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Integrating gridded precipitation and climate change data for landslide assessments in pipeline geohazard management programs

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Presentation outline

01

Introduction and methodology

- Levels of assessments
- Gridded precipitation data
- Landslide susceptibility and hazard
- Level one: Geohazard programs

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Case study in Peru

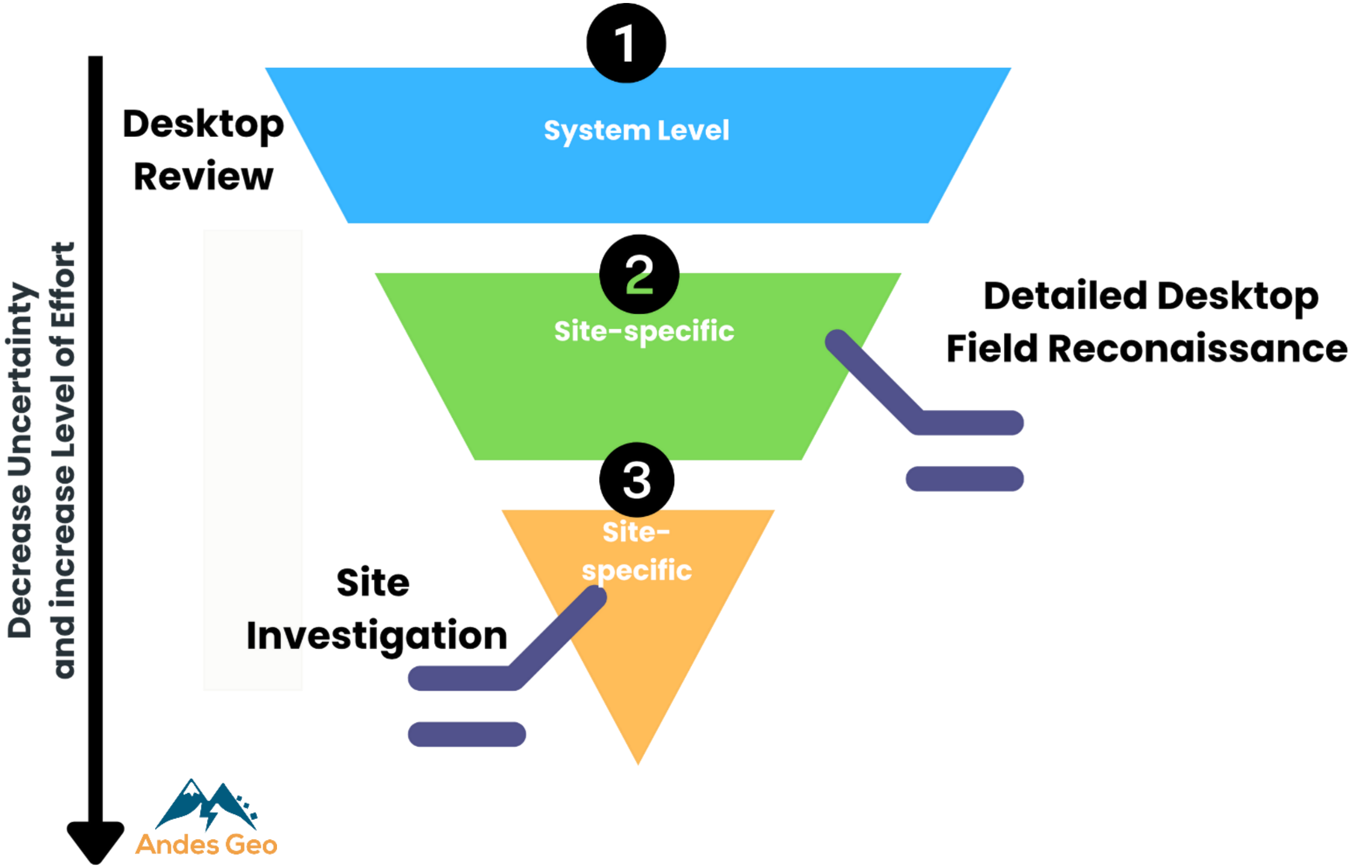
- 11,000 km of linear infrastructure across 3 different geographic zones
- Susceptibility and hazard in homogeneous areas

03

Discussion and conclusions

- Landslide hazard management in pipeline operations
- GeoHAS
- Early warning

Level of assessment



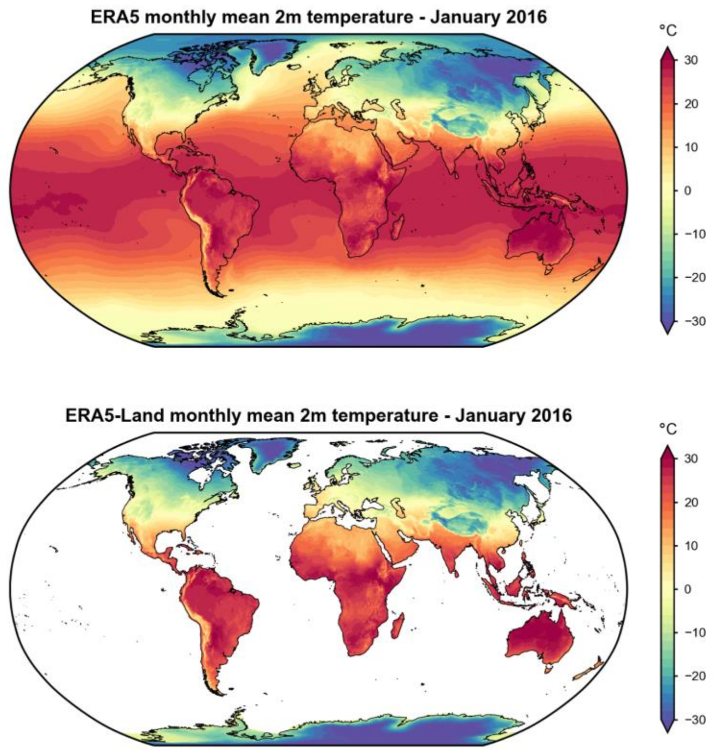
Scope:

- Level 1: consists of a desktop review (existing-data).
- Level 2 in-depth site-specific desktop assessment.
- Level 3 site-specific geotechnical investigations.

Gridded precipitation data

ERA-5 and ERA-5 Land (Hersbach, et al., 2020; Muñoz-Sabater et al., 2021):

1. **Spatial Coverage**: Global.
2. **Resolution**: Approximately 10 km.
3. **Data temporal coverage**: from 1940 to the present
4. **Primary use**: For understanding past weather and climate



Source: Copernicus Reanalysis https://climate.copernicus.eu/climate-reanalysis (Accessed: November 3, 2025).

Gridded precipitation data

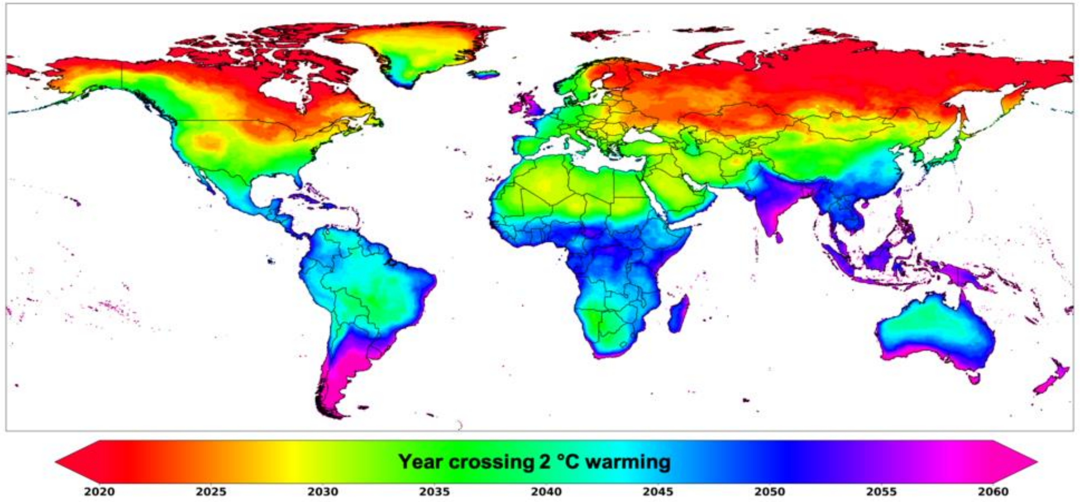


Figure. Spatial pattern of years exceeding the 2-degree warming with respect to the baseline period (1950-1979). The 15-year moving average of the ensemble median of near-surface air temperature from 35 CMIP6 models (SSP585 scenario) was used in detecting the years exceeding the 2-degree warming.

Source: Downscaled Climate Projections (NEX-GDDP-CMIP6) https://www.nasa.gov/nasa-earth-exchange-nex/gddp/downscaled-climate-projections-nex-gddp-cmip6/ (Accessed: November 3, 2025).

