INTEGRATING LOGISTIC REGRESSION AND AUTOMATION TOOLS FOR RAINFALL-INDUCED LANDSLIDE RISK MANAGEMENT IN PIPELINE NETWORKS

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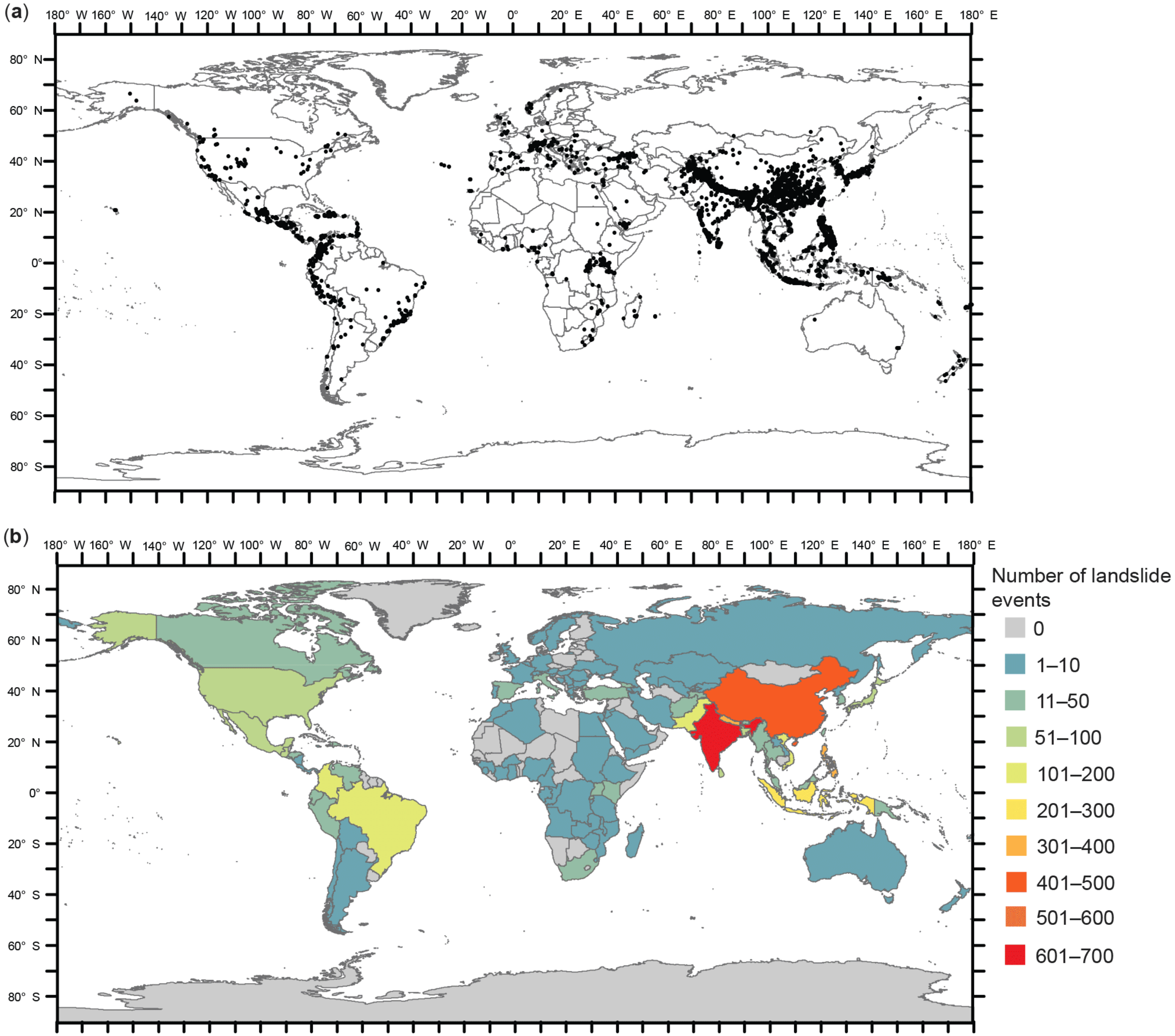
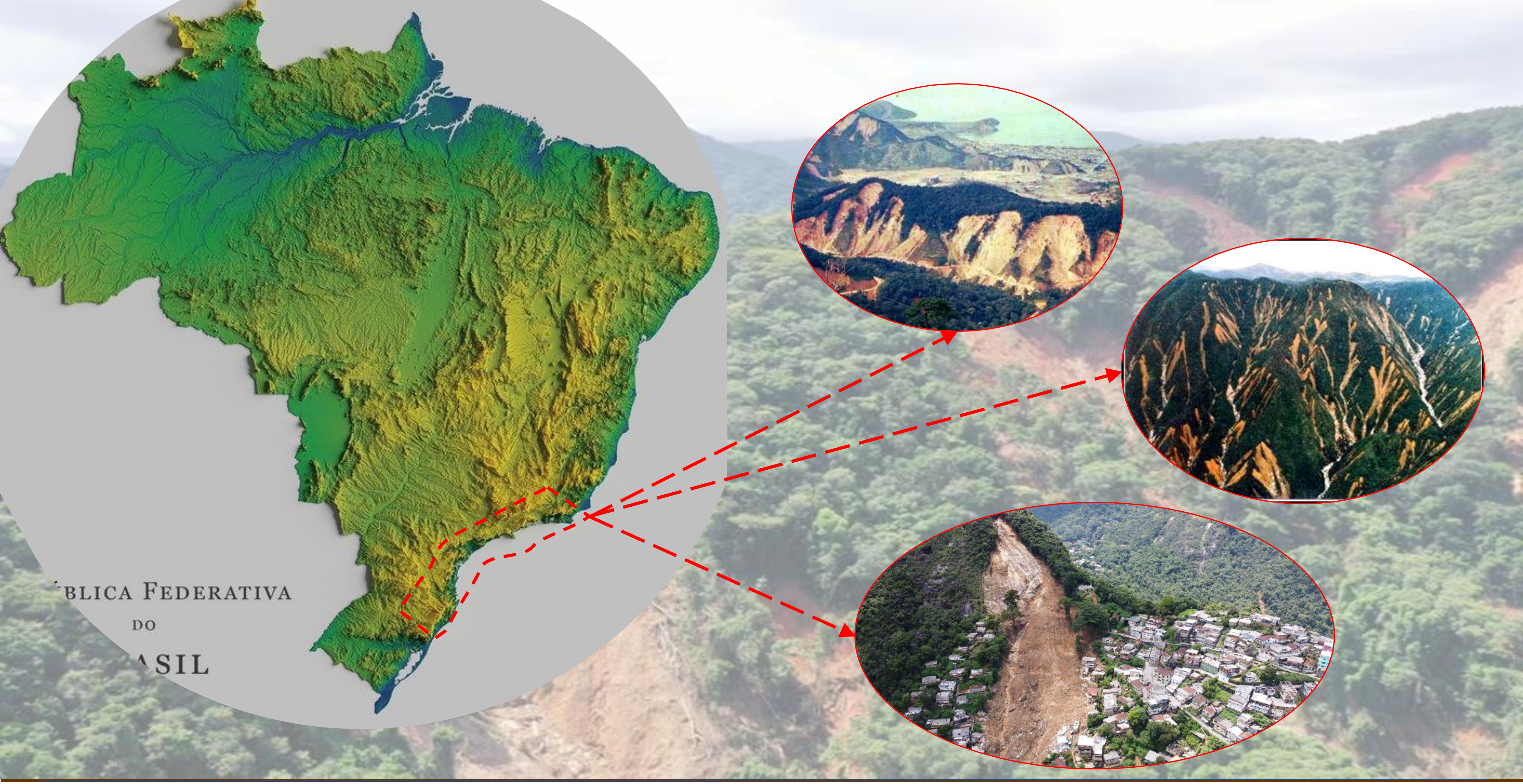
Rainfall induced landslides in Brazil and their consequences to pipelines

- Landslide hotspots: Andes and Serra do Mar (Brazilian Southeast)
- Over 8 million Brazilians live in flood/landslide risk areas; CEMADEN monitors 1,000+ municipalities
- Heavy rainfall events increasing in Central & South America since mid-20th century
- Landslides disrupt transport, energy, water systems, and urban service



ACIEM
PÚBLICA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DO
SIL

Serra do Mar (Sea Ridge):

Extension of 1,500 km;

Slopes with declivity between 35° to 40°;

Rain volumes between 2000 mm to 2500 mm annually (sometimes 4000 mm or higher);

Usually shallow landslides, with 1,5 m to 2,0 m depth, and Debris Flows

Other common mass movements: erosions, soil creeping, slumps, etc;

Santos (2023)

PÚBLICA


Seção escavada
(40x10m)

Rainfall induced landslides risk management in Transpetro

Integrity Management Program (PP-1TP-00124-0)

National Petroleum Agency - ANP resolution 6/2011 (RTDT)

