was found that the largest water supply is located in Gocta, as it has a larger area of high Andean grassland that fulfills the function of capturing and releasing water to the drainage network of the micro-watershed, while the Chinata micro-watershed, which has a minimal area of high Andean grassland in the upper parts, provided less quantity and quality of water (Oliva et al., 2017). Another ecosystem service of high Andean grasslands is the reduction of surface runoff and soil erosion; there is a direct relationship between the proper management of these ecosystems and soil conservation (Vega-Chuquirimay & Torres-Zuñiga, 2013).

Puna grasslands are unique ecosystems that develop in the high Andean regions of Peru. Currently, these ecosystems have been severely reduced due to agricultural and urban expansion (Zari et al., 2019). According to Madrigal-Martínez et al. (2019), the grasslands located in the wet puna were reduced by 7% between 2000 and 2009. In Peru, it has been reported that high Andean grasslands are widely used as a forage source for cattle, camelids, sheep and vicuñas (Cossios-Meza, 2018). Livestock activity can have a double impact on the degradation status of high Andean grasslands. Overgrazing, especially in communal areas, can reduce land productivity. However, well-managed livestock and pastoral practices can also improve ecosystem services (Monge-Salazar et al., 2022). Projections for the year 2100 in the central Andes indicate that rising temperature indices, shrinking glaciers, and expansion of agricultural areas will lead to a change in the surface area of grasslands, and their projection indicates that the extent of grasslands could be reduced by up to 70% (Flores, 2016).

One of the little-studied ecosystem services of high Andean grasslands is the potential for landslide reduction. Studies in similar ecosystems have shown that high Andean grasslands and ecosystems have a significant influence on landslide reduction (Bonnesoeur et al., 2019a; Molina et al., 2019; Tasser et al., 2003). However, the number of studies on landslide prediction in these areas is very small or non-existent.

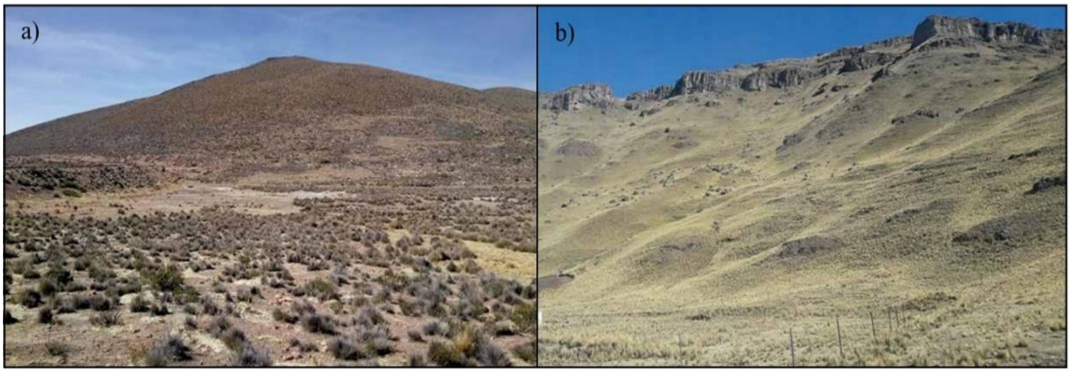

Figure 1. Identification of Peruvian high Andean grasslands: a) dry puna grassland and b) wet Puna grassland. Source MINAM (2019).

One of the main obstacles for landslide prediction is that traditional physical modeling is very complex because there are many variables and complex interactions that trigger landslides; however, other modeling approaches, such as machine learning, are more suitable for these analyses. Landslide prediction models can be divided into two groups: numerical models and data-driven models. Compared to numerical models, data-driven models tend to be more popular due to their perceived simplicity, often more accurate prediction, and lower cost. Data-driven models, especially machine learning techniques have been widely used to "learn" the relationship between landslide occurrence and landslide-related factors (Adnan et al., 2020; Al-Najjar & Pradhan, 2021; Arabameri et al., 2022; Bui et al., 2019; Chang et al., 2023; Gupta & Shukla, 2023; Hassangavyar et al., 2022; Huang et al., 2020; Kainthura & Sharma, 2022; Kuradusenge et al., 2020; Liu et al., 2021; Merghadi et al., 2018; Pham et al., 2018, 2019, 2022; Saha et al., 2023; Sun, Chen, et al., 2023; Sun, Gu, et al., 2023; Tien Bui et al., 2019; Zhang, Fu, et al., 2022; Zhang, Li, et al., 2022; Zhou et al., 2018).

Machine learning is used as a descriptive tool in ecosystem services research, where the automation aspect enables rapid production of large amounts of complex data and predictive modeling. The variety of ways in which it is incorporated into ecosystem services research methodologies highlights its value as an adaptable extension to traditional data analysis across domains (Scowen et al., 2021).

For the above reasons, in this research we want to analyze the scenarios of land cover change from high Andean grasslands to urban or agricultural soils and how these changes can contribute to the increase of annual landslides, so the following question is posed: How does land cover change from high Andean grasslands to agricultural or urban soils increase the annual occurrences of landslides? The hypothesis put forward in this study is that land cover change from high Andean grassland to agricultural or urban land at least doubles annual landslide occurrences.

2. Methodology

2.1. Location

The research was conducted in Peru, located in the central and western regions of South America. The areas of analysis are the high Andean ecosystems of wet puna and dry puna grasslands in the country. For contrasting the influence of these ecosystems on landslides, the agricultural and urban areas of the country were analyzed, as shown in Figure 2. This information was taken from the map of ecosystems in Peru (Table 1).

2.2. Descriptive analysis of factors related to mass movement in high Andean grasslands

The following sections explain the origin and characteristics of the data to be used. Although the data have different spatial and temporal resolutions, the idea is to use the greatest possible temporal extent of each type of data. By cross-referencing the dates of the data types, a database is obtained that is as broad as possible in terms of the factors that cause landslides (precipitation, temperatures, slopes, cover~~,~~ and soil type) and landslides per year.

Precipitation and temperatures

In Peru, there is a historical gridded database of precipitation and temperatures known as the PISCO product (Aybar et al., 2019). The daily precipitation database corresponds to version 2.1, while the daily temperature database (maximum and minimum) is from version 1.1. Both products are available from January 1981 to December 2016 and have a spatial resolution of 0.1 degree (∼ 10 km). These databases are available from the links in Table 1. Precipitation data were extracted for the entire extent of the grasslands, including wet and dry puna grasslands, and a comparative whisker plot was created to assess the variation of precipitation in both grasslands.

Slopes

The digital elevation model was obtained from the Shuttle Radar Topography Mission (SRTM v. 4.1) product (Table 1), which has a spatial resolution of 90 m. Using ArcGIS 10.7 software and this digital elevation model, the slopes in the wet Puna and dry Puna grasslands were identified. Then, a boxplot was used to make a visual comparison of the slope distribution in both ecosystems.

Soil Type

The 8 km resolution soil type map was obtained from FAO-UNESCO. The map was taken from South America Volume IV, whose gridded data were published in 2006. The predominant soil types present in both ecosystems were analyzed. To compare these soil types, a heat map was created with the information on soil and ecosystem type. This heat map allows for the identification of patterns, such as the concentration of certain soil types in specific areas, and how these relate to the ecological characteristics of each ecosystem.

2.3. Descriptive analysis of mass movements

Data on mass movements were taken from the Peruvian National Institute of Civil Defense

(INDECI), from the link shown in Table 1, selecting only emergencies related to mass movements such as landslides, falls, huaycos, avalanches/ floods. The geospatial information complementary to the aforementioned database was extracted from the National Information System for Response and Rehabilitation (SINPAD) of INDECI. The geographic location and dates of landslide occurrence allowed for the extraction of specific spatial and temporal information for each landslide occurrence.

Table 1
Data source

Data	Web link
Rainfall	http://iridl.ldeo.columbia.edu/SOURCES/.SENAMHI/.HSR/.PISCO/index.html?Set-Language=es
Landslides	https://www.datosabiertos.gob.pe/dataset/emergencias-hist%C3%B3ricas-registradas-con-sinpad
DEM	http://srtm.csi.cgiar.org/
Peru's Ecosystems map	https://geoservidor.minam.gob.pe/wp-content/uploads/2019/01/MAPA-NACIONAL-DE-ECOSISTEMAS.zip