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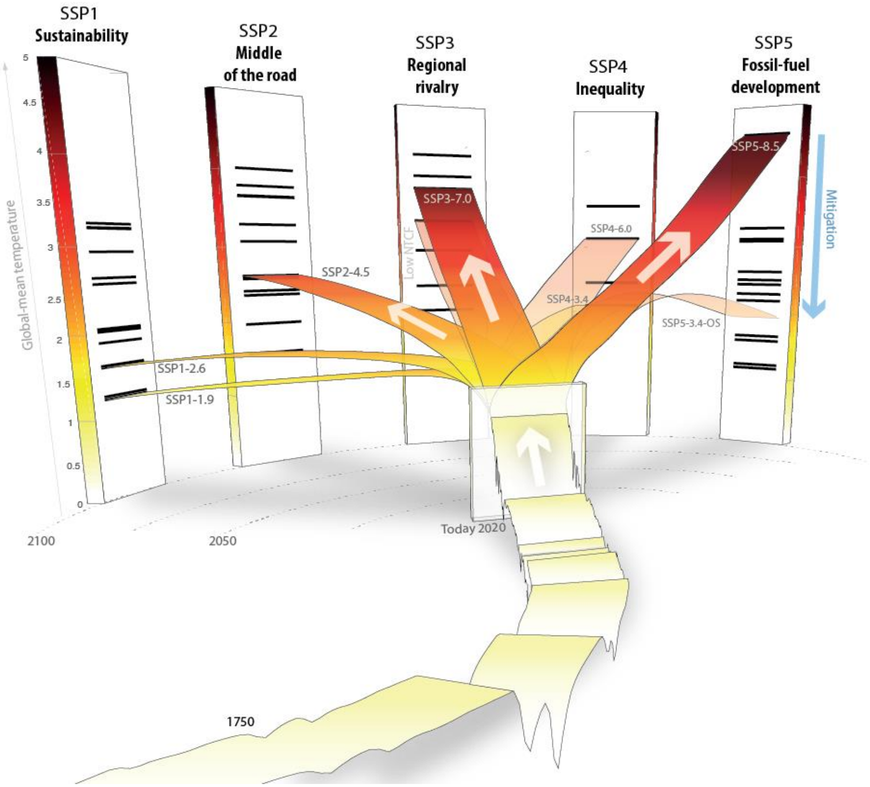
NASA NEX (Thrasher et al., 2022):

1. **Coverage:** Global.
2. **Resolution:** Approximately 25 km.
3. **Data temporal coverage:** historical simulations from 1950 to 2014 and future projections from 2015 to 2100.
4. **Primary use:** For future climate change impact.

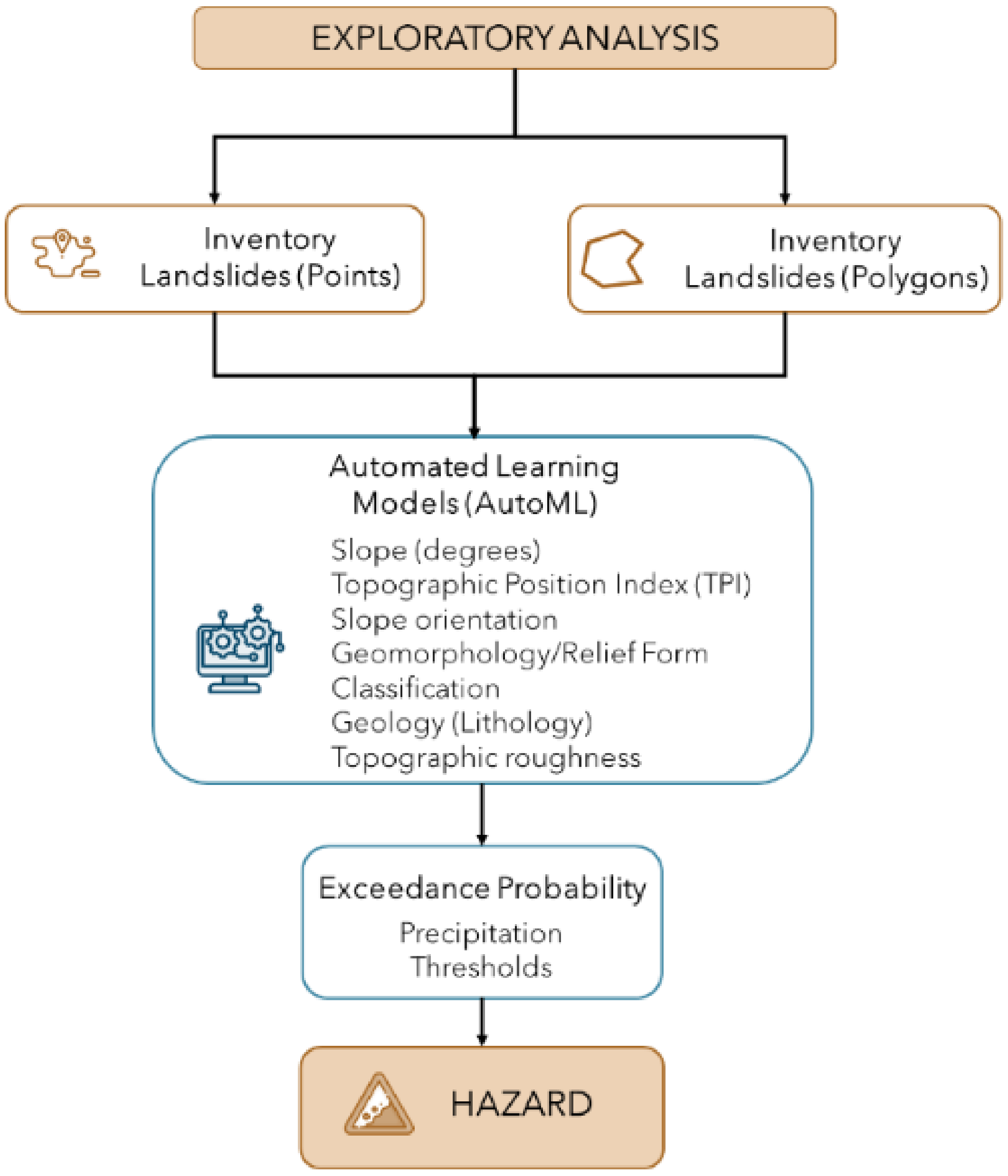
Shared Socioeconomic Pathways

- Shared Socioeconomic Pathways (SSPs) are a set of five alternative global development scenarios that explore how the world might evolve over the 21st century.
- These narratives describe different trends in global demographics, social and economic development, technology, and environmental policies.

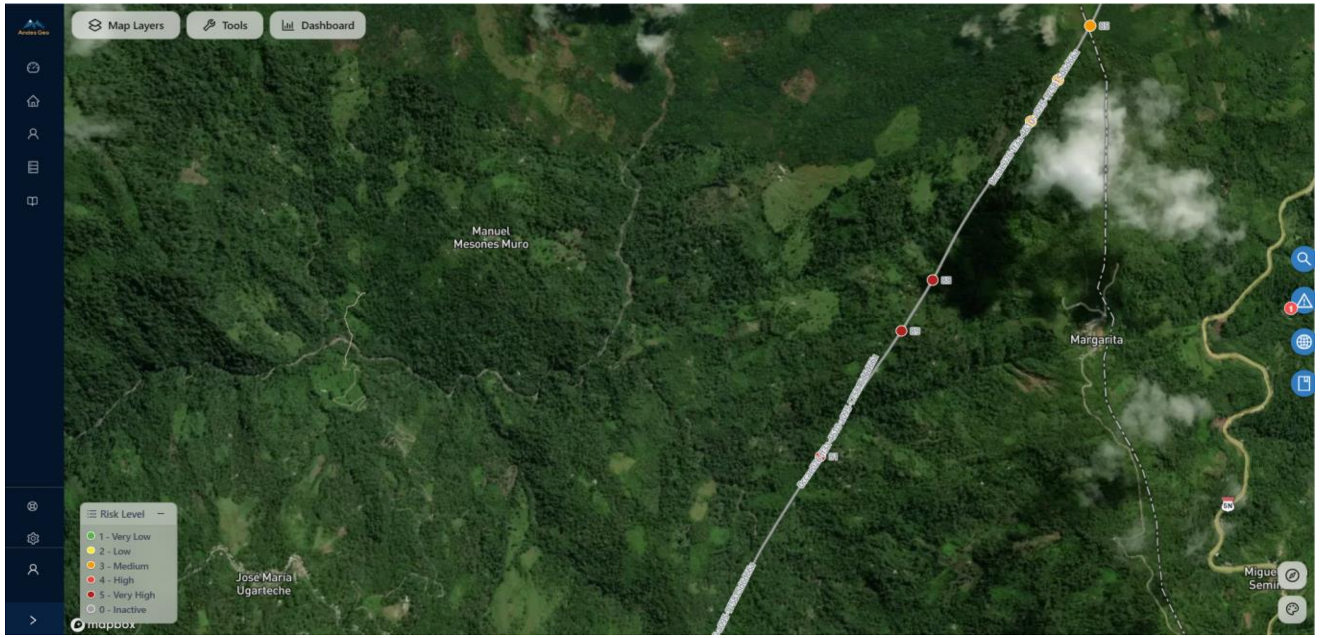


Source: Meinshausen, M., et al. (2020). Geoscientific Model Development, 13(8), 3571–3605. (Data shows global-mean temperature projections under Shared Socioeconomic Pathways, SSPs).

Landslide Susceptibility and Hazard



Landslide Susceptibility



- Landslide **susceptibility** refers to the likelihood of a landslide occurring in a particular area based on local terrain conditions.
- Landslide **hazard i**ncludes the probability of a landslide occurring within a specific time period, its magnitude, and its intensity.
- A key difference is that susceptibility maps show ***where* landslides are** most likely, while hazard maps also consider ***when* they are likely to happen.**

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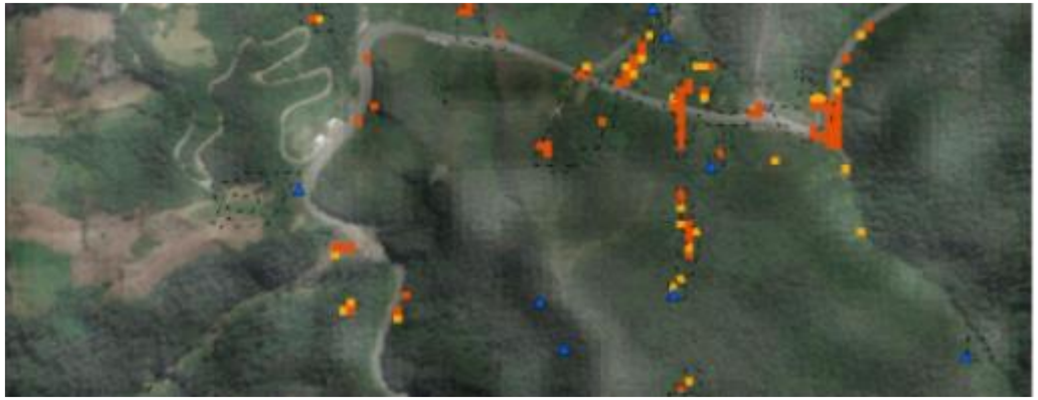
Landslide Susceptibility modeling



- **Data:** region-specific satellite-derived landslide database**.**
- **Covariables:** slope angle, Slope orientation, Topographic Position index (TPI), Lithology, Geomorphological units (ridge, valley, plain, slopes).
- **Model tested:** Logistic Regression, Neural Net, Random Forest, Supported Vector Machine.