Guarantee the safety of the pipeline operations against geotechnical hazards

Failure mode: geotechnical occurrences

Geological Geotechnical Inspection

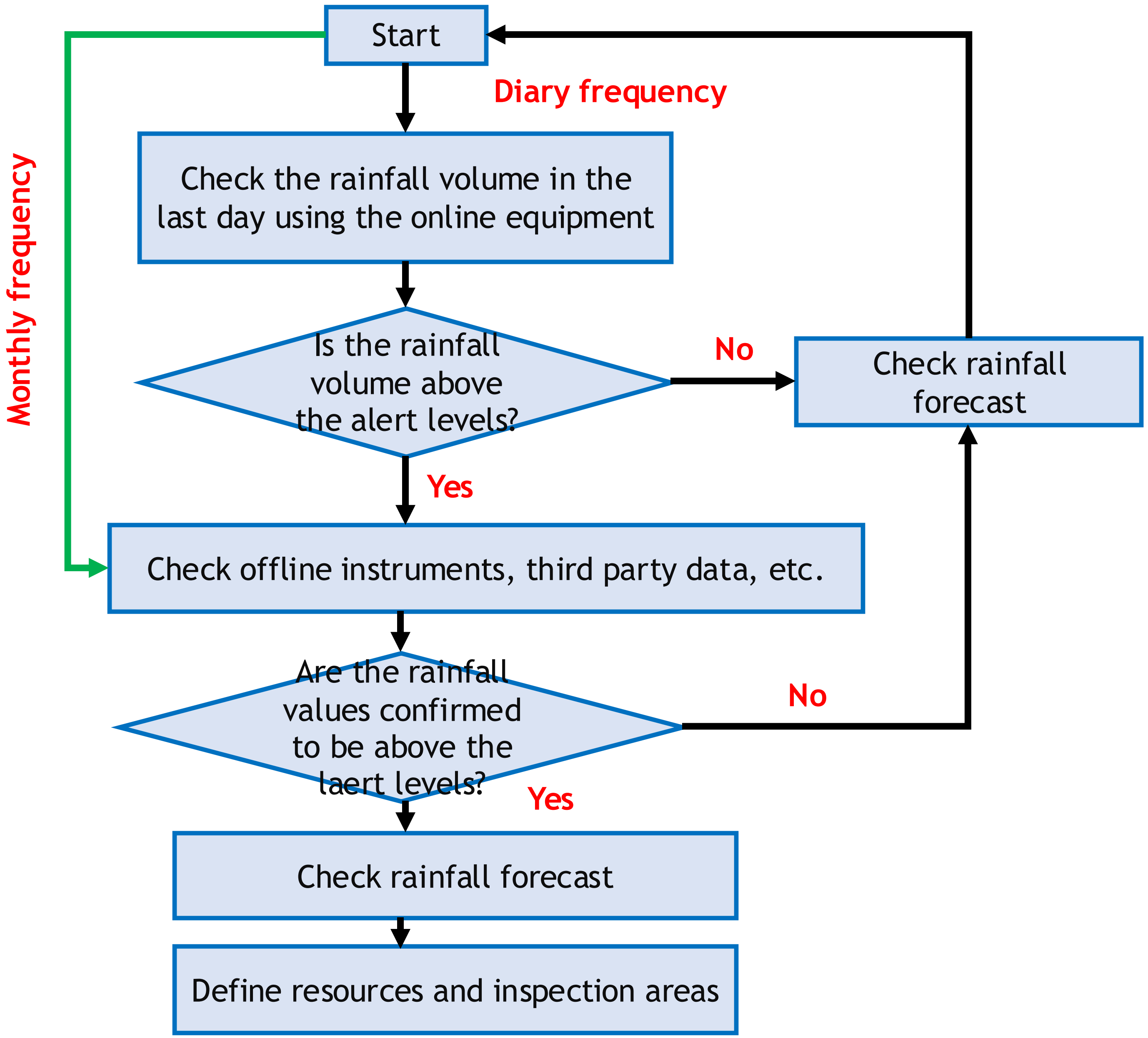
Slope monitoring

Periodic seasonal inspections, on-demand inspections, river crossing inspections, tie-back wall inspections

Geotechnical instrumentation (PG-1TP-00042)

Pluviometric Monitoring (PE-1TP-00053)

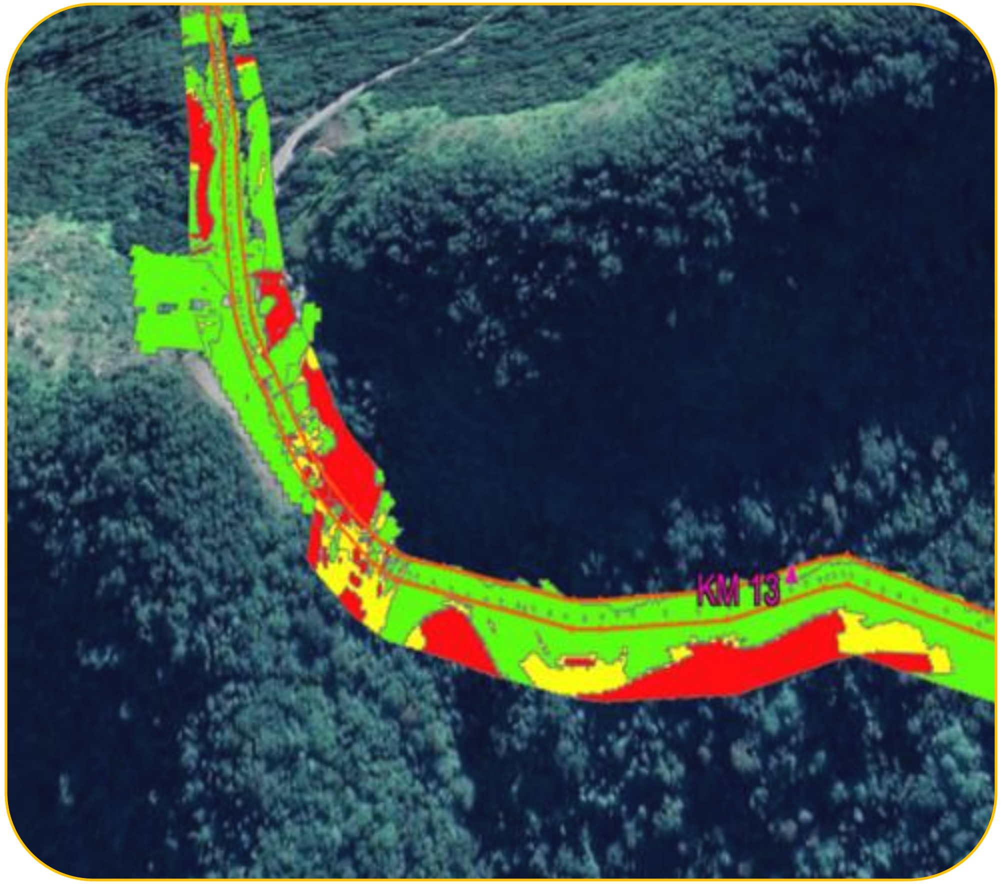
It proposes a routine for the periodic monitoring. It does not stablishes alert levels or the methodology for implementing them.

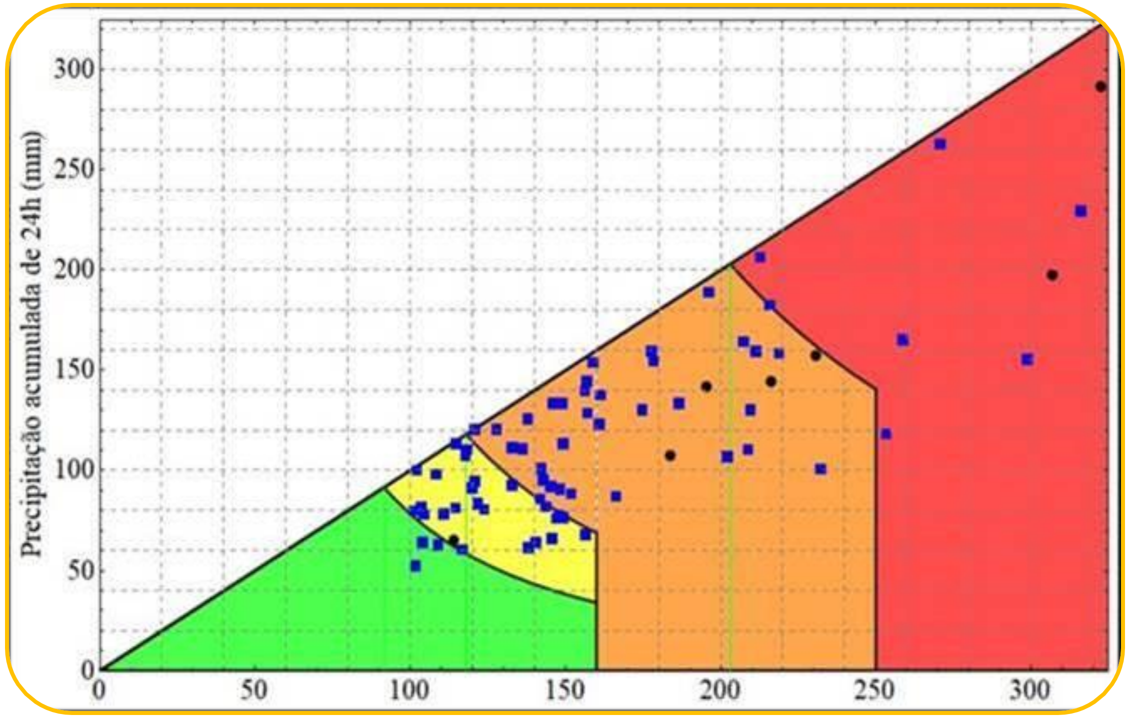

Start
Diary frequency
Monthly frequency
Check the rainfall volume in the last day using the online equipment
Is the rainfall volume above the alert levels?
No
Check rainfall forecast
Yes
Check offline instruments, third party data, etc.
Are the rainfall values confirmed to be above the laert levels?
No
Yes
Check rainfall forecast
Define resources and inspection areas