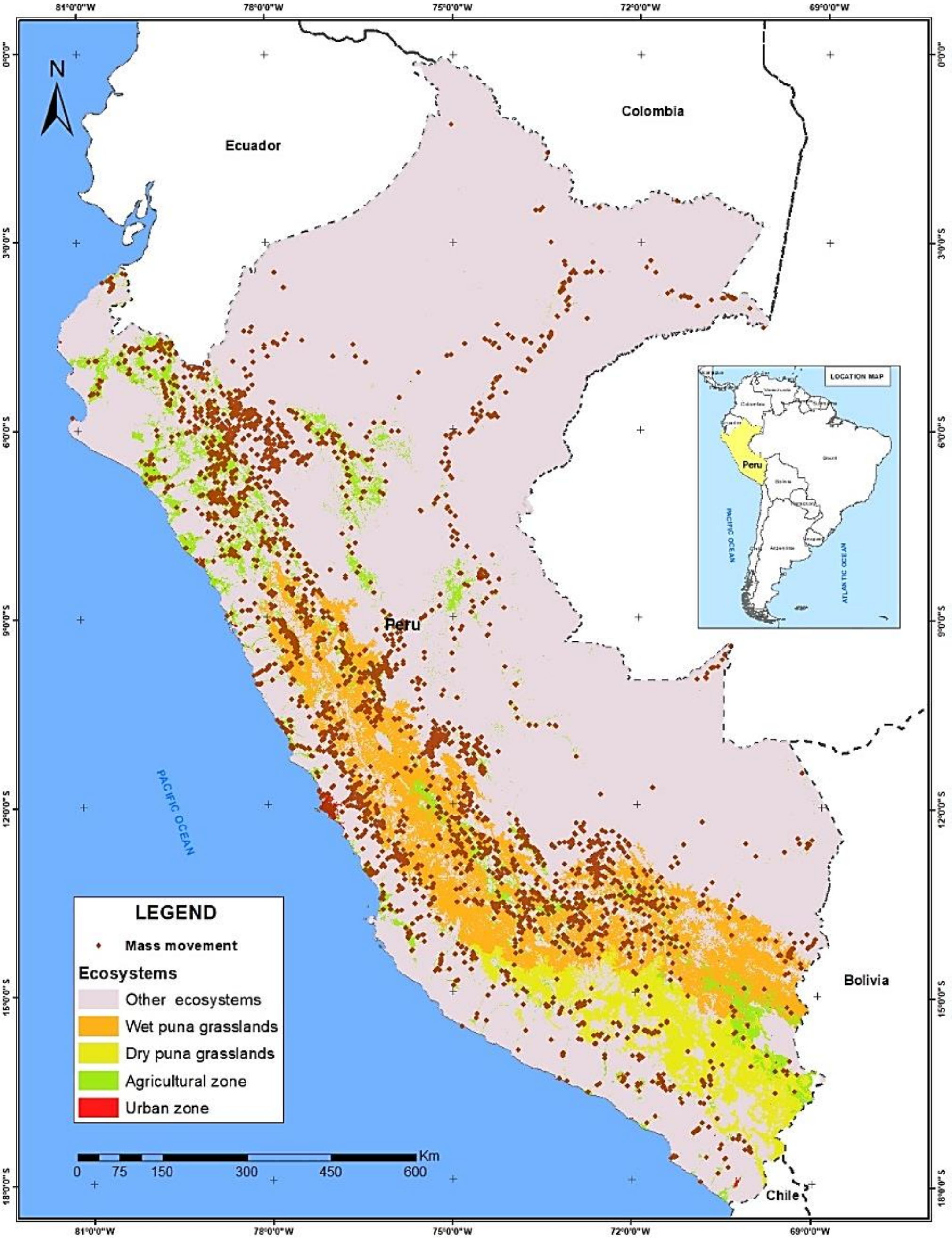

Figure 2. Location of the study area and mass movements in the ecosystems of analysis for the period 2003-2016.

Comparison of mass movements for the period 2003-2016

The annual landslide occurrences for the period 2003 - 2016 were compared by identifying the number of occurrences for each study ecosystem (high Andean grasslands, agricultural areas, and urban areas). The historical annual averages and percentage contribution of landslide occurrences for each ecosystem and/or land use were identified.

Analysis of precipitation and landslide slopes

Previously, climatic and soil type information was analyzed for the entire extent of the grasslands. In this section, the precipitation and slope characteristics of each landslide event are analyzed in order to compare precipitation and slope thresholds for landslide occurrence.

Summary of major landslide damage

Using the INDECI database, the main destruction rates of the different types of landslides (landslides, landslides, mudslides, avalanches/alluvium) were determined.

2.4. Data selection, training, and validation of the mass movement predictive model

Data selection

Landslides are influenced by land use (Chen & Huang, 2013; Chen et al., 2019; Glade, 2003; Karsli et al., 2009; Meneses et al., 2019; Reichenbach et al., 2014; Van Beek & Van Asch, 2004), climatic factors (Borgatti & Soldati, 2018; Khan et al., 2021; Klose et al., 2017; Ma et al., 2020a; Pánek, 2019; Patton et al., 2019; Peres & Cancelliere, 2018; Wood et al., 2020; Zhou et al., 2018), soil type (Cerri et al., 2017; Marin & Velásquez, 2020; Strauch et al., 2018; Wang et al., 2020; Yu et al., 2021; Zhuo et al., 2019), slopes (Marc et al., 2018; Nguyen et al., 2017), and others (Forte et al., 2019; Mind'je et al., 2020; Palladino et al., 2018; Xu et al., 2018).

Based on the above, the variables of precipitation, temperature, evapotranspiration, altitude, slope, latitude and longitude, soil type, and land use (high Andean grassland, agricultural zone, and urban zone) were considered. For the application of the machine learning models, the aforementioned data were first preprocessed and selected. Climatic data from up to 5 days before the emergency occurred were considered because it is believed that these climatic variables can affect the hydrological cycle and the amount of water in the soil at the time of the landslide (Naidu et al., 2018). The result of considering all the variables mentioned above added up to a total of 128 independent numerical variables. This number of variables is impractical for training the machine learning model, so principal component analysis (PCA) was applied, which is a common technique to reduce the dimensionality of the model (Basu et al., 2022; Tang et al., 2020; Zhu et al., 2022). For the present study, a variance threshold of 95% was used. For the application of PCA, Z-score data standardization was previously performed.

Training, validation and prediction

Machine learning is a state-of-the-art analysis tool that has been widely used in landslide prevention (Ma et al., 2020b). Due to the complexity of topographic and geological conditions associated with landslide occurrence, more flexible nonlinear methods, such as machine learning algorithms, support vector machines (SVM), Gaussian processes (GP), random forests (RF), and linear regression (LR) are considered (Micheletti et al., 2013). In this research, once the variables were selected, different machine learning models were trained, and performance was evaluated using the coefficient of determination R^2. To generalize the model, cross-validation was used (Jiang & Wang, 2017). A group size of K=5 was selected for cross-validation, not only because it is an optimal balance between evaluation accuracy and computational burden, but also because K=5 is a widely accepted and default standard in many software environments. Predictions were made in order to identify the annual occurrence of landslides in high Andean grasslands under three different scenarios:

Scenario 1: Setting the average climate, slope, and soil type conditions of wet or dry puna grasslands, the annual number of landslides under vegetation cover or land use of wet or dry puna grasslands is predicted, respectively.

Scenario 2: Setting the average conditions of climate, slopes, and soil type of wet or dry puna grassland, the annual number of landslides under vegetation cover or agricultural land use is predicted.

Scenario 3: Setting the average conditions of climate, slopes, and soil type of wet or dry Puna grassland, the annual number of landslides under vegetation cover or urban land use is predicted.

The prediction scenarios were designed to evaluate the impact of different land uses on the annual occurrence of landslides in high Andean grasslands, as depicted in Figure 3. These scenarios reflect real situations of land use change and expansion in urban and agricultural areas. Given the trend of converting natural ecosystems to agricultural or urban uses, the scenarios seek to simulate average conditions. The relevance of these scenarios lies in their ability to provide prospective information on how land management practices and urban or agricultural expansion could influence landslide frequency, providing a basis for more effective prevention and mitigation strategies.

3. Results and discussion

3.1. Descriptive analysis of high Andean grasslands

In the wet puna grasslands in Peru, the mean annual precipitation recorded is 727.4 mm, with extreme events reaching up to 3062.6 mm, while in the dry puna grasslands, the annual mean is 513.2 mm with maximums up to 1156.3 mm (Figure 4). These data contrast with those recorded in the high Andean zone of Ecuador by Ochoa-Sánchez et al. (2018), where the mean annual precipitation is approximately 1300 mm, characterized by intra-annual uniformity with low seasonality and a marked presence of drizzle, which constitutes 30% of the total annual rainfall. This variability between these high Andean zones could be due to differences in latitudinal climate patterns, in addition to data collection methodologies, with Peruvian data being interpolated from real and satellite stations through SENAMHI's PISCO product, reflecting a more detailed integration of local variability. The implications of these precipitation patterns on landslide susceptibility are significant. In Peru, extreme variability in precipitation, especially in wet puna grasslands, could increase the risk of soil saturation and, consequently, landslide risk (Ochoa-Sánchez et al., 2018).

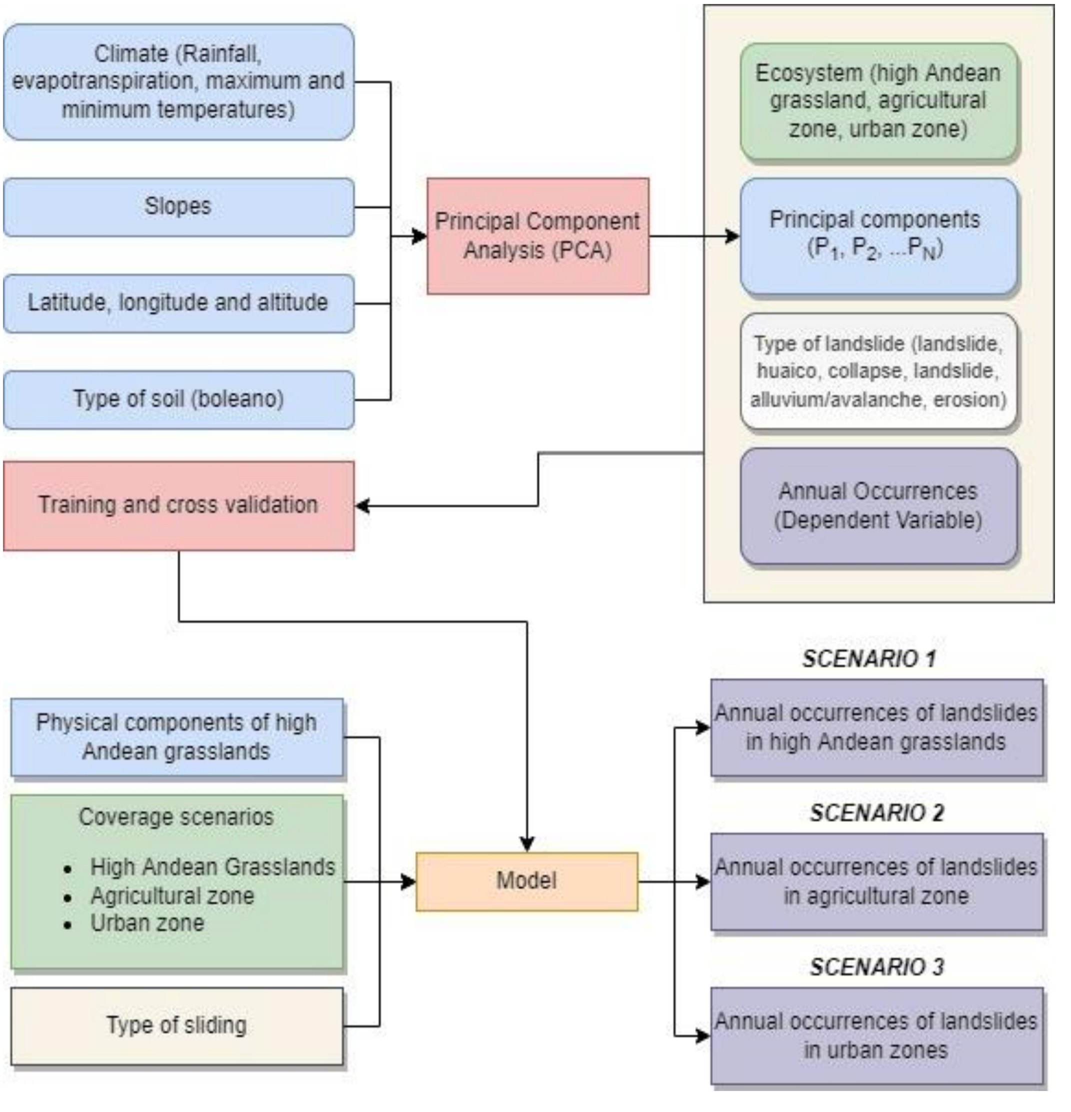

Figure 3. Schematic of the process of data selection, model training, validation and prediction of annual landslide occurrence under different scenarios of vegetation cover or land use.