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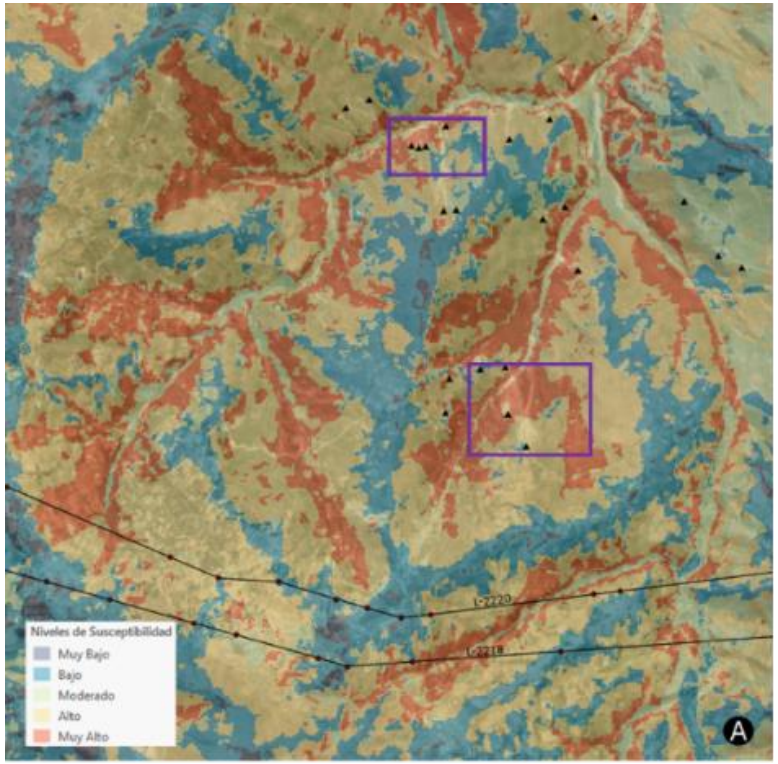
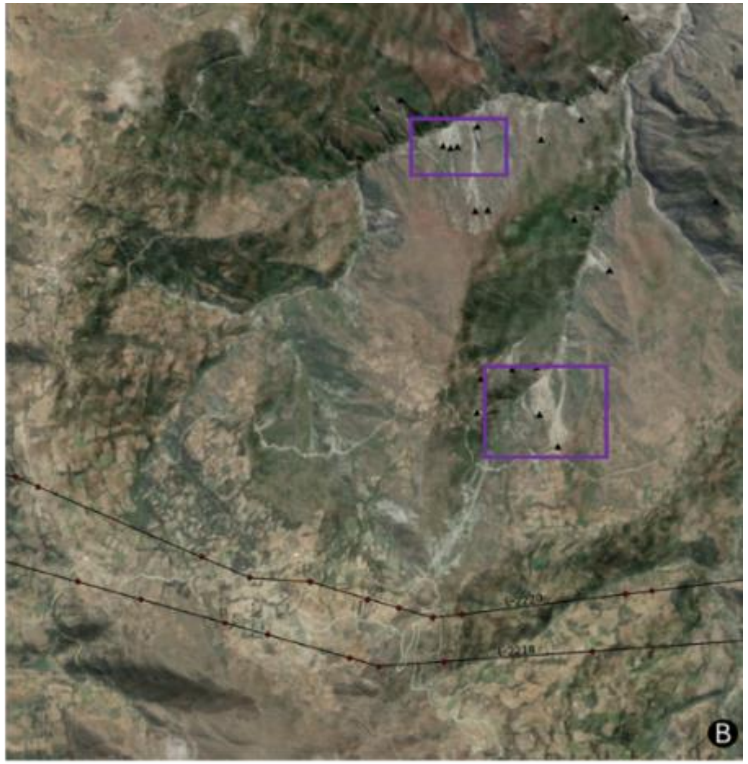
Landslide Susceptibility modeling

Susceptibility Map



Validation Area



Performance Metrics (AUC)

AUC				
model	**mean**	**max**	**min**	**std**
Logistic Regression	0.7483	0.8065	0.6429	0.0552
Neural Network	0.764	0.8465	0.6317	0.0744
Random Forest	0.7846	0.9129	0.6363	0.1096
Support Vector Machine	0.4688	0.763	0.2069	0.2428

Case study in Peru

- **Assets:** 11,000 km of lineal infrastructure
- **Climatic zones:** Coast, Andes, Amazon.
- **Risk assessed:** Landslide, channel change, fluvial erosion, flood, fire, lightning, wind, temperature (high, low).
- **Climate change:** SSP1, 2, 3, 5.

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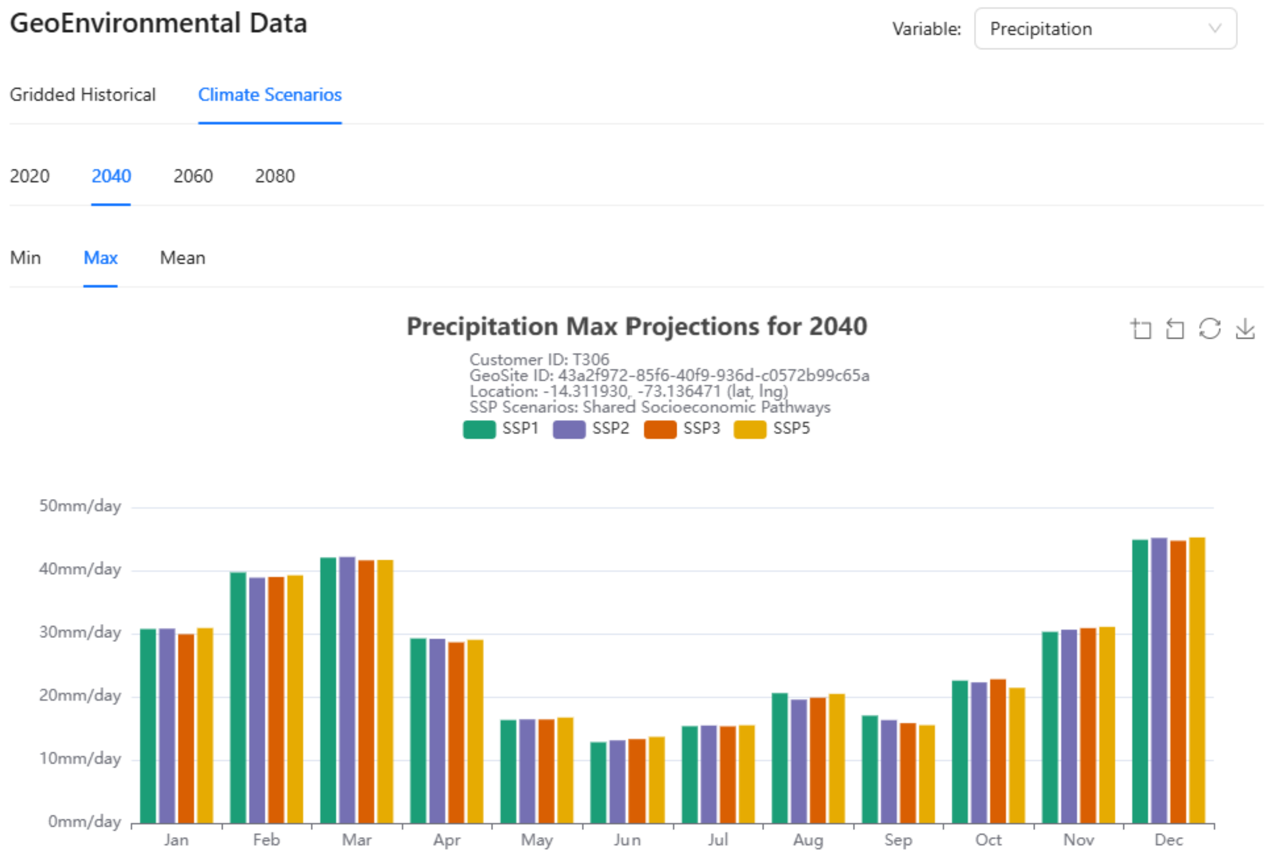

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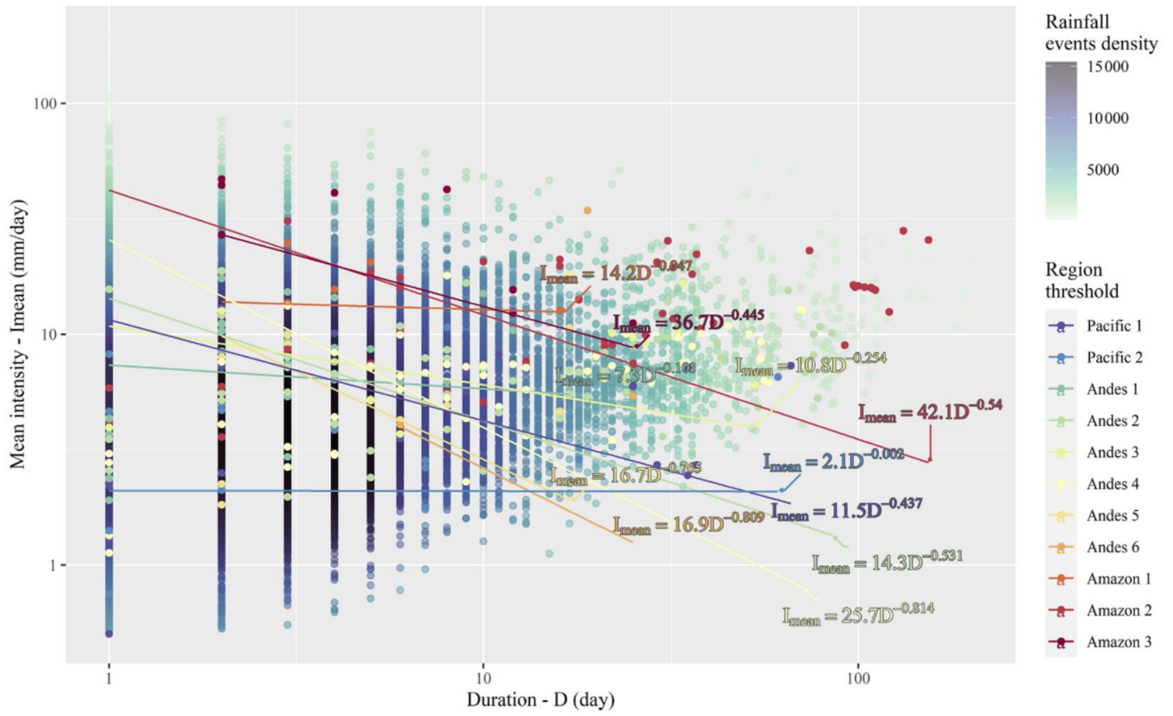
Results