Decision Making

- Landslide susceptibility maps

- Landslide triggering rainfall curves



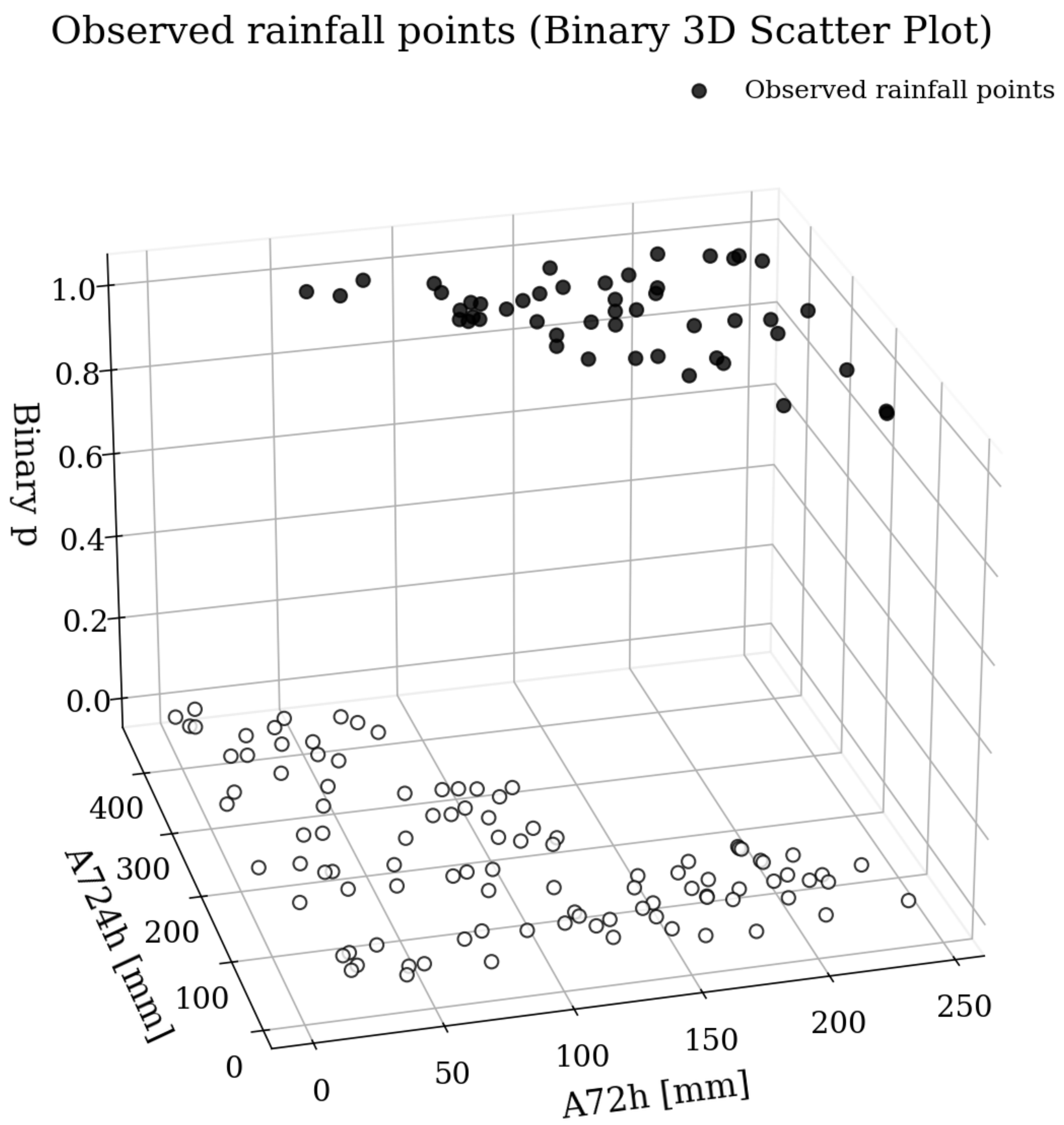


Necessary measures for each susceptible zone

Zone I	Zone II	Zone III	Zone IV
- Keep the periodic monitoring and send short reports.	- Rise the monitoring frequency and reports to 2 times a day. - field inspections in areas that have previously suffered from geotechnical events	- Start extensive inspections of the pipeline regions with rainfall volume in zone III, and with high susceptibility to geotechnical events (previously mapped with a hazard zonation map). - Start an extraordinary geotechnical instrument reading campaign.	- The risk of geotechnical events reaches a very high value. It is suggested that the operator stops the operation of the pipelines located in terrains with high susceptibility to geotechnical events and that reached zone IV.

OK…
SO, WHAT’S THE PROBLEM HERE?

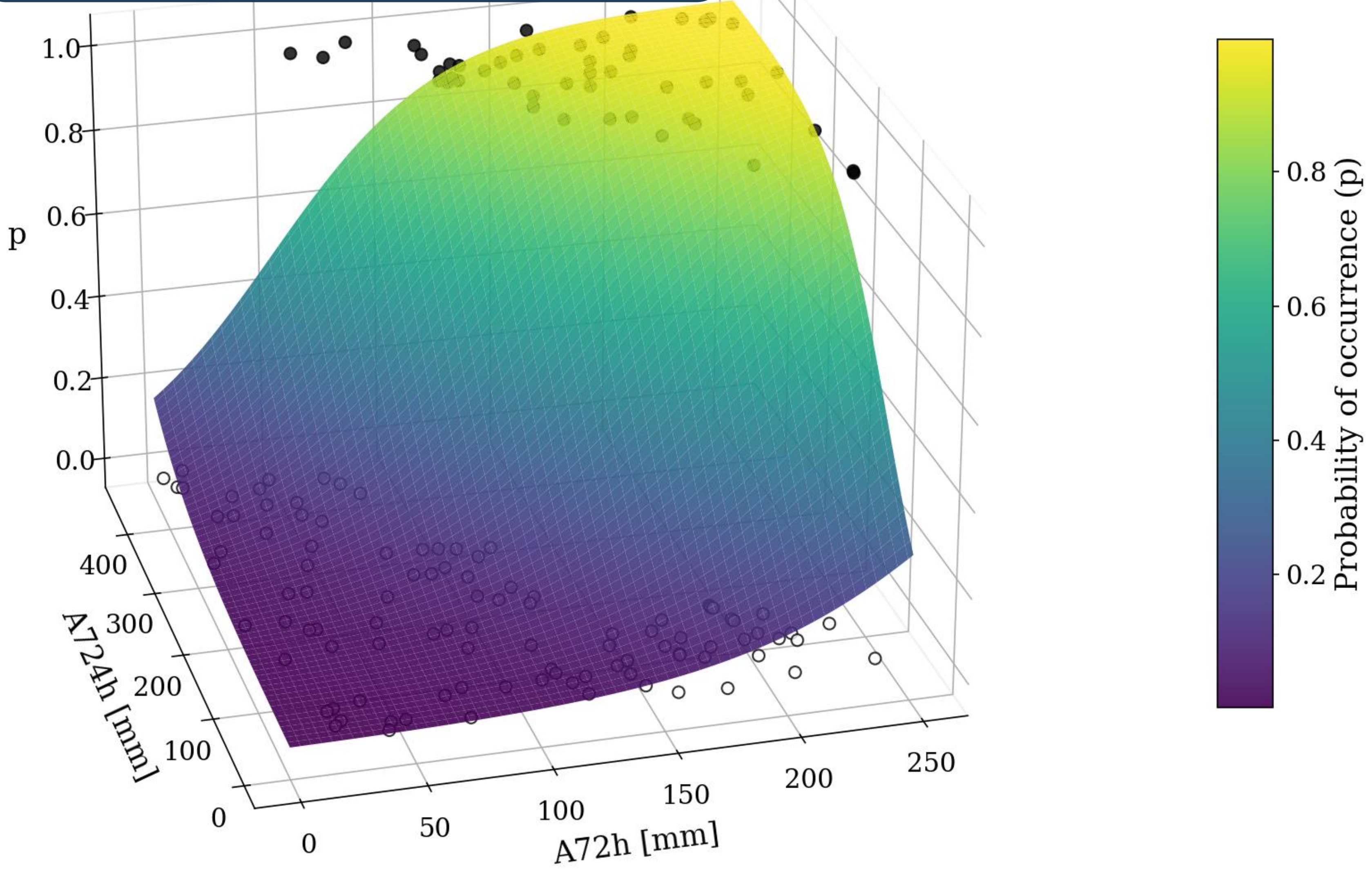
Solving the problem with logistic-regression



Observed rainfall points (Binary 3D Scatter Plot)
Observed rainfall points
Binary p
1.0
0.8
0.6
0.4
0.2
0.0
A724h [mm]
400
300
200
100
0
A72h [mm]
0
50
100
150
200
250

Logistic surface with observed points (hypothetical model)

$$p = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 A_{72h} + \beta_2 A_{24h})]}$$



$$p = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 A_{72h} + \beta_2 A_{24h})]}$$

Chosing

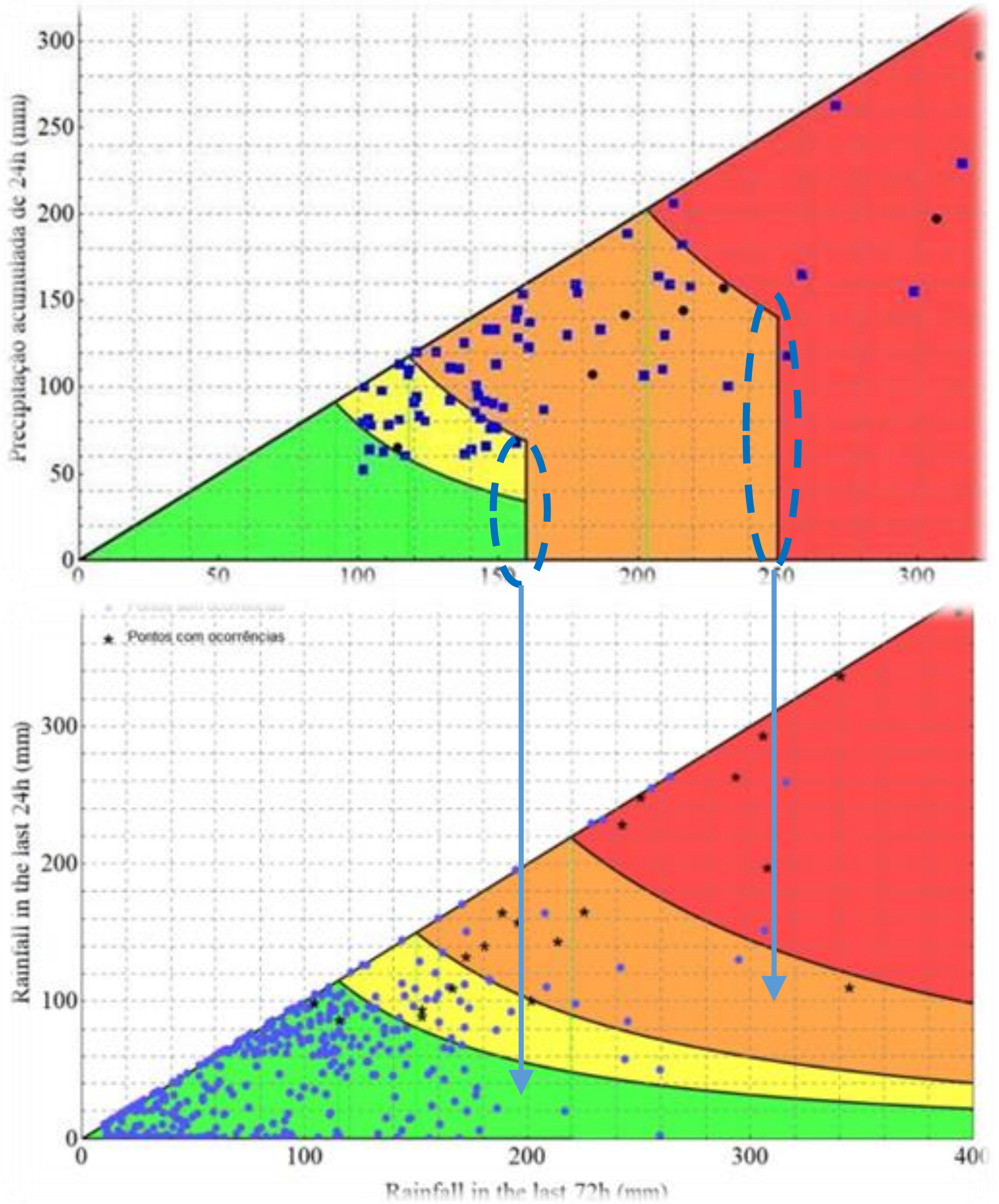
$$\boxed{A_{24h} = \alpha\, A_{72h}^{-\gamma}}$$