In wet puna grasslands, the mean annual maximum temperature is 18.128 °C, with a range of 12.05 to 26.62 °C, and the mean annual minimum temperature is 3.27 °C, with a range of -4.18 to 15.18 °C. For dry puna grasslands, the mean annual maximum temperature is 17.13 °C, with a range of 13.16 to 26.19 °C, and the mean annual minimum temperature is 0.65 °C, with a range of -8.55 to 12.62 °C. The wide temperature fluctuations of the high Andean grasslands in both maximum and minimum temperatures can significantly influence landslides. Low temperatures reaching sub-zero values can cause freeze-thaw cycles of the soil, weakening its structure and increasing susceptibility to landslides, especially when combined with intense precipitation. On the other hand, high maximum temperatures can increase evaporation and reduce soil moisture, decreasing its cohesion and stability, which also favors the occurrence of landslides during rainfall events following dry periods (Perry et al., 2017).

Regarding the slopes, the average value in wet grasslands is 16.93°, with a slope range from 0 to 83.9°, while for dry puna grasslands, the average slope is 10.56°, with a range from 0° to 79.58°. The wide range of slopes in both ecosystems reflects the ruggedness of these areas, which favors the occurrence of landslides (Irigaray et al., 2000a).

Regarding the soil type, in wet puna grasslands, 33.05% Lithosols - Humid Cambisols - Vitric Andosols (I-Bh-Tv-c), 21.76% Lithosols - Luvic Phaeozems - Luvic Kastanozems (I-Hl-Kl-b), and 14.11% Lithosols - Humid Cambisols were found. For dry puna grasslands, the proportions were as follows: 57.6% Lithosols - Vitric Andosols and 33.69% Lithosols - Humid Cambisols - Vitric Andosols. These results highlight the diversity of soils in the high Andean grasslands, partly aligning with the study by Wilcox et al. (1988), which emphasizes the variability of soils due to factors such as topographic position and parent material. Both studies emphasize the significant presence of Vitric Andosols, implying the influence of volcanic material in the formation of soils.

The identified soils, especially the Vitric Andosols and Humid Cambisols, along with the native vegetation of the grasslands, play a decisive role in the stability of these areas. The Andosols, due to their porous structure and high permeability, favor water infiltration, reducing surface saturation that could trigger landslides. The grassland vegetation, adapted to these edaphic conditions, contributes to soil stability by retaining water and protecting against erosion. In contrast, areas with agricultural or urban use lack this natural regulation and retention capacity, increasing the risk of landslides (Wilcox et al., 1988).

The identified soils, especially the Vitric Andosols and Humid Cambisols, along with the native vegetation of the grasslands, play a decisive role in the stability of these areas. The Andosols, due to their porous structure and high permeability, favor water infiltration, reducing surface saturation that could trigger landslides. The grassland vegetation, adapted to these edaphic conditions, contributes to soil stability by retaining water and protecting against erosion. In contrast, areas with agricultural or urban use lack this natural regulation and retention capacity, increasing the risk of landslides (Wilcox et al., 1988).

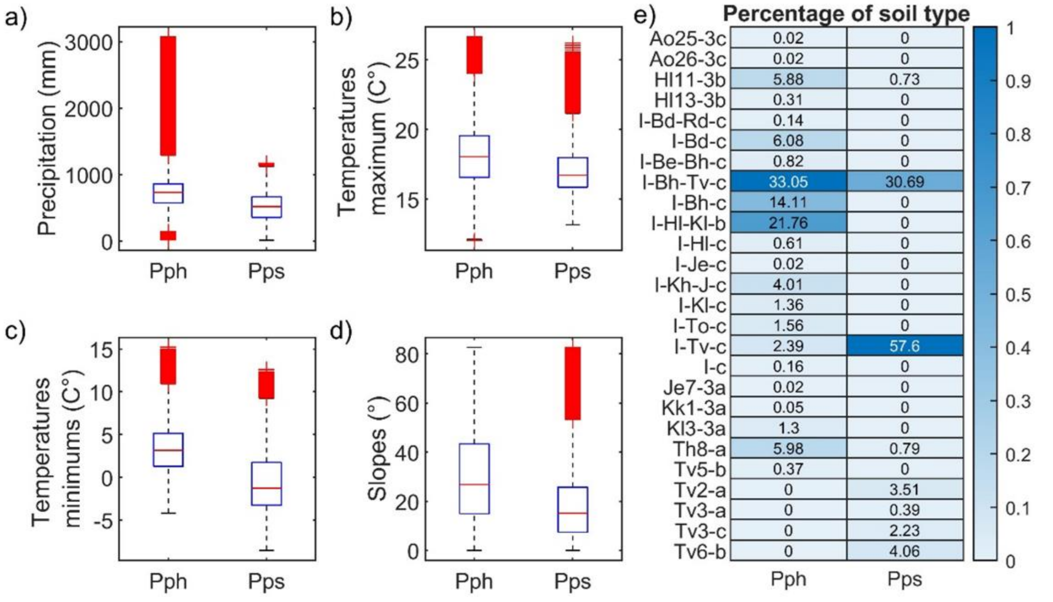

Figure 4. Comparative description of physical characteristics related to landslides in wet puna grasslands (Pph) and dry puna grasslands (Pps).

3.2. Descriptive analysis of mass movements

Comparison of mass movements for the period 2003 - 2016

As can be seen in Figure 5.a, during the analysis period 2003 - 2016, for Peru, the total annual average landslide occurrence is 175.36, the least number of landslides occurring in wet puna and dry puna grasslands, with an annual average of 8.35 and 1.21 respectively. These occurrences only represent 6% of the total, compared to other intervened ecosystems, such as agricultural and urban areas, where 94% of landslides occur. In areas intervened by humans where vegetation has been eliminated, the soil will be bare, predisposed to dry out and erode, leading to landslides later, since there will be greater surface runoff and soil instability. Added to this removal of vegetation cover is soil compaction due to the effects of grazing, the use of tractors for agriculture, urban growth, and road networks, all of which favor landslides (Bonnesoeur et al., 2019b; Persichillo et al., 2017). On the contrary, in the vegetation cover of ecosystems similar to the one in this study, such as moorlands, it has been shown that the presence of these ecosystems is crucial for retaining water, reducing surface runoff, and strengthening the soil, providing it with stability (Pinos-Morocho et al., 2021).

3.3. Analysis of precipitation and landslide slopes

The most critical factors that determine landslides are slope and precipitation, together with the vegetation cover of the ecosystem (Irigaray et al., 2000b). According to Figure 6a and 6b), the average precipitation and slope thresholds for landslides are higher in high Andean grasslands compared to urban and agricultural areas, i.e., higher precipitation and steeper slopes are required in high Andean grasslands for landslides to occur compared to agricultural and urban areas. On the other hand, precipitation thresholds for landslides are lower than those found in other studies, where precipitation thresholds for landslides are lower than those found in other studies (Dahal & Hasegawa, 2008; Posner & Georgakakos, 2015), where threshold precipitation amounts were 98 mm and 140 mm per day, compared to this study, where average precipitation amounts were less than 30 mm, these significantly lower amounts can be explained by the variety of climate in these geographic areas, but mainly by the limitations of the interpolated precipitation data from the PISCO product used in this study. The PISCO product does not capture maximum precipitation very well, especially in areas where there is a low density of weather stations, and the lower the density of weather stations, the greater the bias of the interpolated value, which would explain why the precipitation thresholds are lower values than those found in other studies. Although the PISCO product does not do a great job of showing the highest levels of precipitation, it does an excellent job of showing the differences and general trends in precipitation in different areas. This means that the difference in the average precipitation threshold for landslides in urban, agricultural, and high Andean grassland areas is a good reflection of reality (Aybar et al., 2020).