Case study in Peru

- **Millán-Arancibia and Lavado-Casimiro considered individual thresholds defined in terms of:**
  - E: Total accumulated precipitation (mm).
  - D: Duration of the rainfall event (days).
  - Imax: Maximum daily intensity (mm/day).
  - Imean: Average daily intensity (mm/day).
- **The combination Imean–D showed the best overall performance**
- **The percentile score o**f the local pixel threshold values (D, Imean,Imax, E) are determined for the distributions in each of thesevariables across the 1950-2023 inventory of local precipitation events
- **This percentile score is then normalised** to to obtain the local probability of occurrence of the threshold values for each variable



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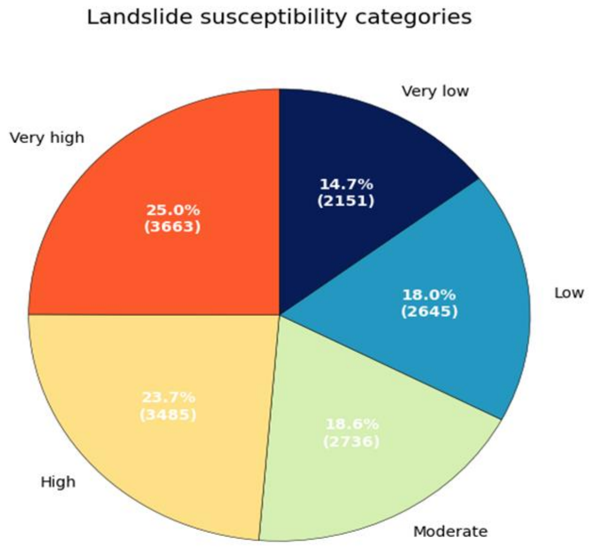
Results

Case study in Peru: Landslide susceptibility categories



Class	Count	%
Very High	3663	25.0
High	3485	23.7
Moderate	2151	18.6
Low	2645	18.0
Very low	2151	14.7

Key Finding: Nearly Half (48.7%) of the Study Area is Highly Susceptible to Landslides.

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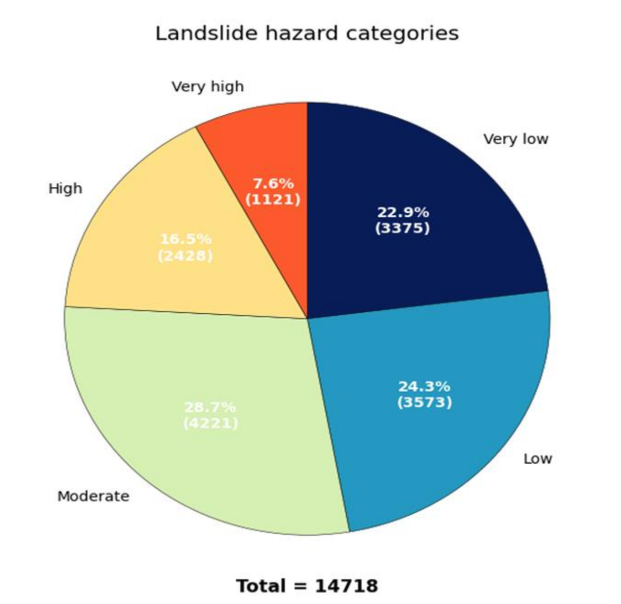
Case study in Peru: Landslide hazard categories

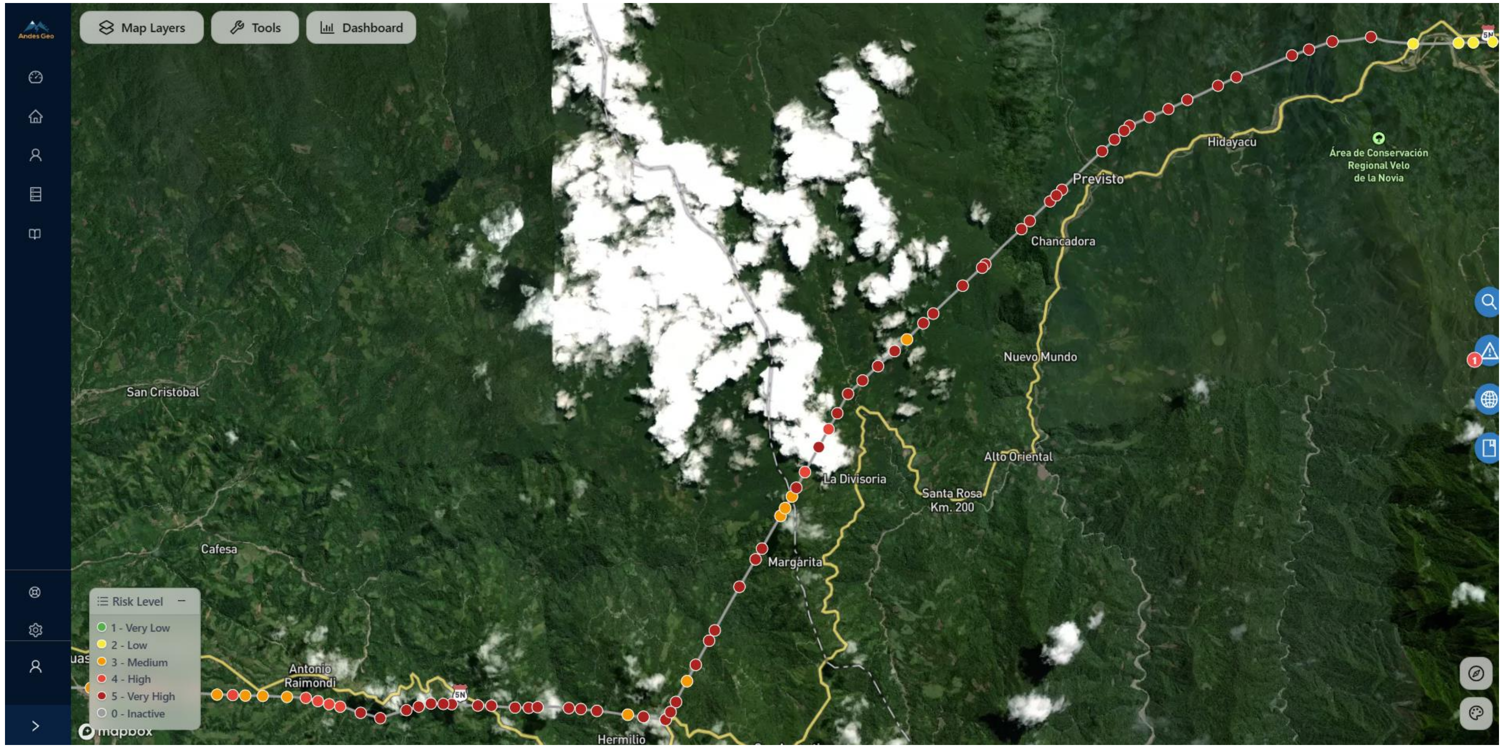


$$Hazard = \left(susceptibility * (precipitation\ threshold\ probability\ + 1)\right)$$

Class	Count	%
Very High	1121	7.6
High	2428	16.5
Moderate	4221	28.7
Low	3573	24.3
Very low	3375	22.9

Landslide hazard management in pipeline operations

- Interactive dashboard
- Import/export features
- Multiple data layers
- 3D visualization
- Early warning
- Climate risk scores