With (Giannecchini *et al.*, 2016)

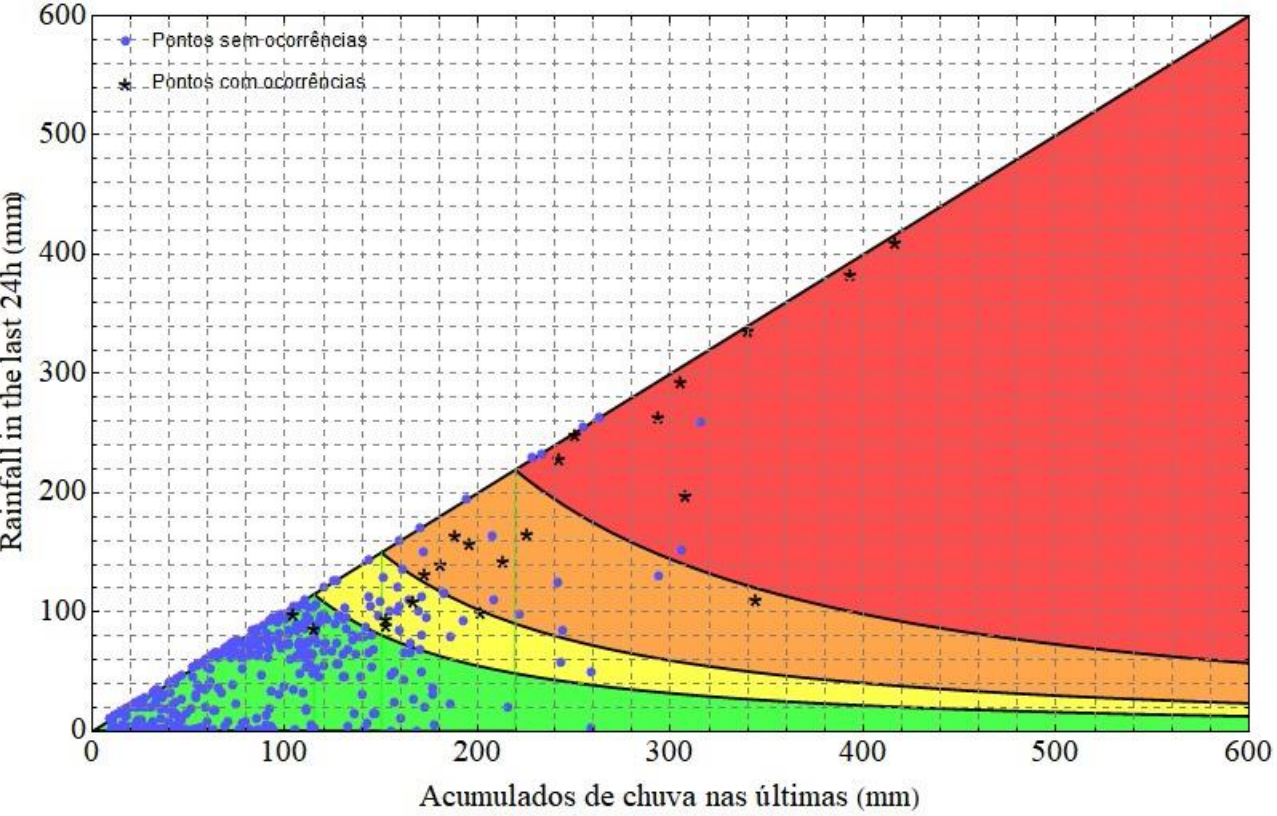
- $\alpha = \exp\left(-\frac{\beta_0}{\beta_2}\right)\left(\frac{1-p}{p}\right)^{-\frac{1}{\beta_2}}$
- $\gamma = -\frac{\beta_1}{\beta_2}$

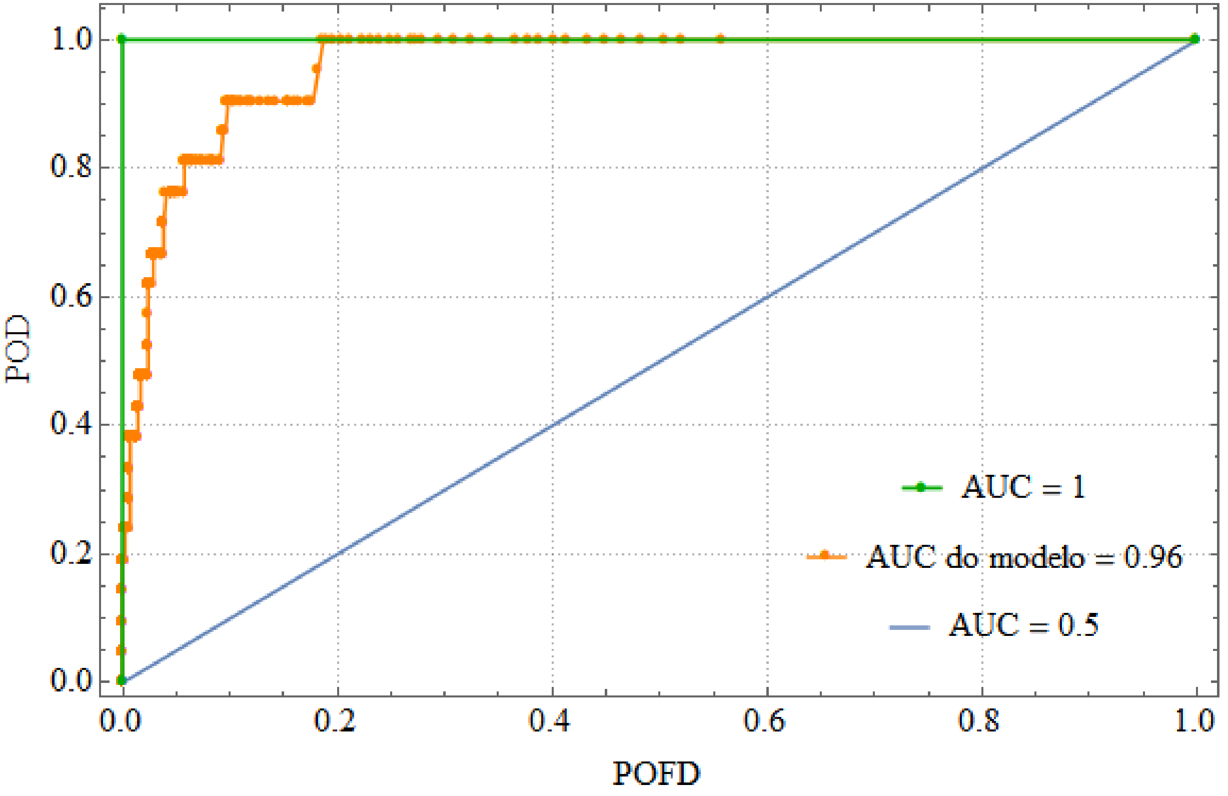
Where:
p(Landslide) is the probability of a landslide event;
β_0 is the intercept;
β_1 and β_2 are coefficients for A_{24h} and A_{72h}, respectively.

- Zone 1: ≤ 5% (Low Susceptibility)
- Zone 2: 5–15%
- Zone 3: 15–60%
- Zone 4: 60% ≤ (High Susceptibility)



Model perfomance and validation





Pipeline Region	AUC
Southern Brazil	0.86
Rio de Janeiro/MG	0.96
São Paulo (OSBAT ROW)	0.95
São Paulo (OSPLAN ROW)	0.97

- Logistic model embedded in a digital decision-support system.
- Field data collected via Microsoft Forms.
- Rainfall curves updated weekly in Power BI.
- Daily alerts sent automatically using Power Automate.
- Response actions follow existing protocol (Mascarenhas et al., 2023).