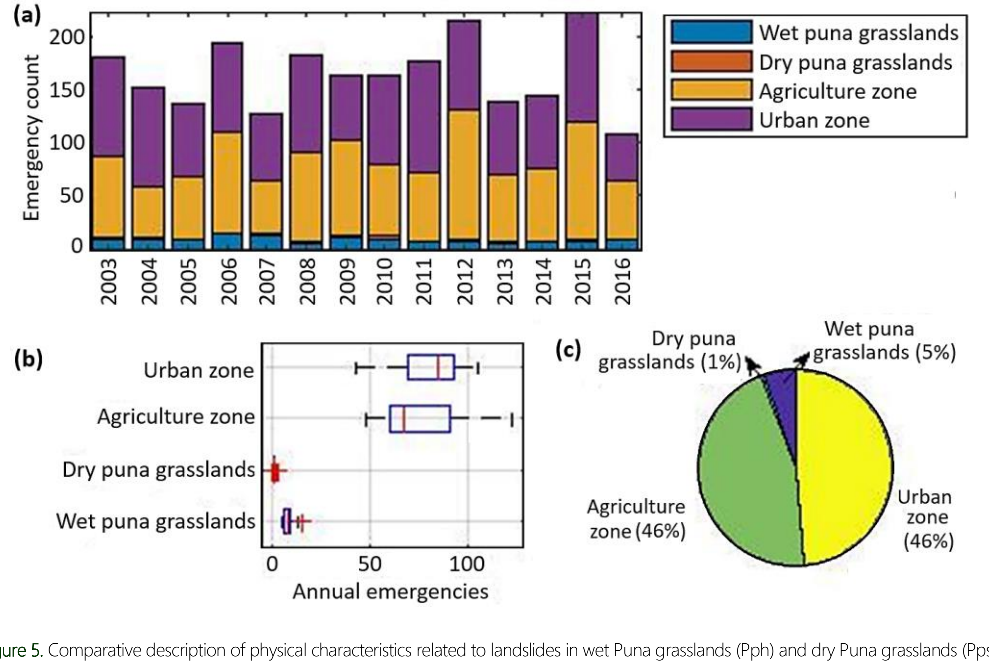

Figure 5. Comparative description of physical characteristics related to landslides in wet Puna grasslands (Pph) and dry Puna grasslands (Pps).

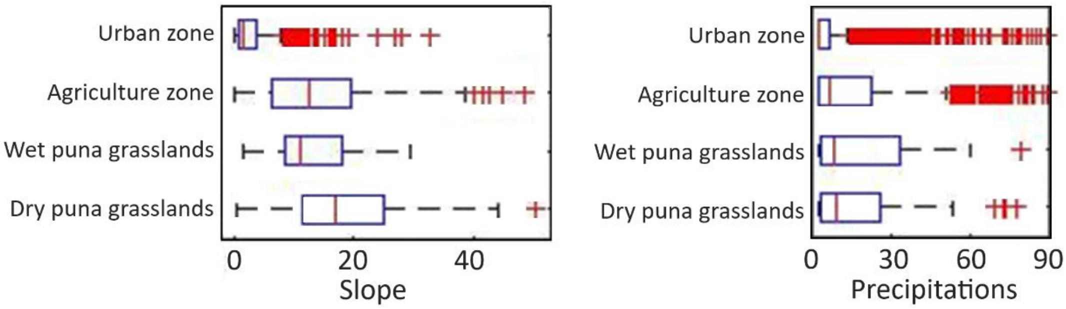

Figure 6. Comparative description of physical characteristics related to landslides in wet Puna grasslands (Pph) and dry Puna grasslands (Pps).

3.4. Summary of the main damage caused by landslides

In Peru, there are different types of landslides, each with its own rate of destruction and lethality. Alluviums occur when water accumulates in lagoons, dams, or reservoirs; when they overflow, they give rise to a violent current of water that quickly drags stones and mud. On the other hand, alluviums/ avalanches are the violent detachment of a large mass of glacier or snow, accompanied in some cases by rocky elements. Both types of landslides mentioned occur with great violence and unexpectedly, which is why these types of landslides present the highest lethality rates and destruction of houses and roads, according to Table 2. Falls are portions of earth, rocks, and vegetation that slide downhill. The main difference between these two types of landslides is that falls, besides occurring during the rainy season, can also occur after a strong earthquake due to the transit of heavy machinery, explosions, construction, and excavations. As we can see in Table 1, landslides are more destructive than falls, and this is because landslides are associated with the dragging of debris and earth flows by the action of water unleashed by events such as heavy rains. This type of landslide is more predictable than falls, as the latter are associated mainly with the rolling of rocks, which tend to be more predictable. The word "huayco" has its origin in the native languages of Peru and means ravine. The huayco is a mixture of mud and stones that advances, in most cases taking the beds of dry ravines, hence its name. As can be seen in Table 2, huaycos have a higher rate of destruction of houses than landslides and falls. This is explained by the fact that the houses are usually located near the banks of bodies of water, in some cases, so the degree of exposure of the houses is greater, while the rate of destruction of roads is lower than that of landslides since the latter occur not only near the riverbeds but throughout the entire area of influence.

Table 2
Average rate of fatalities destroyed houses and collapsed roads per 100 landslides

Landslides	Fatalities	Homes destroyed	Collapsed roads
Alluvium/avalanche	53	589	200
Falls	5	107	11
Landslide	12	198	141
Huaico	8	289	79

3.1. Data selection, training, validation, and limitations of the predictive mass movement model

Data Selection

The principal component analysis identified latitude, slope, and precipitation as key variables, accounting for 94.67% of the cumulative variance using PCA, as shown in Figure 7. Precipitation and slope are recognized as critical factors in landslide occurrence. These findings align with those reported by Kuradusenge et al. (2020a), who found contributions of 40.49% and 32.74% for precipitation and slope, respectively. Regarding slope, Al-Najjar & Pradhan (2021) assigned an importance value of 17.8% to this factor, making it one of the most significant parameters in landslide incidence. Similarly, Liu et al. (2021) found the importance of slope to be 29%, suggesting that it may have even greater relevance in specific contexts. The relationship between latitude and precipitation emerges as an intriguing aspect (Dai et al., 2007) that adds an additional dimension to the understanding of landslides. This association is generally not highlighted as highly significant in the literature, as seen in Bui et al. (2020), where elevation and slope are emphasized more than climatic factors, with values of 23.9% and 16%, respectively. These comparisons suggest that, while slope and precipitation are critical parameters for landslides, latitude may act as an indirect factor reflecting variations in precipitation and other climatic factors, which could be of interest for future research.

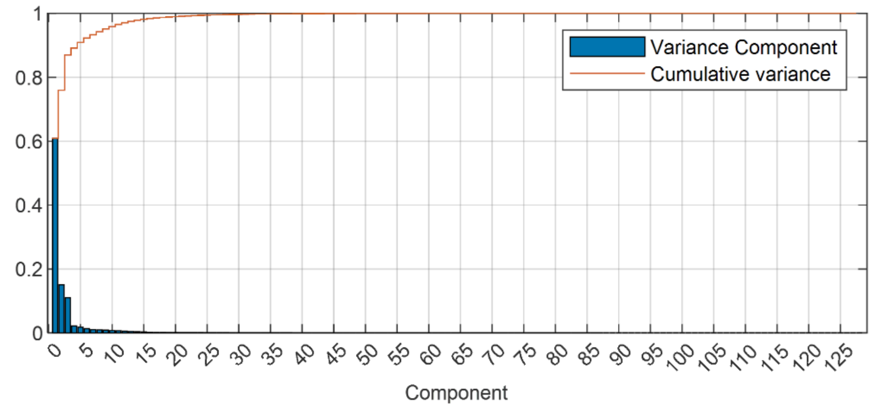

Figure 7. Comparative description of physical characteristics related to landslides in wet Puna grasslands (Pph) and dry Puna grasslands (Pps).

Training, validation and prediction

After selecting suitable data, various machine learning models were trained. Linear Regression and Gaussian Process models showed the best performances, with R^2 coefficients of 0.80 for both, as shown in Table 3. In contrast, Random Forest and Support Vector Machine models achieved R^2 values of 0.66 and 0.64, respectively. Although Random Forest and logistic regression models are commonly used to predict landslides, as seen in previous studies (Brenning, 2005; Goetz et al., 2015; Kuradusenge et al., 2020b; Pham et al., 2018b), these generally focus on binary prediction of landslide occurrence or absence. However, this study aims to quantify the annual frequency of landslides in four different ecosystems: urban areas, agricultural areas, and the high Andean grasslands of wet and dry puna. For this reason, regression models were chosen instead of classification models. An R^2 coefficient of 0.80, as found in this study, means that if the model encounters 100 real landslide events, it can accurately estimate approximately 80 of those events. Using the machine learning models in this study, critical precipitation, and slope thresholds for predicting landslides were determined, indicating that high Andean grasslands require more extreme conditions compared to urban and agricultural areas. Additionally, these models evaluate how urbanization and agricultural expansion influence landslide frequency.

In terms of predictions, changes in land use and their effect on the annual number of landslides were analyzed (Figure 8a and Figure 8b). Table 4 shows that if urban areas are established in wet puna grassland ecosystems, the number of alluviums/ avalanches, falls, landslides and huaycos would increase from 3 to 14, from 7 to 17, from 14 to 25, and from 13 to 24 occurrences per year, respectively, rising from a total of 37 occurrences per year to 79 occurrences. If agricultural areas are established in wet puna ecosystems, the number of alluviums/avalanches, falls, landslides and huaycos would increase from 3 to 14, from 7 to 17, from 14 to 25, and from 13 to 24 occurrences per year, respectively, increasing from a total of 37 occurrences per year to 80 occurrences. Regarding damages, considering the lethality and destruction indices of houses and roads in Table 2, and the predicted figures under the land use change scenarios, the average annual number of fatalities is expected to multiply by a factor of 2.8 and 2.82 (from 4.6 to 12.9 and from 4.6 to 13), the number of houses destroyed would multiply by a factor of 2.4 (from 89.8 to 215.2 and from 89.8 to 216.8), and the number of roads collapsed would multiply by a factor of 2.2 (from 37 to 82.7 and from 37 to 83.2) if urban and agricultural areas are established in wet puna grasslands, respectively.