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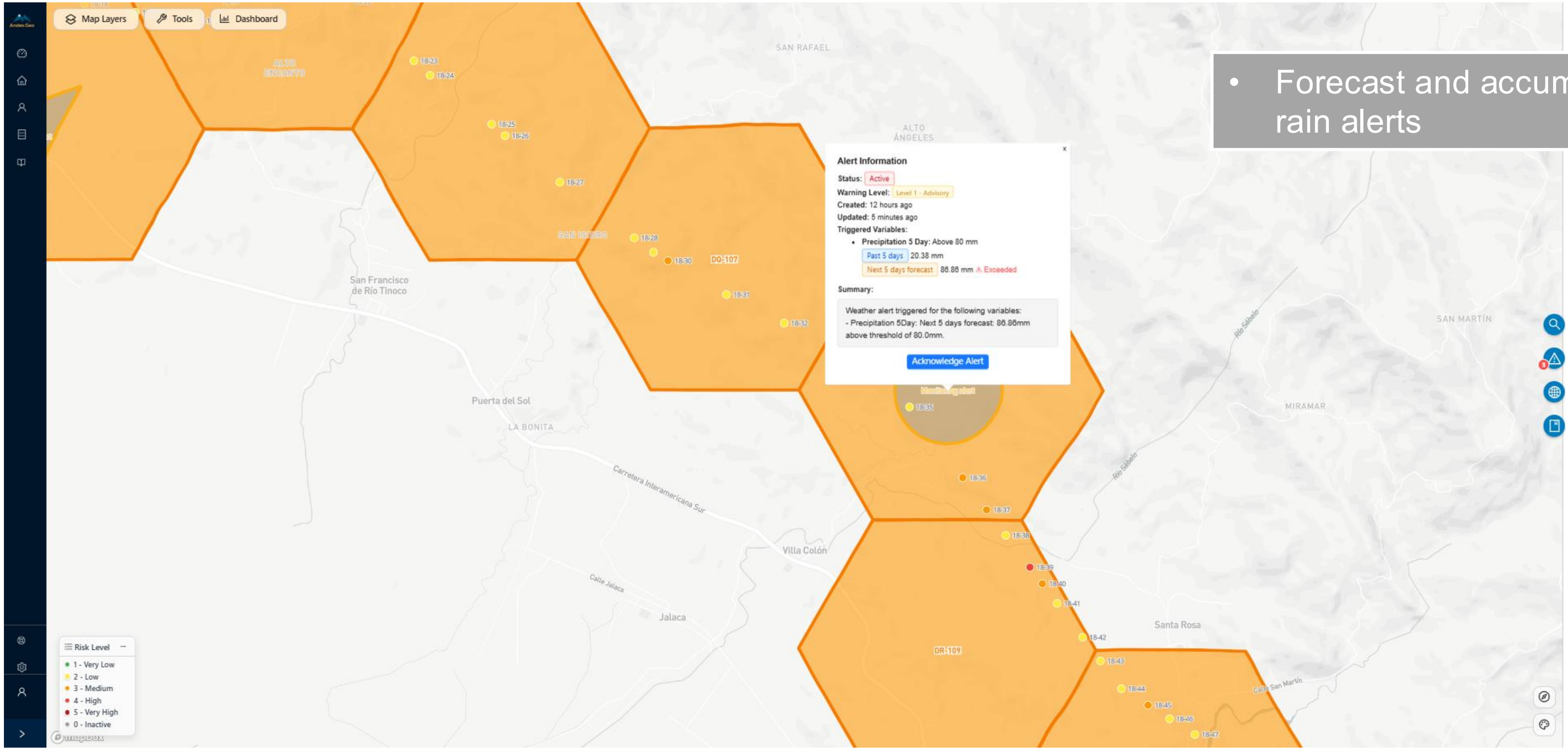
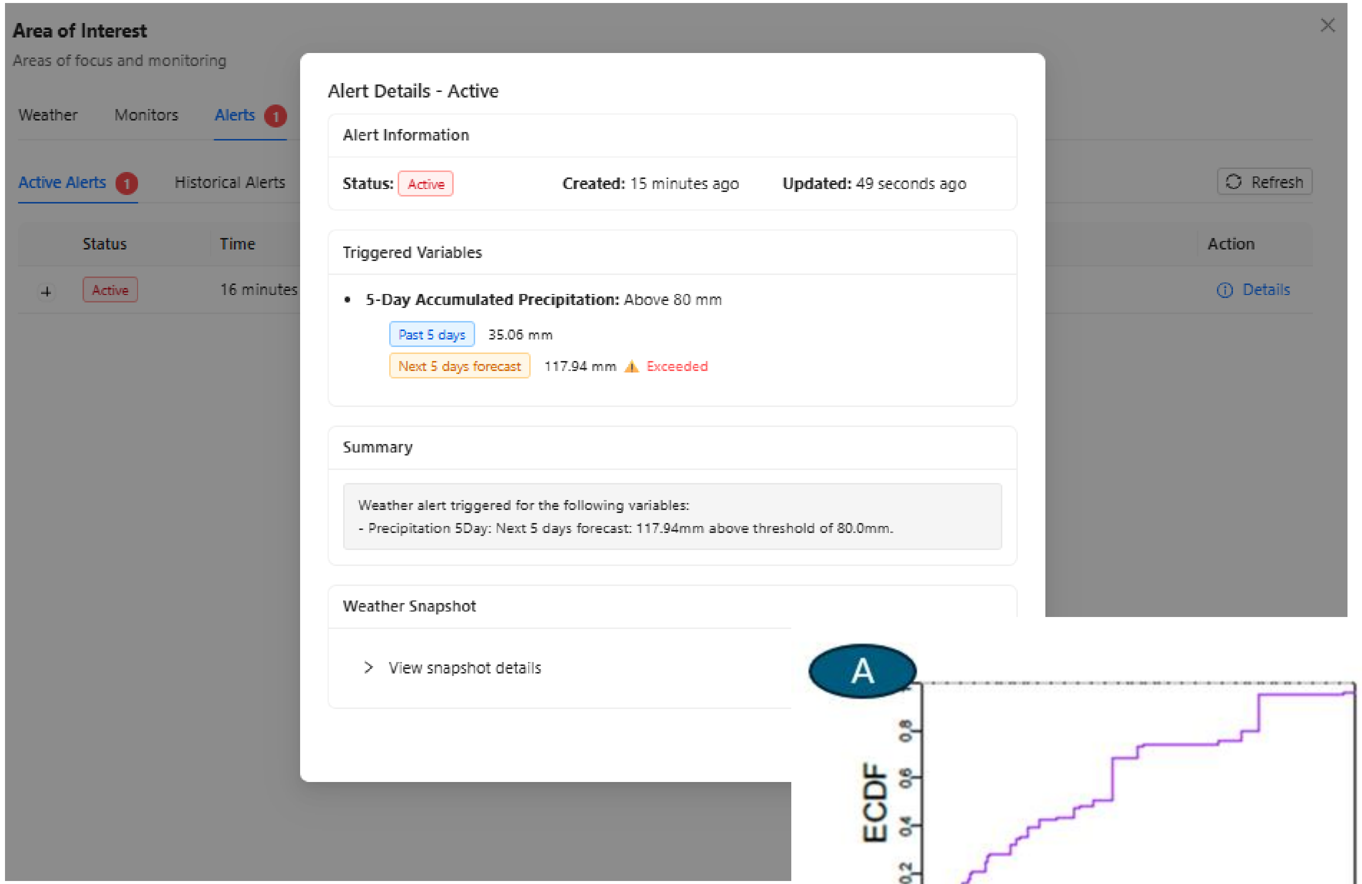
Discussion and Conclusion 1/2



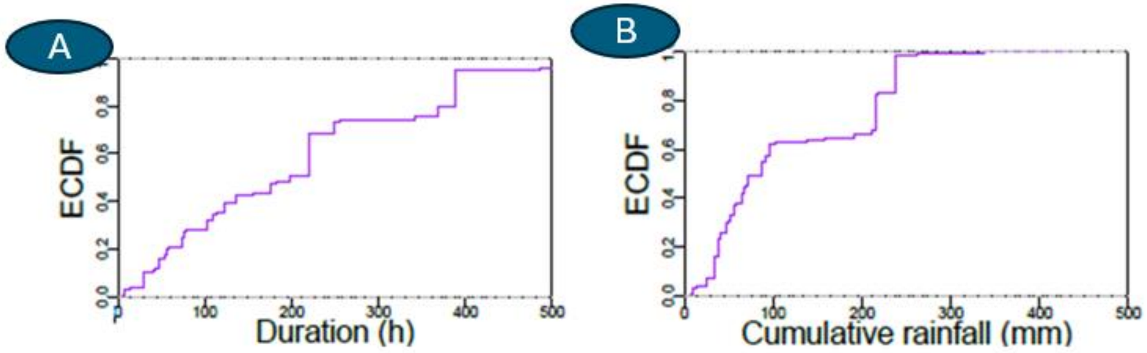
- Forecast and accumulated rain alerts

Fuente: Andes Geo (2025).

Discussion and Conclusion 1/2



- Setting alerts based on estimated thresholds (duration and cumulative rainfall)



Fuente: Andes Geo (2025).