TRANSPETRO

Monitoramento Pluviométrico das Faixas de Dutos - Regional SPPCO

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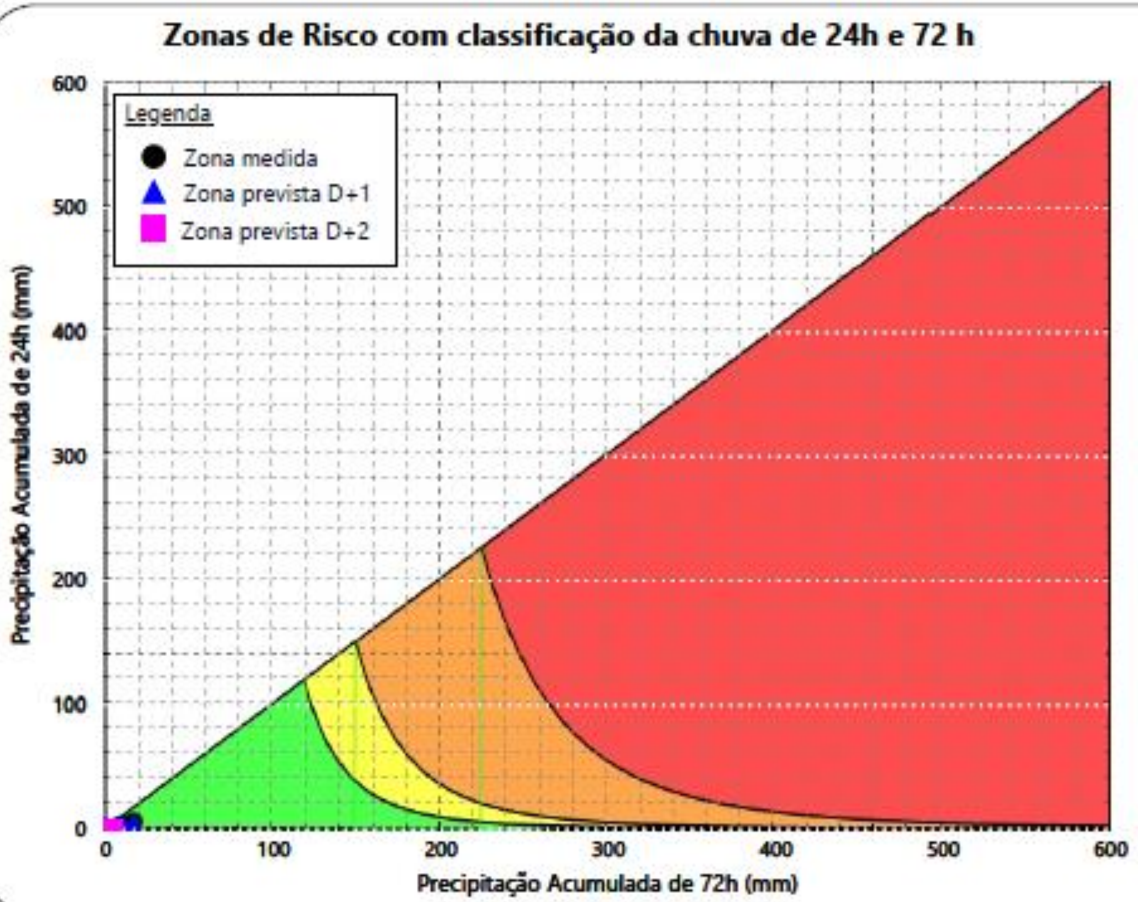
Última atualização

OSPLAN



Máximas Precipitações Acumuladas Ocorridas

	Acc 24h Ocorrido		Acc 72h Ocorrido
Estação =	OSPLAN - km 010+200	Estação =	OSPLAN - km 010+200
Po24h =	5,40	Po72h =	17,0

Zona Atual Máxima: **Zona 1**

Previsões nas próximas 24h (D+1)

Conforme Climatempo

	Acc 24h prevista		Acc 72h prevista
Estação =	OSPLAN - km 010+200	Estação =	OSPLAN - km 010+200
Po24h+1d =	0,0	Po72h+1d =	17,0

Zona Prevista Máxima D+1: **Zona 1**

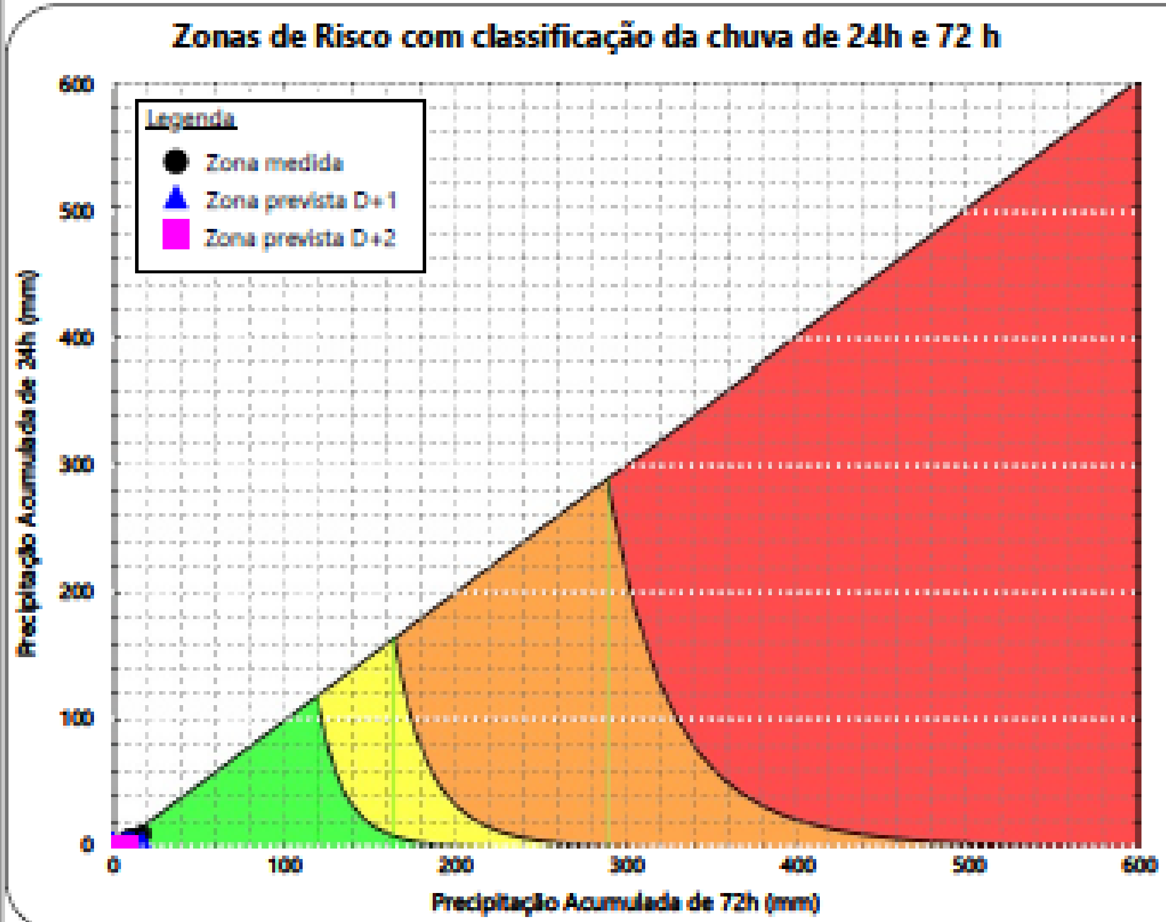
Previsões nas próximas 48h (D+2)

Conforme Climatempo

	Acc 24h prevista		Acc 72h prevista
Estação =	OSPLAN - km 010+200	Estação =	OSPLAN - km 010+200
Po24h+2d =	0,0	Po72h+2d =	5,4

Zona Prevista Máxima D+2: **Zona 1**

OSBAT



Máximas Precipitações Acumuladas Ocorridas

	Acc 24h Ocorrido		Acc 72h Ocorrido
Estação =	OSBAT - km 098	Estação =	OSBAT - km 098
Po24h =	8,40	Po72h =	17,6

Zona Atual Máxima

Zona 1

Previsões nas próximas 24h (D+1)

Conforme Climatempo

	Acc 24h prevista		Acc 72h prevista
Estação =	OSBAT - km 098	Estação =	OSBAT - km 098
Po24h+1d =	0,1	Po72h+1d =	17,7

Zona Prevista Máxima D+1

Zona 1

Previsões nas próximas 48h (D+2)

Conforme Climatempo

	Acc 24h prevista		Acc 72h prevista
Estação =	OSBAT - km 098	Estação =	OSBAT - km 098
Po24h+2d =	0,1	Po72h+2d =	8,5

Zona Prevista Máxima D+2

Zona 1

Situação das Faixas conforme Precipitação Ocorrida

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	Zona 1	Zona 2	Zona 3	Zona 4
OSPLAN	Trecho **km 000+000 a km 003+600** **km 003+600 a km 009+250** **km 009+250 a km 012+300** **km 012+300 a km 016+500** **km 016+500 a km 018+500** **km 018+500 a km 022+400** **km 022+400 a km 026+800** **km 026+800 a km 029+000**	Trecho	Trecho	Trecho
OSBAT	Trecho **km 000+000 a km 006+000** **km 008+100 a km 009+200** **km 009+200 a km 011+000** **km 011+000 a km 013+500** **km 013+500 a km 014+900** **km 014+900 a km 016+000** **km 016+000 a km 017+150** **km 017+150 a km 018+600** **km 022+300 a km 026+300** **km 027+400 a km 029+200** **km 030+400 a km 031+500** **km 035+500 a km 038+000**	Trecho	Trecho	Trecho

Situação das Faixas conforme Precipitação Prevista (D+1)

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	Zona 1	Zona 2	Zona 3	Zona 4
OSPLAN	Trecho km 000+000 a km 003+600 km 003+600 a km 009+250 km 009+250 a km 012+300 km 012+300 a km 016+500 km 016+500 a km 018+500 km 018+500 a km 022+400 km 022+400 a km 026+800 [illegible]	Trecho	Trecho	Trecho
OSBAT	Trecho km 110+000 a km 114+000 km 107+000 a km 108+000 km 105+000 a km 106+000 km 098+000 a km 100+000 km 092+000 a km 093+000 km 089+500 a km 091+000 km 040+050 a km 042+300 km 035+500 a km 038+000 km 030+400 a km 031+500 km 027+400 a km 029+200 km 022+300 a km 026+300 [illegible]	Trecho	Trecho	Trecho

Monitoramento Pluviométrico das Faixas de Dutos

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Ações de Resposta - Precipitação Ocorrida

Nível	Ações de Resposta para valores de Precipitações Ocorridas	Trechos de Faixa - OSPLAN	Trechos de Faixa - OSBAT
Zona I	· Manter o monitoramento periódico das chuvas.	Trecho km 000+000 a km 003+600 km 003+600 a km 009+250 km 009+250 a km 012+300 km 012+300 a km 016+500 km 016+500 a km 018+500 km 018+500 a km 022+400 km 022+400 a km 026+800 km 026+800 a km 029+000 km 029+000 a km 033+000 (ERP)	Trecho km 110+000 a km 114+000 km 107+000 a km 108+000 km 105+000 a km 106+000 km 098+000 a km 100+000 km 092+000 a km 093+000 km 089+500 a km 091+000 km 040+050 a km 042+300 km 035+500 a km 038+000 km 030+400 a km 031+500 km 027+400 a km 029+200 km 022+300 a km 026+300
Zona II	· Aumentar a frequência de monitoramento para 2 vezes ao dia; · Realizar inspeções pontuais em áreas instrumentadas (com histórico de movimentação de solo) e em ocorrências geotécnicas pré-existentes de Grau de Risco Moderado IV ou Alto ou que possuam RI aberta, que estejam situados dentro da região onde foi registrada a pluviometria correspondente à Zona II.	Trecho	Trecho
Zona	· Realizar inspeções nos trechos de serra de alta susceptibilidade a escorregamentos, que estejam situadas dentro da região onde foi registrada a pluviometria correspondente à Zona III; · Realizar leituras extraordinárias em instrumentos geotécnicos pré-selecionados (conforme orientação da IDUTOS) em áreas monitoradas onde foi registrada a pluviometria correspondente à Zona III, devendo ser aguardado o prazo necessário que possibilite tal medição (estiagem da chuva).	Trecho	Trecho
Zona IV	· Indicação de parada operacional, a ser determinada pelo Gerente Responsável.	Trecho	Trecho