Table 3
Performance metrics of machine learning models in predicting annual landslide occurrence

Model	R^2	RMSE
Linear regression	0.80	6.90
Gaussian processes	0.80	6.92
Random Forrest	0.66	9.04
Support Vector Machine	0.64	9.29

Figure 8b and Table 5 show that if urban areas are established in dry puna grassland ecosystems, the number of alluviums/avalanches, falls, landslides and huaycos would increase from 1 to 19, from 1 to 19, from 4 to 22, and from 7 to 25 occurrences per year, respectively, increasing from a total of 12 occurrences per year to 85 occurrences. If agricultural areas are established in dry puna grassland ecosystems, the number of landslides, falls, and mudflows would increase from 1 to 19, from 1 to 19, from 4 to 22, and from 7 to 25 occurrences per year, respectively, increasing from a total of 12 occurrences per year to 86 occurrences. Regarding damages, considering the lethality and destruction indices of houses and roads in Table 2, and the predicted figures under the land use change scenarios, the average annual number of fatalities is expected to multiply by a factor of 10.46 and 10.53 (from 1.5 to 15.7 and from 1.5 to 15.8), the number of houses destroyed would multiply by a factor of 7.48 and 7.55 (from 33.2 to 248.5 and from 33.2 to 250.8), and the number of roads collapsed would multiply by a factor of 7.33 and 7.40 (from 12.4 to 90.9 and from 12.4 to 91.7) if urban and agricultural areas are established in dry puna grasslands, respectively.

Model limitations

The PISCO product, used for precipitation and temperature, struggles to capture extreme precipitation events due to its spatial resolution of approximately 10 km. This may not adequately reflect significant local variations in precipitation, which are key variables for accurate landslide prediction. Additionally, data interpolation based on unevenly distributed stations introduces uncertainties, especially in less monitored areas.

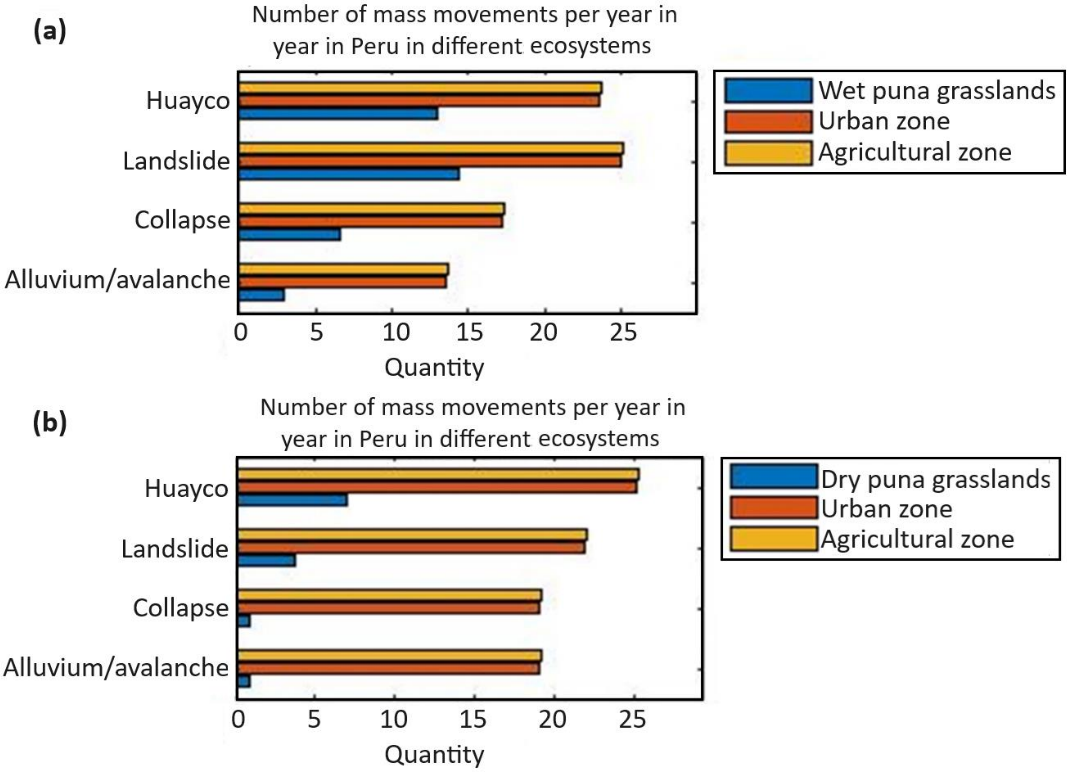

Figure 8. Comparative description of physical characteristics related to landslides in wet Puna grasslands (Pph) and dry Puna grasslands (Pps).

Table 4
Comparative prediction of landslide occurrence and damage when urban and agricultural areas are established in wet puna grasslands

Land use	Damages and losses	Alluvium / avalanches	Collapse	Landslide	Huayco	Total
Wet puna grassland	Occurrences1	3	7	14	13	37
	Fatalities2	1.5	0.3	1.7	1.0	4.6
	Homes destroyed3	17.1	7.0	28.5	37.3	89.8
	Roads collapsed4	5.8	0.7	20.3	10.2	37.0
Urban zone	Occurrences	14	17	25	24	79
	Fatalities	7.2	0.9	3.0	1.9	12.9
	Homes destroyed	79.5	18.3	49.5	67.9	215.2
	Roads collapsed	27.0	1.9	35.3	18.6	82.7
Aguircultural zone	Occurrences	14	17	25	24	80
	Fatalities	7.2	0.9	3.0	1.9	13.0
	Homes destroyed	80.1	18.5	49.7	68.5	216.8
	Roads collapsed	27.2	1.9	35.4	18.7	83.2

[1] Average number of landslides per year; [2] Average number of landslide fatalities per year; [3] Average number of houses destroyed by landslides per year; [4] Average number of roads collapsed due to landslides per year.

Table 5
Comparative prediction of landslide occurrence and damage when urban and agricultural zones are established in dry Puna grasslands

Land use	Damages and losses	Alluvium / avalanches	Falls	Landslide	Huayco	Total
Dry puna grassland	Occurrences[1]	1	1	4	7	12
	Fatalities[2]	0.4	0.0	0.4	0.6	1.5
	Homes destroyed[3]	4.7	1.0	7.3	20.2	33.2
	Roads collapsed[4]	1.6	0.1	5.2	5.5	12.4
Urban zone	Occurrences	19	19	22	25	85
	Fatalities	10.1	1.0	2.6	2.0	15.7
	Homes destroyed	111.9	20.4	43.4	72.8	248.5
	Roads collapsed	38.0	2.1	30.9	19.9	90.9
Aguircultural zone	Occurrences	19	19	22	25	86
	Fatalities	10.2	1.0	2.7	2.0	15.8
	Homes destroyed	113.1	20.5	43.8	73.4	250.8
	Roads collapsed	38.4	2.1	31.2	20.1	91.7

[1] Average number of landslides per year; [2] Average number of landslide fatalities per year; [3] Average number of houses destroyed by landslides per year; [4] Average number of roads collapsed due to landslides per year.

The quality and coverage of landslide data, obtained from INDECI and SINPAD, are limited to recorded and documented events, which could underestimate the actual frequency of landslides, especially in remote areas. Another significant limitation is the use of annual averages for variables such as precipitation and temperature. Landslides occur at specific times and under specific conditions that cannot be fully represented by annual averages. This approach averages the dynamic variables for a given location and sums the occurrences in that area, but it does not reflect daily or seasonal variability that could be critical for understanding and predicting specific landslides. Model accuracy may be limited in areas with sparse or unrepresentative data, such as remote areas without sufficient weather stations or landslide records, where it could underestimate risk.

Relevance for landslide risk management

The model developed to predict the annual occurrence of landslides in high Andean ecosystems is useful primarily for long-term planning and risk management. It can help local authorities and planners assess risks under established land use scenarios and formulate mitigation policies based on annual average conditions. However, the model is not suitable for immediate emergency response, as it is not designed to make real-time operational decisions during specific events. In Peru, technical-normative management instruments aim to guide and regulate the physical and spatial organization of human activities, such as Concerted Development Plans, Land Development Plans, and Urban Development Plans. These plans include the definition of risk and environmental conservation areas. This study provides a detailed method for identifying such areas. Additionally, it is important to note that the predictive models used in this study are more accurate in measuring potential hazards compared to CENEPRED's methods. While CENEPRED estimates risk using an approach that prioritizes hierarchical analysis and assumptions about potential damages, without directly linking hazardous events to actual damages, the models in this study achieve a direct connection between the hazardous phenomenon and the resulting damages.

Relevance for the conservation of high Andean grasslands

The study provides a detailed analysis of the relationship between high Andean grasslands and landslide occurrence, contributing directly to the objectives of Budget Program 0144: Conservation and Sustainable Use of Ecosystems for the Provision of Ecosystem Services. By identifying areas susceptible to landslides and analyzing the contributing factors, this study provides information that can be used in the preparation of specialized studies for ecosystem conservation, implementation of land-use planning processes, monitoring and supervision of ecosystem conservation, and oversight and enforcement of environmental legislation (MINAM, 2019a).

4. Conclusions

The average annual occurrence of landslides in the wet puna, dry puna, agricultural, and urban areas of Peru between 2003 and 2016 is 175.36, with 96% of these occurring in human-impacted areas (agricultural and urban zones), while only 4% occur in high Andean grasslands.

The precipitation and slope thresholds for landslide occurrence are higher in high Andean grasslands compared to agricultural and urban areas. The most destructive landslides are alluviums or avalanches, with mortality, housing destruction, and road collapse rates of 53, 589, and 200 per 100 events, respectively. Using principal component analysis with a 95% variance threshold, the dependent variables for predicting annual landslide occurrence were reduced to up to 6% of the original variables (from 128 to 8 principal components), with precipitation and slope being the variables most associated with the principal components. The best performing machine learning models for predicting annual landslide occurrence were Linear Regression, Gaussian Processes, Random Forest, and Support Vector Machine, with R^2 coefficients of 0.80, 0.80, 0.66, and 0.64, respectively.

Our results show that more landslides have been recorded in agricultural or urban areas than in puna grasslands, with a mean number of occurrences increased by a factor of 2.1 in wet puna and 7.08 in dry puna. This increase in landslide occurrence in agricultural or urban zones raised casualties by a factor of 2.8 in the wet puna region and 10.5 in the dry puna, the number of houses destroyed increased by a factor of 2.4 in the wet puna and 7.51 in the dry puna, and the number of roads destroyed increased by a factor of 2.2 in the wet puna region and 7.37 in the dry Puna. These results provide important insights into the potential benefits of conserving puna grasslands to mitigate risk, independent of other risk factors (slope, soil type, or climatic variability). However, these results heavily depend on the landslide occurrence database, which could be biased towards reporting more landslides in more accessible areas, such as locations near roads or urban areas (Sobrevilla, 2019). To confirm the benefits of conserving puna grasslands for risk reduction, future studies should investigate the causal links between land cover type and landslide occurrence.