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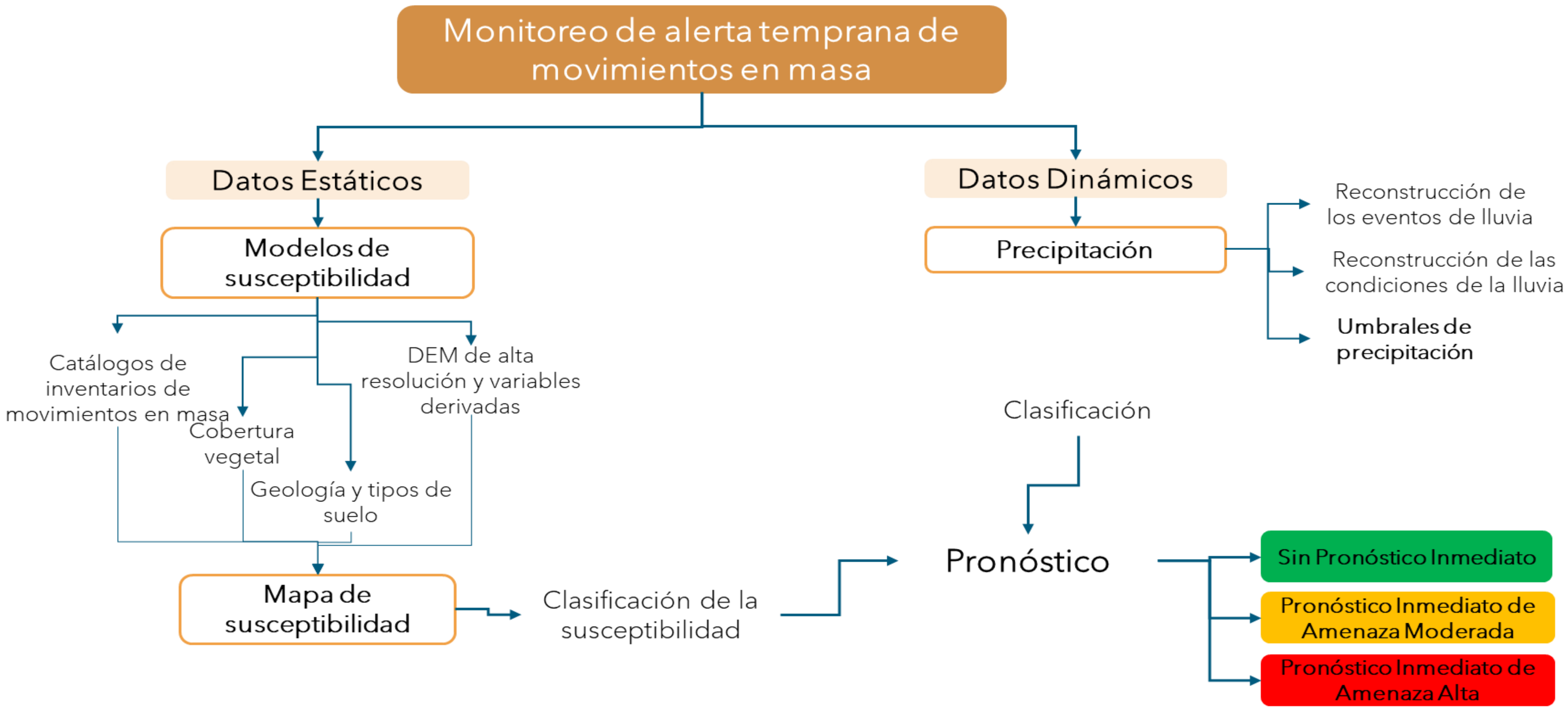
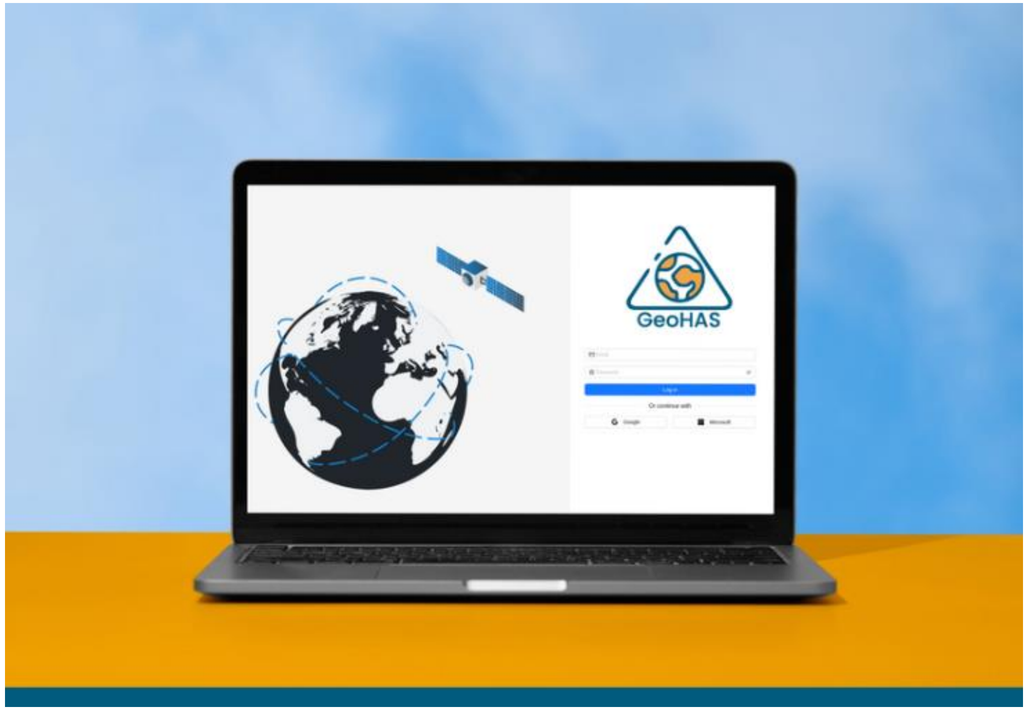
Discussion and Conclusion 1/2



Fuente: Andes Geo (2025).

Discussion and Conclusion 1/2

- ERA5 + CMIP6 → rainfall thresholds for landslide initiation
- Fuse with susceptibility map (Level 2; API RP 1187 aligned)
- Peru corridor (~11,000 km):Very High reduced 25% → 7.6%High reduced 23.7% → 16.5%
- Delivered in GeoHAS: visualize time series, prioritize risk, alerts/EWS, reports & field inspections for compliance



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¡Gracias!

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INTEGRATING GRIDDED PRECIPITATION AND CLIMATE CHANGE DATA FOR LANDSLIDE ASSESSMENTS IN PIPELINE GEOHAZARD MANAGEMENT PROGRAMS

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ABSTRACT

Climate change is increasing the frequency and intensity of geohazards, posing significant challenges to the integrity of pipelines. As extreme weather events increase and geomorphic processes such as landslides and debris flows become more prevalent, there is a pressing need for pipeline operators to incorporate climate adaptation strategies into their geohazard management frameworks. This study presents a methodology for integrating gridded precipitation data to assess shallow landslide hazards (including debris flow initiation) at Level 2 within the context of climate change scenarios. Our approach aligns with the recommendations outlined in API RP 1187 concerning landslide threat management while acknowledging emergent risks associated with climate variability. Utilizing data from ERA-5 Land, we estimate the probability of rainfall reaching or exceeding thresholds that initiate landslides within homogenous precipitation regions along a critical infrastructure corridor in Peru. This probability is subsequently combined with a landslide susceptibility map developed through logistic regression algorithm, allowing for the refinement of landslide hazard classes. This classification facilitates the prioritization of geotechnical hazard management actions. The analysis leverages GeoHAS algorithms for landslide identification and modeling and utilizes the GeoHAS web platform for effective visualization and data management. The study concludes with recommendations for integrating climate change considerations into pipeline geotechnical practices, fostering data-driven approaches to safeguard pipeline infrastructure.

Keywords: Climate change, geohazard management, pipeline integrity, API RP 1187, remote sensing, risk assessment.

NOMENCLATURE

API	Application Programming Interface
ECMWF	European Centre of Medium-Range weather Forecast
GeoHAS	Geospatial Hazard Assessment Solution
IPCC	International Panel on Climate Change
ML	Machine Learning

1. INTRODUCTION

Climate change is transforming the risk landscape for critical infrastructure worldwide, with the frequency and magnitude of extreme weather events increasing at unprecedented rates [1, 2]. The global mean temperature has risen by approximately 1.1°C since pre-industrial times, driving significant changes in precipitation patterns, storm intensity, and the frequency of climate extremes [3]. These changes pose consequential challenges to infrastructure resilience, with annual economic losses from climate-related disasters exceeding $280 billion globally in recent years [4]. For pipeline infrastructure, which spans diverse geographical and climatic zones, the implications are particularly severe. Linear infrastructure systems are uniquely vulnerable to multiple geohazards along their routes, including landslides, floods, and debris flow phenomena [5]. The critical importance of maintaining continuous pipeline operations for energy security and economic stability, combined with the rising costs of climate-related infrastructure damage—which have increased by 250% over the past two decades [6] —underscores the pressing need for enhanced geohazard management strategies that explicitly account for climate change impacts.

Traditional geohazard assessment methodologies, while valuable for historical risk characterization, face limitations in addressing the non-stationary nature of climate-driven hazards [7]. Historical precipitation records, which form the basis of conventional hazard frequency analyses, may no longer represent future conditions under climate change scenarios [8]. Static risk assessment approaches that assume temporal stationarity for hazard occurrences are increasingly inadequate for capturing the dynamic evolution of geohazard threats in a changing climate. Furthermore, quantifying climate uncertainty in hazard models remains a substantial challenge, particularly when translating global climate projections to local-scale hazard assessments [9]. Among the various geohazard threats to pipeline infrastructure, landslides represent a particularly complex challenge due to their sensitivity to changing precipitation patterns and the potential for cascading failures [10]. The compounding effects of multiple hazard types, such as the interaction between increased precipitation intensity and antecedent soil moisture conditions, further complicate risk assessment and management strategies [11].

Recent industry practice for pipeline landslide management is guided by established standards and guidelines, including the American Petroleum Institute's Recommended Practice 1187, which provides comprehensive recommendations for managing landslide threats [12]. This standard outline level assessment requirements and methodologies, emphasizing the importance of systematic hazard identification and characterization along pipeline corridors.

However, significant gaps remain in current approaches, particularly regarding the integration of climate adaptation strategies into geohazard management frameworks. The limited incorporation of gridded climate data and future climate projections into hazard assessments represents a critical weakness in current practice. Additionally, the lack of standardized methods for quantifying climate uncertainty in geohazard models hinders consistent risk evaluation across different pipeline systems and regions [14]. There is a pressing need for probabilistic and quantitative approaches to hazard assessment that can accommodate climate variability and provide robust risk metrics for decision-making [15]. Moreover, the dynamic nature of climate-driven risks necessitates constant reassessment and trend analysis, moving beyond static risk evaluations to embrace adaptive management strategies [16].

Technological advances in the last decade have created unprecedented opportunities for enhancing climate-informed geohazard assessments. The availability of high-resolution gridded climate data, particularly through reanalysis products such as ERA5-Land, provides comprehensive spatial and temporal coverage of meteorological variables essential for hazard modeling [17]. ERA5-Land offers hourly data at 0.1° × 0.1° resolution from 1950 to present, enabling detailed analysis of precipitation patterns and extremes [18]. High-resolution precipitation products derived from satellite observations and ground-based measurements further enhance the ability to characterize rainfall thresholds for landslide initiation [19]. Long-term climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) provide multiple scenarios of future climate conditions, enabling probabilistic assessment of future hazard evolution [20]. Computational and analytical capabilities have advanced with sophisticated machine learning algorithms applicable to landslide modeling.