Monitoramento Pluviométrico das Faixas de Dutos

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Última atualização

Ações de Resposta - Precipitação Prevista (D+1)

Nível	Ações de Resposta para valores de Precipitações prevista	Trechos de Faixa	
		OSPLAN	OSBAT
Zona I	• Manter o monitoramento periódico das chuvas.	Trecho km 000+000 a km 003+600 km 003+600 a km 009+250 km 009+250 a km 012+300 km 012+300 a km 016+500 km 016+500 a km 018+500 km 018+500 a km 022+400 km 022+400 a km 026+800 km 026+800 a km 029+000 km 029+000 a km 033+000 (ERP) km 033+000 (ERP) a km 036+500 km 036+500 a km 039+630	Trecho km 000+000 a km 006+000 km 008+100 a km 009+200 km 009+200 a km 011+000 km 011+000 a km 013+500 km 013+500 a km 014+900 km 014+900 a km 016+000 km 016+000 a km 017+150 km 017+150 a km 018+600 km 022+300 a km 026+300 km 027+400 a km 029+200 km 030+400 a km 031+500
Zona II	• Manter o monitoramento periódico das chuvas.	Trecho	Trecho
Zona III	• Informar às equipes que estão no sobreaviso das áreas com possibilidade de chuvas correspondente à Zona III (com antecedência de até 48h).	Trecho	Trecho
Zona IV	• Informar a Gerência Responsável sobre a possibilidade de parada operacional (com antecedência de até 48h); • Informar as Gerências / Gerências Setoriais da PIL e OP sobre a possibilidade de parada operacional com 48h de antecedência (no horário administrativo). *	Trecho	Trecho

* Período de antecedência a ser avaliado em função da assertividade das previsões.
IDUTOS – Gerência de Integridade de Dutos
PIL – Gerência de Programação e Integração Logística
OP – Gerência de Operações CNCL

Conclusion

SUMMARY OF LOGISTIC REGRESSION MODEL FOR LANDSLIDE RISK

Improved Rainfall Thresholds

The model enhances rainfall thresholds to better predict landslide events with high sensitivity at low probabilities.

Dynamic Decision Making

Supports probabilistic decisions and updates susceptibility curves to improve operational efficiency and resilience.

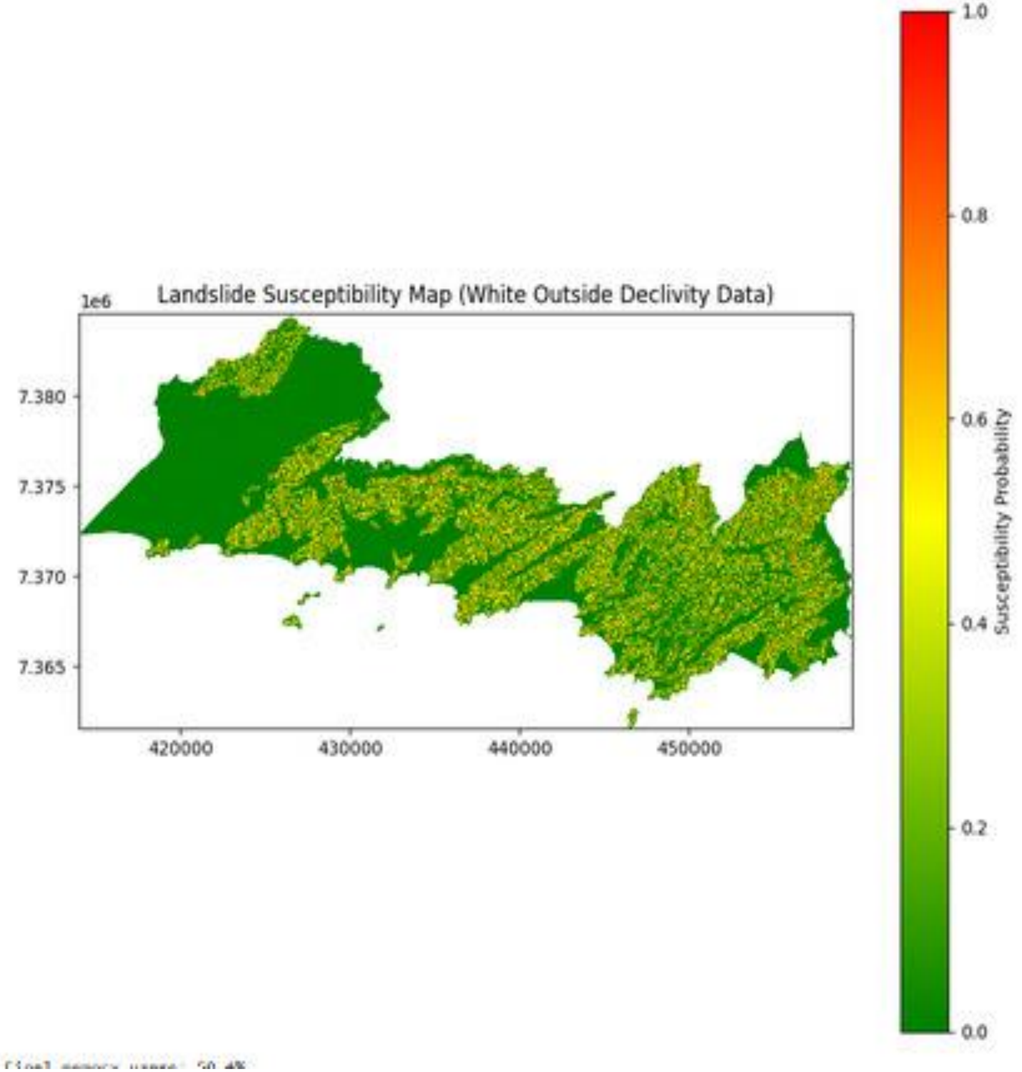
Threshold Performance Variability

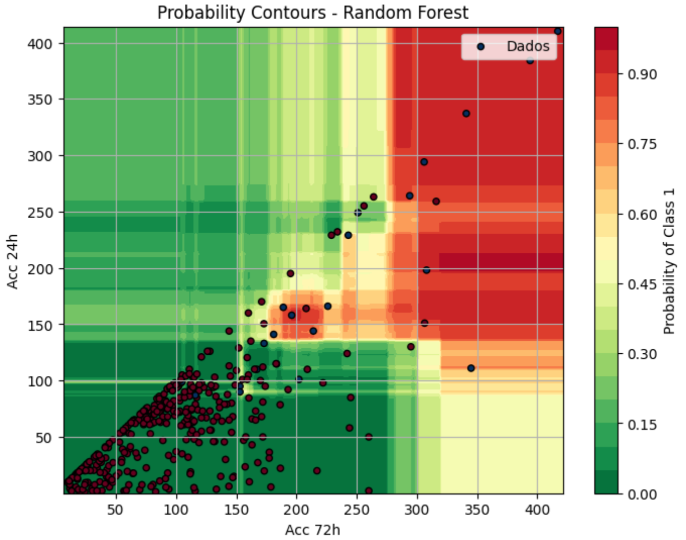
Optimal at 10% probability threshold; performance declines significantly beyond 60%, affecting safety.

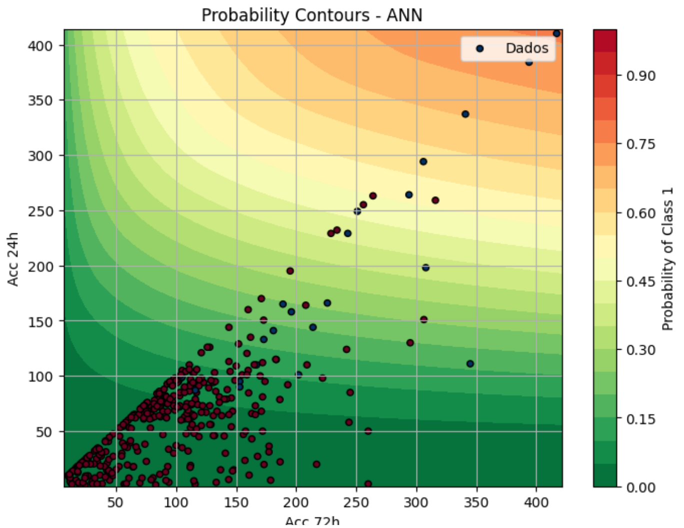
Model Limitations and Future Research

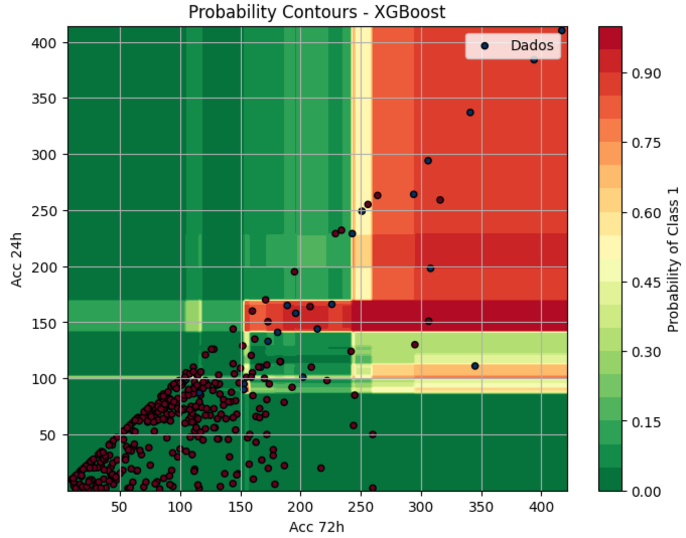
Dependent on data quality and missing terrain variables; future work includes ensemble learning and sensor data integration.