It is recommended that future research extends the study to other ecosystems, analyzing similar ecosystems in different regions of the world to compare results and trends. It is also important to explore causal links, investigating the underlying mechanisms between land cover change and increased landslides. Additionally, developing more advanced predictive models and exploring more sophisticated machine learning models, such as deep neural networks, could improve the accuracy of predictions. Investigating daily or seasonal climatic variability is crucial to better understand landslide patterns in relation to extreme events. Using high-resolution data can help improve prediction accuracy and capture more significant local events.

In terms of policy formulation, the findings of this study are relevant for ecosystem conservation, land-use planning, disaster risk management, and the protection of life and property. The information provided can be used by decision-makers to develop mitigation and preparedness strategies, guide land use, and protect communities from natural disasters.

Acknowledgements

Alberto Cerna Cueva was funded by the "Premio Nacional Cultura del Agua 2021 - H2O Investigaciones" through a cooperation agreement between the National Water Authority of Peru (ANA) and Forest Trends Association of the Natural Infrastructure for Water Security (NIWS) project. This publication is made possible thanks to the generous support of the American people through the United States Agency for International Development (USAID) and the Government of Canada. The contents are the responsibility of the authors and do not necessarily reflect the views of USAID, the U.S. Government, or the Government of Canada. The authors thank Vivien Bonnesoeur for her helpful comments on the final manuscript.

ORCID

A. F. Cerna-Cueva https://orcid.org/0000-0001-7448-558X
K. L. Uriarte-Barraza https://orcid.org/0000-0001-7450-5528
G. I. Lobatón-Tarazona https://orcid.org/0000-0002-8567-0606
W. Saenz-Corrales https://orcid.org/0000-0001-8160-5033
C. Aguirre-Escalante https://orcid.org/0000-0003-0683-8675
P. Coaguila-Rodriguez https://orcid.org/0009-0002-2117-5240
M. Reategui-Inga https://orcid.org/0000-0002-5417-6509

References

Adnan, M. S. G., Rahman, M. S., Ahmed, N., Ahmed, B., Rabbi, Md. F., & Rahman, R. M. (2020). Improving Spatial Agreement in Machine Learning-Based Landslide Susceptibility Mapping. *Remote Sensing*, *12*(20). https://doi.org/10.3390/rs12203347

Alavi-Murillo, G., Diels, J., Gilles, J., & Willems, P. (2022). Soil organic carbon in Andean high-mountain ecosystems: importance, challenges, and opportunities for carbon sequestration. *Regional Environmental Change*, *22*(4), 128. https://doi.org/10.1007/s10113-022-01980-6

Al-Najjar, H. A. H., & Pradhan, B. (2021). Spatial landslide susceptibility assessment using machine learning techniques assisted by additional data created with generative adversarial networks. *Geoscience Frontiers*, *12*(2), 625–637. https://doi.org/10.1016/J.GSF.2020.09.002

Arabameri, A., Chandra Pal, S., Rezaie, F., Chakrabortty, R., Saha, A., Blaschke, T., Di Napoli, M., Ghorbanzadeh, O., & Thi Ngo, P. T. (2022). Decision tree based ensemble machine learning approaches for landslide susceptibility mapping. *Geocarto International*, *37*(16), 4594–4627. https://doi.org/10.1080/10106049.2021.1892210

Aybar, C., Fernández, C., Huerta, A., Lavado, W., Vega, F., & Felipe-Obando, O. (2020). Construction of a high-resolution gridded rainfall dataset for Peru from 1981 to the present day. *Hydrological Sciences Journal*, *65*(5), 770–785. https://doi.org/10.1080/02626667.2019.1649411

Basu, T., Das, A., & Swades, P. (2022). Application of geographically weighted principal component analysis and fuzzy approach for unsupervised landslide susceptibility mapping on Gish River Basin, India. *Geocarto International*, *37*(5), 1294–1317. https://doi.org/10.1080/10106049.2020.1778105

Bonnesoeur, V., Locatelli, B., Guariguata, M. R., Ochoa-Tocachi, B. F., Vanacker, V., Mao, Z., Stokes, A., & Mathez-Stiefel, S. L. (2019a). Impacts of forests and forestation on hydrological services in the Andes: A systematic review. *Forest Ecology and Management*, *433*, 569–584. https://doi.org/10.1016/J.FORECO.2018.11.033

Bonnesoeur, V., Locatelli, B., Guariguata, M. R., Ochoa-Tocachi, B. F., Vanacker, V., Mao, Z., Stokes, A., & Mathez-Stiefel, S. L.

(2019b). Impacts of forests and forestation on hydrological services in the Andes: A systematic review. *Forest Ecology and Management*, *433*, 569–584. https://doi.org/10.1016/J.FORECO.2018.11.033

Borgatti, L., & Soldati, M. (2018). The influence of Holocene climatic changes on landslide occurrence in Europe. In *Landslides* (1st ed., pp. 111–116). Routledge. https://doi.org/10.1201/9780203749197-8

Brenning, A.: Spatial prediction models for landslide hazards: review, comparison and evaluation. *Nat. Hazards Earth Syst. Sci.*, *5*, 853–862, https://doi.org/10.5194/nhess-5-853-2005, 2005.

Bui, D. T., Shahabi, H., Omidvar, E., Shirzadi, A., Geertsema, M., et al. (2019). Shallow Landslide Prediction Using a Novel Hybrid Functional Machine Learning Algorithm. *Remote Sensing*, *11*(8), 931. https://doi.org/10.3390/RS11080931

Bui, D. T., Tsangaratos, P., Nguyen, V. T., Liem, N. Van, & Trinh, P. T. (2020). Comparing the prediction performance of a Deep Learning Neural Network model with conventional machine learning models in landslide susceptibility assessment. *CATENA*, *188*, 104426. https://doi.org/10.1016/J.CATENA.2019.104426

Cerri, R. I., Reis, F. A. G. V., Gramani, M. F., Giordano, L. C., & Zaine, J. E. (2017). Landslides Zonation Hazard: relation between geological structures and landslides occurrence in hilly tropical regions of Brazil. *Anais Da Academia Brasileira de Ciências*, *89*(4), 2609–2623. https://doi.org/10.1590/0001-3765201720170224

Chang, Z., Huang, J., Huang, F., Bhuyan, K., Meena, S. R., & Catani, F. (2023). Uncertainty analysis of non-landslide sample selection in landslide susceptibility prediction using slope unit-based machine learning models. *Gondwana Research*, *117*, 307–320. https://doi.org/https://doi.org/10.1016/j.gr.2023.02.007

Chen, C. Y., & Huang, W. L. (2013). Land use change and landslide characteristics analysis for community-based disaster mitigation. *Environmental Monitoring and Assessment*, *185*(5), 4125–4139. https://doi.org/10.1007/S10661-012-2855-Y/METRICS

Chen, L., Guo, Z., Yin, K., Pikha Shrestha, D., & Jin, S. (2019). The influence of land use and land cover change on landslide susceptibility: A case study in Zhushan Town, Xuan'en County (Hubei, China). *Natural Hazards and Earth System Sciences*, *19*(10), 2207–2228. https://doi.org/10.5194/NHESS-19-2207-2019

Cossios-Meza, E. D. (2018). *Informe sobre estado y tendencias de la diversidad de ecosistemas del Perú*. https://cdn.www.gob.pe/uploads/document/file/321470/Estado_y_tendencias_ecosistemas.pdf

Dahal, R. K., & Hasegawa, S. (2008). Representative rainfall thresholds for landslides in the Nepal Himalaya. *Geomorphology*, *100*(3–4), 429–443. https://doi.org/10.1016/J.GEOMORPH.2008.01.014

Dai, A., Lin, X., & Hsu, K.-L. (2007). The frequency, intensity, and diurnal cycle of precipitation in surface and satellite observations over low- and mid-latitudes. *Climate Dynamics 2007 29:7*, *29*(7), 727–744. https://doi.org/10.1007/S00382-007-0260-Y

Flores, E. (2016). Cambio Climático: Pastizales Altoandinos y Seguridad Alimentaria. *Revista de Glaciares y Ecosistemas de Montaña*, *1*(1), 73–80. https://doi.org/10.36580/rgem.i1.73-80

Forte, G., Pirone, M., Santo, A., Nicotera, M. V., & Urciuoli, G. (2019). Triggering and predisposing factors for flow-like landslides in pyroclastic soils: the case study of the Lattari Mts. (southern Italy). *Engineering Geology*, *257*, 105137. https://doi.org/10.1016/J.ENGGEO.2019.05.014

Glade, T. (2003). Landslide occurrence as a response to land use change: a review of evidence from New Zealand. *CATENA*, *51*(3–4), 297–314. https://doi.org/10.1016/S0341-8162(02)00170-4

Goetz, J. N., Brenning, A., Petschko, H., & Leopold, P. (2015). Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. *Computers & Geosciences*, *81*, 1-11. https://doi.org/10.1016/j.cageo.2015.04.007.