The main objective of this paper is to showcase a methodology for integrating gridded precipitation data with landslide susceptibility assessment to support climate-informed pipeline geohazard management. Specifically, we aim to (1) develop a methodology for integrating gridded precipitation data from ERA5-Land with landslide susceptibility mapping to create probabilistic hazard assessments; (2) establish a framework for incorporating climate change scenarios into Level 2 pipeline geohazard assessments that aligns with API RP 1187 guidelines; and (3) demonstrate the practical application of this approach through a case study in Peru, showcasing how data science advances can enhance infrastructure resilience planning. The data analysis and display is performed in GeoHAS, a dashboard and framework that integrates several of these algorithms as part of its geohazard assessment workflow

1

2. METHODS

2.1 Data

2.1.1 ERA-5 Land

To characterize historical precipitation patterns and estimate rain events, we employed data from the ERA-5 Land reanalysis product [17, 18], accessed via the European Centre for Medium-Range Weather Forecasts (ECMWF) API. For projections of precipitation under climate change scenarios, we utilized the NASA NEX-GDDP-CMIP6 models [21], with a specific focus on Shared Socioeconomic Pathways (SSPs) 1, 2, 3, and 5 across multiple bi-decadal periods leading up to the year 2100. This methodological approach allowed for a comprehensive analysis of precipitation dynamics under varying socioeconomic and climatic conditions at the asset level. Tables 1 and 2 describe the characteristics of these datasets.

TABLE 1: ERA-5 LAND DATA SPECIFICATIONS

General specifications	
Data source	ECMWF
Temporal resolution	Variable, hourly
Spatial Resolution	~10 km / 0.1
Spatial coverage	Global
Data Collection Period	January-February 2025

TABLE 2: NASA NEX-GDDP-CMIP6 DATA SPECIFICATION

General specifications	
Data source	NASA Earth Exchange (NEX)
Temporal resolution	Daily
Spatial Resolution	~27 km / 0.25 degree
Spatial coverage	Global
Data Collection Period	October-December 2024
Notes	Aggregated ensemble and resampled to ERA5-Land resolution

ERA-5 Land data used ranges from 1950 to 2023 and was processed into daily datasets of minimum, maximum, and average daily precipitation values (Figure 1). These values were interpolated to assets locations (and extrapolated when assets locations in coastal regions are beyond the edge of the ERA5-Land dataset footprint). The regional values were averaged from all ERA5-Land cells intersecting the region's footprint. Multiplicative delta values between 2000-2019 and future bi-decades are computed using the NASA NEX-GDDP-CMIP6 downscaled GCM data and resampled to the ERA5-analysis.

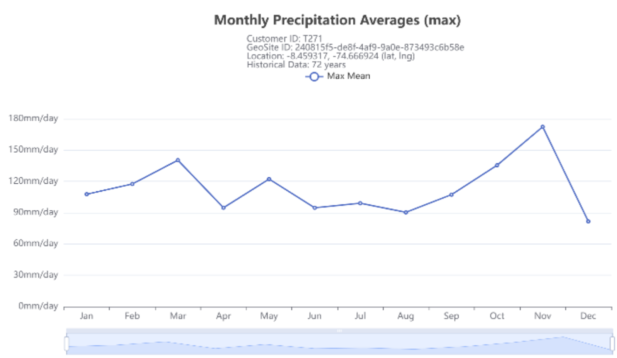

FIGURE 1: MONTHLY PRECIPITATION HISTORICAL DATA AS DISPLAYED IN THE GEOHAS PLATFORM, WITH MONTHS PLOTTED ON THE X-AXIS AND PRECIPITATION IN MM ON THE Y-AXIS. THE VISUALIZATION DATASET INCLUDES DATA FROM 1950 TO 2023 FOR THE MINIMUM, MAXIMUM, MEAN, AND STANDARD DEVIATION STATISTICS.

2.1.2 Landslide Susceptibility Data

We ran landslide susceptibility models using different algorithms to identify and prioritize geohazard sites along linear infrastructure. The landslide susceptibility model was developed using mass movement inventories and terrain variables describing locations affected by mass movements. The mass movement inventories were produced using a remote sensing method to map changes in land cover after major, landslide-triggering rainfall events; and the following landscape characteristics were used as model co-variables: Slope angle, Slope orientation, Topographic Position index (TPI), Lithology, Geomorphological units (ridge, valley, plain, slopes). The algorithms tested included Logistic Regression, Neural Network, Random Forest and Supported Vector machine. The models were tested using the Area Under the Curve (AUC) metric and we chose the Logistic Regression model since it performed better (AUC 0.78-0.85, Table 3) across the different physiographic regions of Peru.

TABLE 3: AUC VALUES FOR THE DIFFRENT LANSDLIDE SUSCEPTIBILITY MODELS

AUC				
model	**mean**	**max**	**min**	**std**
Logistic Regression	0.7483	0.8065	0.6429	0.0552
Neural Network	0.764	0.8465	0.6317	0.0744
Random Forest	0.7846	0.9129	0.6363	0.1096
Support Vector Machine	0.4688	0.763	0.2069	0.2428

2.2 Study Area

The study area encompasses a critical infrastructure corridor in Peru of approximately 11,000 km, traversing the main physiographic regions of the country: the Andes, Amazon, and Coast (Figure 2). The corridor, primarily located in the Andean regions, represents an electrical transmission infrastructure that connects the northwest and southwest of the country. These regions display significant geographical and climatic contrasts: the Andes include steep, unstable slopes prone to frequent landslides, while the low-elevation, arid coast remains vulnerable to other hazards associated with extreme events (e.g, flooding, winds, etc.,).

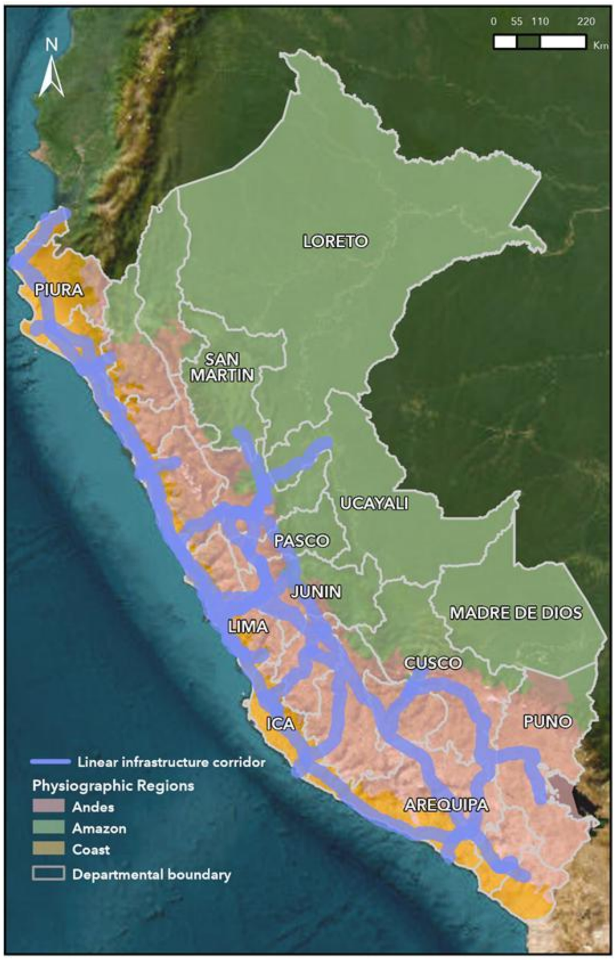

FIGURE 2: LOCATION OF THE STUDY AREA.

2.3 GeoHAS

The Geospatial Hazard Assessment Solution (GeoHAS) is Andes Geo's web application for identifying, assessing, managing, and adapting to geohazard risks for pipelines and other critical infrastructure (Figure 3). GeoHAS combines remote sensing, machine learning, probabilistic modeling, and climate science to create a user-friendly web application that provides access to critical geohazard and climate data, supporting asset integrity management and pipelines. GeoHAS includes modules to tackle different components of the geohazard risk assessment process, such as tools for monitoring channel planform displacement, landslide susceptibility and hazard modeling, and early warning system, making it a flexible, data-based solution for infrastructure operators.

GeoHAS supports pipeline and other critical infrastructure operators in understanding their current exposure and preparing for future changes using a 3-tier prioritization approach. Tiered assessment approaches have become the industry standard for managing geohazards in the pipeline sector, with most guidelines and best practices organizations suggesting a three-tiered approach that progresses from generalized hazard screening (Level 1) to detailed site-specific evaluations (Level 3) [12-22-23]. Each level of study is proportional to the level of effort. complexity and potential consequences to the integrity of the system. In summary:

- Level 1 consists of a desktop review, which includes an initial risk ranking and site prioritization.
- Level 2 involves conducting field reconnaissance and a more in-depth site-specific desktop assessment.
- Level 3 entails a detailed field site study, which includes site-specific geotechnical investigations.

After the base line assessment to define priority ranking and classification is performed, risk management and mitigation strategies are implemented. Sites are monitored and assessments are repeated on a yearly basis or after major meteorological events to make sure no significant changes or damages have occurred and that the right level of priority is assigned to the site.

Risk management includes site specific geotechnical engineering work, as well as continuous monitoring of sites and early warning to highlight locations that may be impacted by extreme weather events. Rainfall thresholds for landslide initiation are implemented on a regional basis to inform the early warning system.

2.4 Rainfall Thresholds

After having identified the sites most susceptible to landslides we implemented rainfall thresholds for landslide initiation following the approach outlined in the paper "Rainfall thresholds estimation for shallow landslides in Peru from gridded daily data" [24], which proposes a set of critical thresholds for shallow landslides in Peru. These thresholds were applied to the historical series of the ERA5-Land dataset, corresponding to the period 1950–2023. The analysis consisted of calculating the probability of precipitation events exceeding different thresholds. Precipitation events were defined based on a daily minimum precipitation of 1 mm for the Andes and Amazon regions and 0.5 mm for the Pacific region.

Millán-Arancibia and Lavado-Casimiro [24] considered individual thresholds defined in terms of:

- E: Total accumulated precipitation (mm).
- D: Duration of the rainfall event (days).
- Imax: Maximum daily intensity (mm/day).
- Imean: Average daily intensity (mm/day).

And bivariate threshold curves:

- Imax–D: Relationship between maximum intensity and event duration.
- Imean–D: Relationship between average intensity and event duration.

The combination Imean–D showed the best overall performance, achieving a TSS (True Skill Statistics) value of 0.65 in calibration and 0.42 in validation, supporting its use as the primary criterion for regional hazard analysis [24].