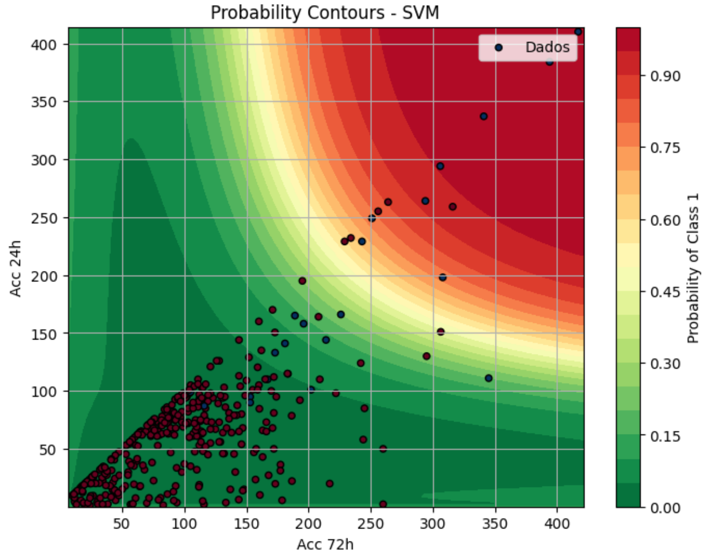
DEVELOPMENTS IN PROGRESS











¡Gracias!

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INTEGRATING LOGISTIC REGRESSION AND AUTOMATION TOOLS FOR RAINFALL-INDUCED LANDSLIDE RISK MANAGEMENT IN PIPELINE NETWORKS

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ABSTRACTS

Pipelines traversing geotechnically sensitive terrains are particularly vulnerable to rainfall-induced landslides and debris flows. In Brazil, the Serra do Mar mountainous region presents significant geohazard challenges for pipeline integrity management. To address this, Transpetro implemented a rainfall monitoring protocol using empirical rainfall thresholds to inform operational decisions. However, recent operational demands and the expansion of the monitored network highlighted limitations in the existing protocol — particularly regarding its conservative nature and static decision boundaries. This study presents the development and application of a logistic regression model to enhance the rainfall-based decision-making protocol for pipeline response actions. The model replaces static threshold curves with probabilistic susceptibility zones derived from logistic regression, using accumulated rainfall data over 24 and 72 hours as predictors. By leveraging a database of rainfall events and associated geotechnical incidents, we updated the susceptibility curves to reflect probability-based zones, allowing for more realistic and dynamic responses to increasing rainfall risk. Key improvements include: (i) optimization of rainfall thresholds by means of a continuous probabilistic limit; (ii) annual curve updates through and automated emission of alerts by means of Microsoft Power Bi and Power Automate; and (iii) performance validation of the logistic models via Receiver operator Characteristic (ROC) curves and Area Under the Curve (AUC) indicators. These enhancements resulted in more accurate risk classification, reduced false positives, and shorter operational downtimes for pipelines. The updated protocol enables tailored responses depending on the intersecting susceptibility class of each pipeline segment and the real-time rainfall-based probability zone. It also recommends operational adjustments rather than mandatory shutdowns in high-risk scenarios, supporting more nuanced risk-informed decision-making. The methodology was applied to three major operational regions (São Paulo, Southern Brazil, and Rio de Janeiro/Minas Gerais), each showing significant reductions in unnecessary inspections and shutdowns, while maintaining or improving safety standards. This approach exemplifies how geotechnical risk management can benefit from data science tools in pipeline operations. It also sets a precedent for broader implementation across pipeline networks, especially in tropical or mountainous environments where rainfall-induced hazards are prevalent.

1. Introduction

Rainfall-induced landslides and debris flows are among the most critical natural threats to pipeline infrastructure, especially in geologically sensitive and high-rainfall environments such as Brazil's Serra do Mar. These mass movement events, often triggered by intense or prolonged rainfall, can lead to severe consequences, including ruptures in pipeline systems, environmental degradation, service interruptions, and costly emergency interventions. In this context, managing the geotechnical risks associated with rainfall has become a central challenge for infrastructure operators like Transpetro, the pipeline logistics branch of PETROBRAS.

In the Serra do Mar region, where pipeline corridors frequently traverse steep slopes with high geotechnical susceptibility, rainfall-induced landslides represent a significant challenge for risk management (Amarasinghe *et al.*, 2024) These landslides can cause not only physical damage to the pipelines and ancillary infrastructure but also pose serious environmental and social risks due to potential product leakage in ecologically sensitive areas (Cunha, 2016). Additionally, the combination of rugged terrain, dense vegetation, and limited access hinders rapid response and inspection activities, increasing the importance of reliable predictive models for proactive decision-making. Managing these risks requires tools that can anticipate hazardous conditions with precision, allowing for the timely implementation of preventive measures while minimizing disruptions to operations.

To mitigate these risks, Transpetro has historically employed a rainfall threshold-based protocol to trigger field inspections and operational responses. These thresholds were based on accumulated rainfall over short durations (24 and 72 hours) and defined conservative action limits (Mascarenhas *et al.*, 2023). This protocol combines a susceptibility map along with rainfall threshold curves to pinpoint where risk control actions are to be taken. While effective in avoiding incidents, this deterministic and static approach often led to unnecessary field mobilizations, excessive resource allocation, and even temporary pipeline shutdowns in the absence of actual slope instability. The limitations of such rigid frameworks become especially pronounced in large-scale pipeline networks where regional variability in rainfall response and slope susceptibility demand more flexible and location-specific decision-making tools.

In response to this need, the present work introduces a probabilistic and data-driven methodology to refine and improve the existing rainfall-based risk management protocol. By applying logistic regression models to a comprehensive historical database of rainfall and landslide events along pipeline corridors, the project aims to derive statistically robust rainfall thresholds that quantify the probability of slope failure as a continuous function of rainfall accumulation (Giannecchini *et al.*, 2016). Other modifications based on experience of the application of the previous model were also implemented. The model outputs are used to define zones of landslide susceptibility, which are then integrated into a decision-support system guiding operational actions in real time.

This approach builds upon and contributes to a growing body of literature on rainfall thresholds and probabilistic modeling of landslides (e.g., Caine, 1980; Guzzetti et al., 2022; Giannecchini et al., 2024). It aligns with international recommendations for quantitative landslide risk assessment (Corominas et al., 2014) and leverages recent advances in geospatial data management and machine learning integration in geotechnical applications (Pourghasemi et al., 2020; Alcântara et al., 2024).

The remainder of this paper presents the methodology adopted, including data processing, model construction and validation, and implementation in an operational setting. Results are discussed in terms of model performance, improvements in operational efficiency, and implications for broader risk management practices in pipeline systems exposed to hydrological hazards.

2. Methodology

The methodological framework consisted of five main stages designed to address the operational need for improved, location-specific predictions of rainfall-induced landslide susceptibility along pipeline corridors: data collection, data preprocessing, model construction, model validation, and operational integration.

2.1 Data Collection and Processing

Rainfall and landslide data were collected from Transpetro's geotechnical monitoring program in three major operational regions: Southern Region, Rio de Janeiro/Minas Gerais, and São Paulo.

Separate models were calibrated for each operational region to reflect local geomorphological, climatic, and operational characteristics. Four diagrams were plotted for these regions: two for São Paulo (OSBAT and OSPLAN ROWs, one for the southern region and one for Rio de Janeiro/Minas Gerais region. This division was stablished considering geological/geotechnical similarities or differences ROWs in each operational region, and data quality.

Events were classified as landslide occurrences (1) or non-occurrences (0). Rainfall parameters included accumulated precipitation over 24 hours and 72 hours. Only georeferenced and time-referenced events were considered.

Separate models were calibrated for each operational region to reflect local geomorphological, climatic, and operational characteristics.

2.2 Logistic Regression Model

A binary logistic regression model was used to estimate the probability of landslide occurrence as a function of the antecedent accumulated rainfall in 24h and 72h, namely A_{24h} and A_{72h}. The model has the following form:

$$p = \frac{1}{1 + \exp\left[-(\beta_0 + \beta_1 A_{72h} + \beta_2 A_{24h})\right]}$$

Where:

- P(Landslide) is the probability of a landslide event;
- β_0 is the intercept;
- β_1 and β_2 are coefficients for A_{24h} and A_{72h}, respectively.

The binary logistic regression implies that A_{24h} and A_{72h} are related through the usual empirical power law relation usually adopted when studying rainfall thresholds (Safeland, 2012):

$$A_{24h} = \alpha\, A_{72h}^{-\gamma}$$

Where α and γ are defined by (Giannechinni et al, 2016):

$$\alpha = \exp\left(-\frac{\beta_0}{\beta_2}\right)\left(\frac{1-p}{p}\right)^{-\frac{1}{\beta_2}}$$

and

$$\gamma = -\frac{\beta_1}{\beta_2}$$

The model is fitted using the database. Fixing the fitted γ value, we choose failure probabilities p accordingly to the operational parameters, and use the resulting parallel curves as thresholds to rainfall susceptibility zones. Each of these zones define operational response actions accordingly to the probability of failure that it poses to the slopes in the region of the pipelines. The definition of 4 landslide susceptibility zones follows the same approach as done in Mascarenhas *et al.* (2023).

The continuous probability output from the model was divided into four zones:

- Zone 1: < 05% (Low Susceptibility)
- Zone 2: 05–15%
- Zone 3: 15–60%
- Zone 4: <= 60% (High Susceptibility)

2.2 Model Validation

Model performance was evaluated using ROC curves and the Area Under the Curve (AUC) metric. Sensitivity and specificity values were analyzed for each region. Data visualization was performed using *Wolfram Mathematica* (Wolfram Research, 2016)

Model performance was evaluated using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics, which quantify the trade-off between true positive rate (sensitivity) and false positive rate (1 - specificity). Models achieving AUC values above 0.85 were considered satisfactory for operational deployment. Additionally, the performance assessment of the models is based on the number of true positive (TP), false negative (FN), false positive (FP), and true negative (TN) events. From these, various metrics are derived, such as the probability of detection (POD), probability of false detection (POFD), and probability of false alarm (POFA). Additional indicators include the efficiency score (Ef), the Hanssen and Kuipers score (HK, 1965), the Euclidean distance to the perfect classifier (δ).