Gupta, S. K., & Shukla, D. P. (2023). Handling data imbalance in machine learning based landslide susceptibility mapping: a case study of Mandakini River Basin, North-Western Himalayas. *Landslides*, *20*(5), 933–949. https://doi.org/10.1007/s10346-022-01998-1

Hassangavyar, M. B., Damaneh, H. E., Pham, Q. B., Linh, N. T. T., Tiefenbacher, J., & Bach, Q.-V. (2022). Evaluation of re-sampling methods on performance of machine learning models to predict landslide susceptibility. *Geocarto International*, *37*(10), 2772–2794. https://doi.org/10.1080/10106049.2020.1837257

Huang, F., Cao, Z., Guo, J., Jiang, S. H., Li, S., & Guo, Z. (2020). Comparisons of heuristic, general statistical and machine learning models for landslide susceptibility prediction and mapping. *CATENA*, *191*, 104580. https://doi.org/10.1016/J.CATENA.2020.104580

Irigaray, C., Lamas, F., El Hamdouni, R., Fernández, T., & Chacón, J. (2000a). The importance of the precipitation and the susceptibility of the slopes for the triggering of landslides along the roads. *Natural Hazards*, *21*(1), 65–81. https://doi.org/10.1023/A:1008126113789/METRICS

Irigaray, C., Lamas, F., El Hamdouni, R., Fernández, T., & Chacón, J. (2000b). The Importance of the Precipitation and the Susceptibility of the Slopes for the Triggering of Landslides Along the Roads. *Natural Hazards 2000 21:1*, *21*(1), 65–81. https://doi.org/10.1023/A:1008126113789

Jiang, G., & Wang, W. (2017). Error estimation based on variance analysis of k-fold cross-validation. *Pattern Recognition*, *69*, 94–106. https://doi.org/10.1016/J.PATCOG.2017.03.025

Kainthura, P., & Sharma, N. (2022). Hybrid machine learning approach for landslide prediction, Uttarakhand, India. *Scientific Reports*, *12*(1), 20101. https://doi.org/10.1038/s41598-022-22814-9

Karsli, F., Atasoy, M., Yalcin, A., Reis, S., Demir, O., & Gokceoglu, C. (2009). Effects of land-use changes on landslides in a landslide-prone area (Ardesen, Rize, NE Turkey). *Environmental Monitoring and Assessment*, *156*(1–4), 241–255. https://doi.org/10.1007/S10661-008-0481-5/METRICS

Khan, S., Kirschbaum, D. B., & Stanley, T. (2021). Investigating the potential of a global precipitation forecast to inform landslide prediction. *Weather and Climate Extremes*, *33*, 100364. https://doi.org/10.1016/J.WACE.2021.100364

Klose, M., Auerbach, M., Herrmann, C., Kumerics, C., & Gratzki, A. (2017). Landslide Hazards and Climate Change Adaptation of Transport Infrastructures in Germany. *Advancing Culture of Living with Landslides*, 535–541. https://doi.org/10.1007/978-3-319-59469-9_48

Kuradusenge, M., Kumaran, S., & Zennaro, M. (2020). Rainfall-Induced Landslide Prediction Using Machine Learning Models: The Case of Ngororero District, Rwanda. *International Journal of Environmental Research and Public Health 2020, Vol. 17, Page 4147*, *17*(11), 4147. https://doi.org/10.3390/IJERPH17114147

Liu, Z., Gilbert, G., Cepeda, J. M., Lysdahl, A. O. K., Piciullo, L., Hefre, H., & Lacasse, S. (2021). Modelling of shallow landslides with machine learning algorithms. *Geoscience Frontiers*, *12*(1), 385–393. https://doi.org/10.1016/J.GSF.2020.04.014

Ma, Z., Mei, G., & Piccialli, F. (2020a). Machine learning for landslides prevention: a survey. *Neural Computing and Applications 2020 33:17*, *33*(17), 10881–10907. https://doi.org/10.1007/S00521-020-05529-8

Ma, Z., Mei, G., & Piccialli, F. (2020b). Machine learning for landslides prevention: a survey. *Neural Computing and Applications 2020 33:17*, *33*(17), 10881–10907. https://doi.org/10.1007/S00521-020-05529-8

Madrigal-Martínez, S., Miralles I García, J. L., Molina, L., & Lima, P. (2019). Land-change dynamics and ecosystem service trends across the central high-Andean Puna. *Scientific Reports 2019 9:1*, *9*(1), 1–12. https://doi.org/10.1038/s41598-019-46205-9

Marc, O., Stumpf, A., Malet, J. P., Gosset, M., Uchida, T., & Chiang, S. H. (2018). Initial insights from a global database of rainfall-induced landslide inventories: The weak influence of slope and strong influence of total storm rainfall. *Earth Surface Dynamics*, *6*(4), 903–922. https://doi.org/10.5194/ESURF-6-903-2018

Marin, R. J., & Velásquez, M. F. (2020). Influence of hydraulic properties on physically modelling slope stability and the definition of rainfall thresholds for shallow landslides. *Geomorphology*, *351*, 106976. https://doi.org/10.1016/J.GEOMORPH.2019.106976

Meneses, B. M., Pereira, S., & Reis, E. (2019). Effects of different land use and land cover data on the landslide susceptibility zonation of road networks. *Natural Hazards and Earth System Sciences*, *19*(3), 471–487. https://doi.org/10.5194/NHESS-19-471-2019

Merghadi, A., Abderrahmane, B., & Tien Bui, D. (2018). Landslide Susceptibility Assessment at Mila Basin (Algeria): A Comparative Assessment of Prediction Capability of Advanced Machine Learning Methods. *ISPRS International Journal of Geo-Information 2018*, *Vol. 7*, *Page 268*, *7*(7), 268. https://doi.org/10.3390/IJGI7070268

Micheletti, N., Foresti, L., Robert, S., Leuenberger, M., Pedrazzini, A., Jaboyedoff, M., & Kanevski, M. (2013). Machine Learning Feature Selection Methods for Landslide Susceptibility Mapping. *Mathematical Geosciences*, *46*(1), 33–57. https://doi.org/10.1007/S11004-013-9511-0

Mills, S. C., Parra Sanchez, E., Socolar, J. B., Bousfield, C., Coffey, B., Barlow, J., Quintero, J. M. O., Haugaasen, T., & Edwards, D. P. (2023). Avian biodiversity losses from grazing of high Andean páramo. *Biological Conservation*, *286*, 110298. https://doi.org/https://doi.org/10.1016/j.biocon.2023.110298

MINAM. (2019a). *Guía rápida del Programa Presupuestal 0144: Conservación y uso sostenible de ecosistemas para la provisión de servicios ecosistémicos*. https://repositoriodigital.minam.gob.pe/handle/123456789/699

MINAM. (2019b). *Mapa Nacional de Ecosistemas del Perú - Memoria Descriptiva*. Ministerio Del Ambiente. https://cdn.www.gob.pe/uploads/document/file/309735/Memoria_descriptiva_mapa_Nacional_de_Ecosistemas.pdf

Mind'je, R., Li, L., Nsengiyumva, J. B., Mupenzi, C., Nyesheja, E. M., Kayumba, P. M., Gasirabo, A., & Hakorimana, E. (2020). Landslide susceptibility and influencing factors analysis in Rwanda. *Environment*, *Development and Sustainability*, *22*(8), 7985–8012. https://doi.org/10.1007/S10668-019-00557-4/METRICS

Molina, A., Vanacker, V., Rosas, M. B., Bonnesoeur, V., Román, F., Ochoa-Tocachi, B., & Buytaert, W. (2019). *Infraestructura natural para la gestión de riesgos de erosión e inundaciones en los Andes: ¿Qué sabemos?* ForestTrends. https://www.forest-trends.org/wp-content/uploads/2021/06/Infraestructura-natural-para-la-gestion-de-riesgos-de-erosion-e-inundaciones-en-los-Andes.pdf

Monge-Salazar, M. J., Tovar, C., Cuadros-Adriazola, J., Baiker, J. R., Montesinos-Tubée, D. B., Bonnesoeur, V., Antiporta, J., Román-Dañobeytia, F., Fuentealba, B., Ochoa-Tocachi, B. F., & Buytaert, W. (2022). Ecohydrology and ecosystem services of a natural and an artificial bofedal wetland in the central Andes. *Science of The Total Environment*, *838*, 155968. https://doi.org/10.1016/J.SCITOTENV.2022.155968

Mosquera, G. M., Hofstede, R., Bremer, L. L., Asbjornsen, H., Carabajo-Hidalgo, A., et al. (2023). Frontiers in páramo water resources research: A multidisciplinary assessment. *Science of The Total Environment*, *892*, 164373. https://doi.org/https://doi.org/10.1016/j.scitotenv.2023.164373

Naidu, S., Sajinkumar, K. S., Oommen, T., Anuja, V. J., Samuel, R. A., & Muraleedharan, C. (2018). Early warning system for shallow landslides using rainfall threshold and slope stability analysis. *Geoscience Frontiers*, *9*(6), 1871–1882. https://doi.org/10.1016/J.GSF.2017.10.008

Nguyen, T. S., Likitlersuang, S., Ohtsu, H., & Kitaoka, T. (2017). Influence of the spatial variability of shear strength parameters on rainfall induced landslides: a case study of sandstone slope in Japan. *Arabian Journal of Geosciences*, *10*(16), 1–12. https://doi.org/10.1007/S12517-017-3158-Y/FIGURES/16

Ochoa-Sánchez, A., Crespo, P., & Célleri, R. (2018). Quantification of rainfall interception in the high Andean tussock grasslands. *Ecohydrology*, *11*(3), e1946. https://doi.org/https://doi.org/10.1002/eco.1946

Oliva, M., Robert, ;, Torres, P., Salas, R., Gamarra, O., Leiva, S., Collazos, R., Luis, J., & Quintana, M. (2017). Cuantificación del área de pajonal de las microcuencas de Gocta y Chinata y su potencial como reserva de carbono. *Scientia Agropecuaria*, *8*(3), 233–241. https://doi.org/10.17268/sci.agropecu.2017.03.06

Palladino, M. R., Viero, A., Turconi, L., Brunetti, M. T., Peruccacci, S., Melillo, M., Luino, F., Deganutti, A. M., & Guzzetti, F. (2018). Rainfall thresholds for the activation of shallow landslides in the Italian Alps: the role of environmental conditioning factors. *Geomorphology*, *303*, 53–67. https://doi.org/10.1016/J.GEOMORPH.2017.11.009

Pánek, T. (2019). Landslides and Quaternary climate changes—The state of the art. *Earth-Science Reviews*, *196*, 102871. https://doi.org/10.1016/J.EARSCIREV.2019.05.015