2.5 Combination of landslide susceptibility and rainfall thresholds

The susceptibility classes are mapped from the logistic regression model output values and then converted to hazard scores multiplying by the precipitation probability values. The precipitation probability values were calculated by extracting the frequency of occurrence of these thresholds on a yearly basis from climate data time series. Since there are many zero-value precipitation pixels, to avoid multiplying by zero, we added 1 to the precipitation probability values:

Hazard = (susceptibility * (precipitation + 1)

This way, if the precipitation is zero, the susceptibility score remains unchanged, and if precipitation is not zero, the score will increase. The values are then classified according to Table 4.

TABLE 4: LANDSLIDE SUCEPTIBILIY AND HAZARD CLASSES

Class	Value
Very High	> 0.4510
High	0.1134 -0.0830
Moderate	0.0830 -0.0641
Low	0.0641-0.0001
Very low	< 0.0001

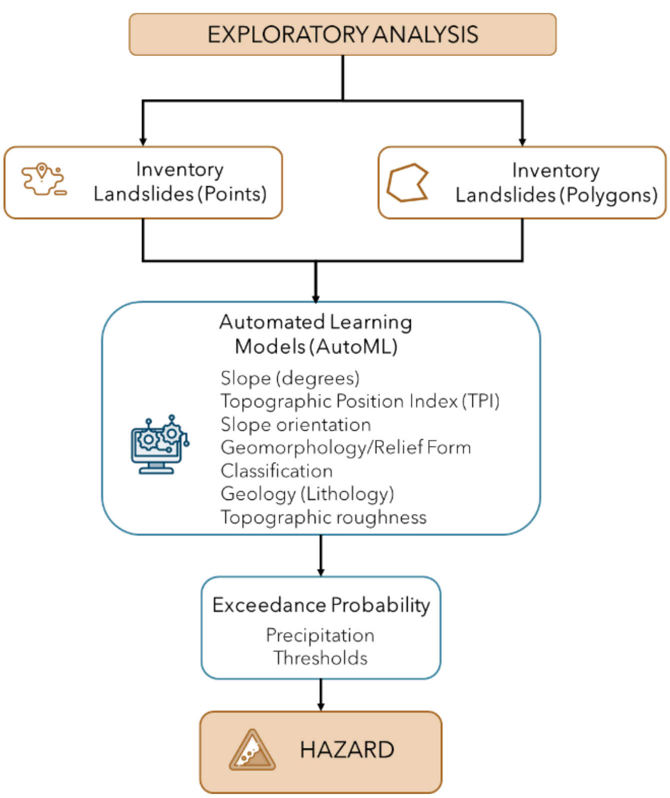

FIGURE 3: METHODOLOGY WORKFLOW DIAGRAM.

3. RESULTS AND DISCUSSION

3.1 Landslide susceptibility and rainfall thresholds

The use of rainfall thresholds and landslide susceptibility maps allows for refinement of landslide hazard sites. When considering only landslide susceptibility areas based on static landscape variables (e.g., topography. Lithology, geomorphological units etc.) the landslide trigger (rainfall) is not considered, and the landslide hazard may not be correctly mapped. Combining the landslide susceptibility map, which answers the question “where landslide may be” with the temporal dimension given by the definition of landslide threshold, which answer the question “when landslide may be”, we offer more accurate landslide hazard assessments.

For example, some high landslide susceptibility zones may be in some arid areas where rainfall thresholds for landslide initiation are rarely met, while other areas in more rainstorm-prone regions may be at higher hazard levels given the more frequent rainfall events.

After the combination between susceptibility values and precipitation probabilities we observe a reduction of the number of assets in “very high” and “high” categories, going from 25% to 7.6 % for “very high” class and from 23.7 % to 16.5 % for the “high” class (Table 5, 6 and Figure 4). This reduction of the number of assets in “very high” and “high” class helps identifying sites more likely to experience landslides, ultimately helping in risk prioritization efforts.

The shift towards embedding rainfall into landslide susceptibility model is documented in scientific literature [19, 25] and becoming more common in professional practice as shown in this paper. We think that systematically developing landslide susceptibility maps and the definition of landslide thresholds combined with early warning system can reduce pipeline integrity incidents, allowing for reducing financial losses and protecting the public and the environment.

TABLE 5: ASSETS COUNT AND PERCENTAGE IN EACH LANDSLIDE SUCEPTIBILIY CLASSES

Class	Count	%
Very High	3663	25.0
High	3485	23.7
Moderate	2151	18.6
Low	2645	18.0
Very low	2151	14.7

TABLE 6: ASSETS COUNT AND PERCENTAGE IN LANDSLIDE HAZARD CLASSES

Class	Count	%
Very High	1121	7.6
High	2428	16.5
Moderate	4221	28.7
Low	3573	24.3
Very low	3375	22.9

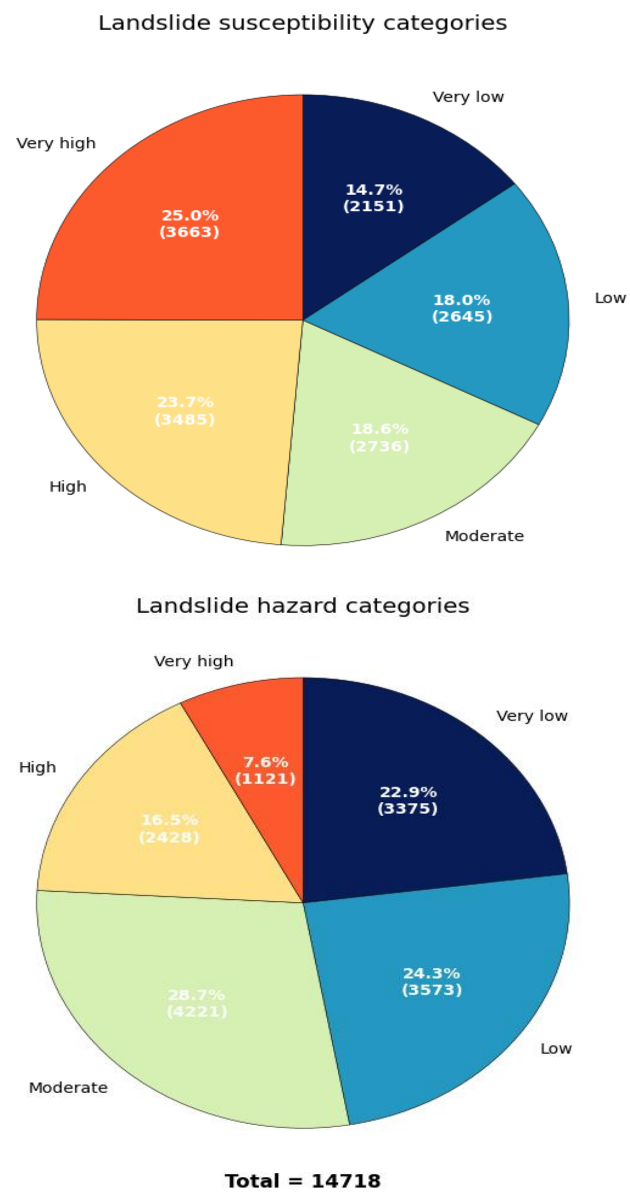

FIGURE 4: PIE CHARTS SHIWING ASSETS COUNT AND PERCENTAGE IN LANSLIDE SUCEPTIBILITY AND HAZARD CLASSES

3.2 Gridded precipitation data and triggering events

Gridded regional and global climate models operate at resolutions of 10–250 km, whereas landslide triggering-storms often occur at sub-kilometre scales, and many relevant atmospheric processes are not explicitly represented. Moreover, these triggering events also occur at sub-daily timescales, but many climate projections provide only daily or coarser temporal outputs [15] leading to an underestimation of extreme events in gridded precipitation data.

However, the alternative, of using local weather station data is hindered by the scarce spatial distributing of weather station and their inconsistency in data quality leading to inconsistent data coverage. Ultimately, the use of gridded precipitation data instead of weather station data has become prevalent since the gridded data is of more consistent spatial distribution and quality [27]. And it is sufficient to implement more conservative thresholds derived from gridded data when applied to higher resolution forecasting models (and or weather station data near a triggering event) or to make sure that the data used for definition of the thresholds and the data used for monitoring and forecasting have the same spatial and temporal resolution in order to capture future triggering events.

3.3 Landslide and climate Change

Assessing landslide hazards in the context of climate change is challenging due to the inherent uncertainties and the complex interplay among landslide-controlling factors, compounded by limitations in climate data. Extreme precipitation events—typically short and intense—are the primary triggers of shallow failures. Although a warmer climate is expected to increase both their intensity and frequency, local-scale variability remains difficult to model, and projections of extreme precipitation are generally less reliable than those of temperature [28]. In addition, inventories that directly link precipitation events with mass movement occurrence are incomplete.

Despite these challenges, strong evidence supports a thermodynamic relationship: extreme precipitation intensity increases by approximately 7% per 1 °C of warming, known as temperature scaling or Clausius–Clapeyron scaling [29-30-31]. This relationship, although simplified, provides a valuable framework for anticipating future hazard conditions based on the more robust temperature projections offered by climate models. Integrating climate change projections into geohazards management solutions supports long-term understanding of hazard trends and risk mitigation planning.

4. 2CONCLUSION

In this study we showed an application of the use of ERA-5 and CMIP6 precipitation data to reconstruct past and future minimum, maximum and average values and explore time-series to extract rainfall thresholds for landslide initiation. We then combine rainfall thresholds with a landslide susceptibility map to better refine hazard prioritization at a Level 2 assessment, aligned with recommendations outlined in API RP 1187. This workflow has been applied in Peru to a linear infrastructure corridor of about 11,000 km; the combination of landslide susceptibility with rainfall probability reduced the number of sites in "very high" and "high" categories from 25% to 7.6 % and 23.7 % to 16.5 % respectively.

The results are available in GeoHAS, a web platform that allows pipeline operators to access these climate data time series for effective data visualization, geohazard management, long -term planning and risk mitigation prioritization. GeoHAS also supports alert and early warning systems for day-to-day management operations, and users can download reports and include filed inspection to track changes while complying with regulations.

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