Patton, A. I., Rathburn, S. L., & Capps, D. M. (2019). Landslide response to climate change in permafrost regions. *Geomorphology*, *340*, 116–128. https://doi.org/10.1016/J.GEOMORPH.2019.04.029

Peres, D. J., & Cancelliere, A. (2018). Modeling impacts of climate change on return period of landslide triggering. *Journal of Hydrology*, *567*, 420–434. https://doi.org/10.1016/J.JHYDROL.2018.10.036

Perry, L. B., Seimon, A., Andrade-Flores, M. F., Endries, J. L., Yuter, S. E., et al. (2017). Characteristics of Precipitating Storms in Glacierized Tropical Andean Cordilleras of Peru and Bolivia. *Annals of the American Association of Geographers*, *107*(2), 309–322. https://doi.org/10.1080/24694452.2016.1260439

Persichillo, M. G., Bordoni, M., & Meisina, C. (2017). The role of land use changes in the distribution of shallow landslides. *Science of The Total Environment*, *574*, 924–937. https://doi.org/10.1016/J.SCITOTENV.2016.09.125

Pham, B. T., Prakash, I., & Tien Bui, D. (2018). Spatial prediction of landslides using a hybrid machine learning approach based on Random Subspace and Classification and Regression Trees. *Geomorphology*, *303*, 256–270. https://doi.org/10.1016/J.GEOMORPH.2017.12.008

Pham, B. T., Shirzadi, A., Shahabi, H., Omidvar, E., Singh, S. K., et al. (2019). Landslide Susceptibility Assessment by Novel Hybrid Machine Learning Algorithms. *Sustainability 2019, Vol. 11*, *Page 4386*, *11*(16), 4386. https://doi.org/10.3390/SU11164386

Pham, B. T., Vu, V. D., Costache, R., Phong, T. Van, Ngo, T. Q., Tran, T.-H., Nguyen, H. D., Amiri, M., Tan, M. T., Trinh, P. T., Le, H. Van, & Prakash, I. (2022). Landslide susceptibility mapping using state-of-the-art machine learning ensembles. *Geocarto International*, *37*(18), 5175–5200. https://doi.org/10.1080/10106049.2021.1914746

Pinos-Morocho, D., Morales-Matute, O., & Durán-López, M. E. (2021). Suelos de páramo: Análisis de percepciones de los servicios ecosistémicos y valoración económica del contenido de carbono en la sierra sureste del Ecuador. *Revista de*

Ciencias Ambientales, *55*(2), 157–179. https://doi.org/10.15359/RCA.55-2.8

Posner, A. J., & Georgakakos, K. P. (2015). Soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador. *Landslides 2015 12:6*, *12*(6), 1179–1196. https://doi.org/10.1007/S10346-015-0618-X

Reichenbach, P., Busca, C., Mondini, A. C., & Rossi, M. (2014). The Influence of Land Use Change on Landslide Susceptibility Zonation: The Briga Catchment Test Site (Messina, Italy). *Environmental Management*, *54*(6), 1372–1384. https://doi.org/10.1007/S00267-014-0357-0/TABLES/3

Ríos-Touma, B., Rosero, P., Morabowen, A., Guayasamin, J. M., Carson, C., Villamarín-Cortez, S., Solano-Ugalde, A., Tobes, I., & Cuesta, F. (2023). Biodiversity responses to land-use change in the equatorial Andes. *Ecological Indicators*, *156*, 111100. https://doi.org/https://doi.org/10.1016/j.ecolind.2023.111100

Saha, S., Majumdar, P., & Bera, B. (2023). Deep learning and benchmark machine learning based landslide susceptibility investigation, Garhwal Himalaya (India). *Quaternary Science Advances*, *10*, 100075. https://doi.org/https://doi.org/10.1016/j.qsa.2023.100075

Scowen, M., Athanasiadis, I. N., Bullock, J. M., Eigenbrod, F., & Willcock, S. (2021). The current and future uses of machine learning in ecosystem service research. *Science of The Total Environment*, *799*, 149263. https://doi.org/10.1016/J.SCITOTENV.2021.149263

Sobrevilla, L. (2019). Influence of land cover on soil mass movements in the mountains of Apurímac, Peru - CIFOR Knowledge. In *AgroParisTech*.

Strauch, R., Istanbulluoglu, E., Siddhartha Nudurupati, S., Bandaragoda, C., Gasparini, N. M., & Tucker, G. E. (2018). A hydroclimatological approach to predicting regional landslide probability using Landlab. *Earth Surface Dynamics*, *6*(1), 49–75. https://doi.org/10.5194/ESURF-6-49-2018

Sun, D., Chen, D., Zhang, J., Mi, C., Gu, Q., & Wen, H. (2023). Landslide Susceptibility Mapping Based on Interpretable Machine Learning from the Perspective of Geomorphological Differentiation. *Land*, *12*(5). https://doi.org/10.3390/land12051018

Sun, D., Gu, Q., Wen, H., Xu, J., Zhang, Y., Shi, S., Xue, M., & Zhou, X. (2023). Assessment of landslide susceptibility along mountain highways based on different machine learning algorithms and mapping units by hybrid factors screening and sample optimization. *Gondwana Research*, *123*, 89–106. https://doi.org/https://doi.org/10.1016/j.gr.2022.07.013

Tang, Y., Feng, F., Guo, Z., Feng, W., Li, Z., Wang, J., Sun, Q., Ma, H., & Li, Y. (2020). Integrating principal component analysis with statistically-based models for analysis of causal factors and landslide susceptibility mapping: A comparative study from the loess plateau area in Shanxi (China). *Journal of Cleaner Production*, *277*, 124159. https://doi.org/10.1016/J.JCLEPRO.2020.124159

Tasser, E., Mader, M., & Tappeiner, U. (2003). Effects of land use in alpine grasslands on the probability of landslides. *Basic and Applied Ecology*, *4*(3), 271–280. https://doi.org/10.1078/1439-1791-00153

Tien Bui, D., Hoang, N. D., Nguyen, H., & Tran, X. L. (2019). Spatial prediction of shallow landslide using Bat algorithm optimized machine learning approach: A case study in Lang Son Province, Vietnam. *Advanced Engineering Informatics*, *42*, 100978. https://doi.org/10.1016/J.AEI.2019.100978

Van Beek, L. P. H., & Van Asch, T. W. J. (2004). Regional assessment of the effects of land-use change on landslide hazard by means of physically based modelling. *Natural Hazards*, *31*(1), 289–304. https://doi.org/10.1023/B:NHAZ.0000020267.39691.39/METRICS

Vega-Chuquirimay, E., & Torres-Zuñiga, D. (2013). *Manejo Y Conservación De Pasturas Naturales Y Cultivos Temporales*. DESCO. https://www.descosur.org.pe/wp-content/uploads/2014/12/Manual008.pdf

Wang, S., Zhang, K., van Beek, L. P. H., Tian, X., & Bogaard, T. A. (2020). Physically-based landslide prediction over a large region: Scaling low-resolution hydrological model results for high-resolution slope stability assessment. *Environmental Modelling & Software*, *124*, 104607. https://doi.org/10.1016/J.ENVSOFT.2019.104607

Wilcox, B. P., Allen, B. L., & Bryant, F. C. (1988). Description and classification of soils of the high-elevation grasslands of central Peru. *Geoderma*, *42*(1), 79–94. https://doi.org/https://doi.org/10.1016/0016-7061(88)90024-9

Wood, J. L., Harrison, S., Reinhardt, L., & Taylor, F. E. (2020). Landslide databases for climate change detection and attribution. *Geomorphology*, *355*, 107061. https://doi.org/10.1016/J.GEOMORPH.2020.107061

Xu, C., Sun, Q., & Yang, X. (2018). A study of the factors influencing the occurrence of landslides in the Wushan area. *Environmental Earth Sciences*, *77*(11), 1–8. https://doi.org/10.1007/S12665-018-7584-2/METRICS

Yu, X., Zhang, K., Song, Y., Jiang, W., & Zhou, J. (2021). Study on landslide susceptibility mapping based on rock–soil characteristic factors. *Scientific Reports 2021 11:1*, *11*(1), 1–27. https://doi.org/10.1038/s41598-021-94936-5

Zari, L., Andrea, C., & Leyda, R. (2019). *Pajonales | SPDA Actualidad Ambiental*. Sociedad Peruana de Derecho Ambiental. https://www.actualidadambiental.pe/pajonales/

Zhang, T., Fu, Q., Wang, H., Liu, F., Wang, H., & Han, L. (2022). Bagging-based machine learning algorithms for landslide susceptibility modeling. *Natural Hazards*, *110*(2), 823–846. https://doi.org/10.1007/s11069-021-04986-1

Zhang, T., Li, Y., Wang, T., Wang, H., Chen, T., Sun, Z., Luo, D., Li, C., & Han, L. (2022). Evaluation of different machine learning models and novel deep learning-based algorithm for landslide susceptibility mapping. *Geoscience Letters*, *9*(1), 26. https://doi.org/10.1186/s40562-022-00236-9

Zhou, C., Yin, K., Cao, Y., Intrieri, E., Ahmed, B., & Catani, F. (2018). Displacement prediction of step-like landslide by applying a novel kernel extreme learning machine method. *Landslides*, *15*(11), 2211–2225. https://doi.org/10.1007/S10346-018-1022-0/METRICS

Zhu, L., Wang, G., Huang, F., Li, Y., Chen, W., & Hong, H. (2022). Landslide Susceptibility Prediction Using Sparse Feature Extraction and Machine Learning Models Based on GIS and Remote Sensing. *IEEE Geoscience and Remote Sensing Letters*, *19*. https://doi.org/10.1109/LGRS.2021.3054029

Zhuo, L., Dai, Q., Han, D., Chen, N., Zhao, B., & Berti, M. (2019). Evaluation of Remotely Sensed Soil Moisture for Landslide Hazard Assessment. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(1), 162–173. https://doi.org/10.1109/JSTARS.2018.2883361