2.5 Operational Integration

The logistic model was incorporated into an automated data acquisition and decision-support system. Field reports are expected to be submitted via Microsoft Forms, feeding a SharePoint-based database that updates weekly rainfall-likelihood curves in Power BI dashboards.

A daily bulletin is sent via e-mail through automation using Microsoft Power Automate to engineers, managers and other workers involved with the response actions' process. The corresponding actions to each rainfall level has not been changed, and they fully described in Mascarenhas *et al.* (2023).

3. Results and Discussion

The logistic regression models developed for the three operational regions demonstrated strong predictive capacity and practical utility. Each model achieved an Area Under the ROC Curve (AUC) greater than 0.85, confirming their effectiveness in distinguishing between rainfall events that did and did not result in landslides.

Table 1 summarizes the performance metrics.

Table 1. Performance of logistic regression models by region

Region	AUC
Southern Brazil	**0.86**
Rio de Janeiro/MG	**0.96**
São Paulo (OSBAT ROW)	**0.95**
São Paulo (OSPLAN ROW)	**0.97**

More performance metrics are shown in Table 1 through Table 4

Table 1. OSBAT performance metrics.

Probability	TP	FN	FP	TN	POD	POFD	POFA	Ef	HK	δ
5%	9	0	23	131	**1.**	0.149351	0.71875	0.858896	**0.850649**	1
10%	7	2	14	140	0.777778	0.0909091	0.666667	0.90184	0.686869	**0.149351**
15%	6	3	13	141	0.666667	0.0844156	0.684211	0.90184	0.582251	0.240098
20%	6	3	11	143	0.666667	0.0714286	0.647059	0.91411	0.595238	0.343856
25%	6	3	7	147	0.666667	0.0454545	0.538462	0.93865	0.621212	0.340901
30%	5	4	6	148	0.555556	0.038961	0.545455	0.93865	0.516595	0.336418
35%	5	4	4	150	0.555556	0.025974	0.444444	0.95092	0.529582	0.446149
40%	4	5	2	152	0.444444	0.012987	0.333333	**0.957055**	0.431457	0.445203
45%	3	6	2	152	0.333333	0.012987	0.4	0.95092	0.320346	0.555707
50%	2	7	2	152	0.222222	0.012987	0.5	0.944785	0.209235	0.666793
55%	2	7	1	153	0.222222	0.00649351	0.333333	0.95092	0.215729	0.777886
60%	2	7	0	154	0.222222	**0.**	**0.**	**0.957055**	0.222222	0.777805
65%	2	7	0	154	0.222222	**0.**	**0.**	**0.957055**	0.222222	0.777778
70%	2	7	0	154	0.222222	**0.**	**0.**	**0.957055**	0.222222	0.777778
75%	2	7	0	154	0.222222	**0.**	**0.**	**0.957055**	0.222222	0.777778
80%	2	7	0	154	0.222222	**0.**	**0.**	**0.957055**	0.222222	0.777778
85%	1	8	0	154	0.111111	**0.**	**0.**	0.95092	0.111111	0.777778
90%	1	8	0	154	0.111111	**0.**	**0.**	0.95092	0.111111	0.888889
95%	1	8	0	154	0.111111	**0.**	**0.**	0.95092	0.111111	0.888889

Table 2. OSPLAN performance metrics.

Probability	TP	FN	FP	TN	POD	POFD	POFA	Ef	HK	δ
5%	7	0	12	150	**1.**	0.0740741	0.631579	0.928994	0.925926	1
10%	7	0	9	153	**1.**	0.0555556	0.5625	0.946746	**0.944444**	0.0740741
15%	6	1	8	154	0.857143	0.0493827	0.571429	0.946746	0.80776	**0.0555556**
20%	6	1	8	154	0.857143	0.0493827	0.571429	0.946746	0.80776	0.151152
25%	5	2	8	154	0.714286	0.0493827	0.615385	0.940828	0.664903	0.151152
30%	5	2	6	156	0.714286	0.037037	0.545455	0.952663	0.677249	0.289951
35%	5	2	5	157	0.714286	0.0308642	0.5	**0.95858**	0.683422	0.288105
40%	3	4	5	157	0.428571	0.0308642	0.625	0.946746	0.397707	0.287376
45%	2	5	4	158	0.285714	0.0246914	0.666667	0.946746	0.261023	0.572261
50%	1	6	2	160	0.142857	0.0123457	0.666667	0.952663	0.130511	0.714712
55%	0	7	2	160	0.	0.0123457	1.	0.946746	−0.0123457	0.857232
60%	0	7	1	161	0.	0.00617284	1.	0.952663	−0.00617284	1.00008
65%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.00002
70%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.
75%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.
80%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.
85%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.
90%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.
95%	0	7	0	162	0.	**0.**	**0**	**0.95858**	0.	1.

Table 3. RJMG ROWs performance metrics.

Probability	TP	FN	FP	TN	POD	POFD	POFA	Ef	HK	δ
5%	19	2	46	371	**0.904762**	0.110312	0.707692	0.890411	**0.79445**	1
10%	17	4	25	392	0.809524	0.059952	0.595238	0.93379	0.749572	**0.145736**
15%	16	5	17	400	0.761905	0.0407674	0.515152	0.949772	0.721137	0.199688
20%	14	7	12	405	0.666667	0.028777	0.461538	0.956621	0.63789	0.24156
25%	13	8	10	407	0.619048	0.0239808	0.434783	0.958904	0.595067	0.334573
30%	10	11	9	408	0.47619	0.0215827	0.473684	0.954338	0.454608	0.381706
35%	10	11	8	409	0.47619	0.0191847	0.444444	0.956621	0.457006	0.524254
40%	9	12	7	410	0.428571	0.0167866	0.4375	0.956621	0.411785	0.524161
45%	9	12	6	411	0.428571	0.0143885	0.4	0.958904	0.414183	0.571675
50%	8	13	6	411	0.380952	0.0143885	0.428571	0.956621	0.366564	0.57161
55%	8	13	4	413	0.380952	0.00959233	0.333333	**0.961187**	0.37136	0.619215
60%	7	14	3	414	0.333333	0.00719424	0.3	**0.961187**	0.326139	0.619122
65%	6	15	3	414	0.285714	0.00719424	0.333333	0.958904	0.27852	0.666705
70%	5	16	1	416	0.238095	0.00239808	0.166667	**0.961187**	0.235697	0.714322
75%	5	16	1	416	0.238095	0.00239808	0.166667	**0.961187**	0.235697	0.761909
80%	4	17	0	417	0.190476	**0.**	**0.**	**0.961187**	0.190476	0.761909
85%	3	18	0	417	0.142857	**0.**	**0.**	0.958904	0.142857	0.809524
90%	2	19	0	417	0.0952381	**0.**	**0.**	0.956621	0.0952381	0.857143
95%	0	21	0	417	0.	**0.**	**0.**	0.952055	0.	0.904762

Table 4 – SOUTH REGIONS ROWs performance metrics.

Probability	TP	FN	FP	TN	POD	POFD	POFA	Ef	HK	δ
5%	10	0	31	35	**1.**	0.469697	0.756098	0.592105	0.530303	1
10%	9	1	21	45	0.9	0.318182	0.7	0.710526	**0.581818**	0.469697
15%	7	3	13	53	0.7	0.19697	0.65	0.789474	0.50303	**0.333526**
20%	6	4	10	56	0.6	0.151515	0.625	0.815789	0.448485	0.358883
25%	4	6	7	59	0.4	0.106061	0.636364	0.828947	0.293939	0.427735
30%	4	6	5	61	0.4	0.0757576	0.555556	0.855263	0.324242	0.609302
35%	4	6	4	62	0.4	0.0606061	0.5	0.868421	0.339394	0.604764
40%	4	6	2	64	0.4	0.030303	0.333333	0.894737	0.369697	0.603053
45%	4	6	2	64	0.4	0.030303	0.333333	0.894737	0.369697	0.600765
50%	4	6	2	64	0.4	0.030303	0.333333	0.894737	0.369697	0.600765
55%	4	6	0	66	0.4	**0.**	0.	**0.921053**	0.4	0.600765
60%	3	7	0	66	0.3	**0.**	0.	0.907895	0.3	0.6
65%	3	7	0	66	0.3	**0.**	0.	0.907895	0.3	0.7
70%	3	7	0	66	0.3	**0.**	0.	0.907895	0.3	0.7
75%	1	9	0	66	0.1	**0.**	0.	0.881579	0.1	0.7
80%	1	9	0	66	0.1	**0.**	0.	0.881579	0.1	0.9
85%	0	10	0	66	0.	**0.**	**Indeterminate**	0.868421	0.	0.9
90%	0	10	0	66	0.	**0.**	**Indeterminate**	0.868421	0.	1.
95%	0	10	0	66	0.	**0.**	**Indeterminate**	0.868421	0.	1.

The models produced smooth and interpretable probability surfaces that align well with expert knowledge of regional rainfall patterns and slope behavior. Figure 1 through Figure 4 presents the probabilistic curves, showing the gradient of landslide probability. Additionally, Figure 5 through Figure 8 show the ROC curve for each fit.

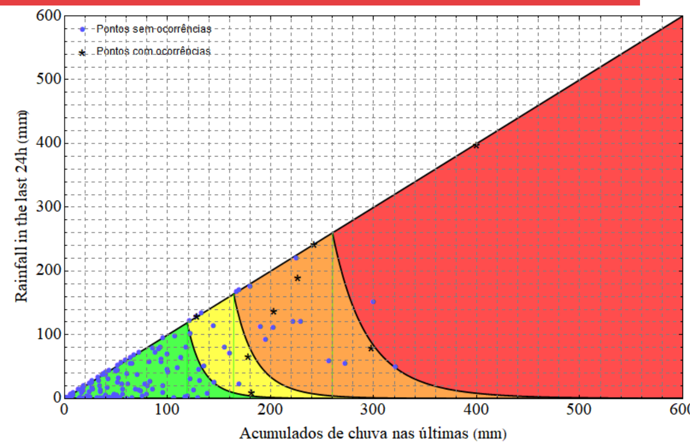

Figure 1. OSBAT logistic regression curves for landslide susceptibility

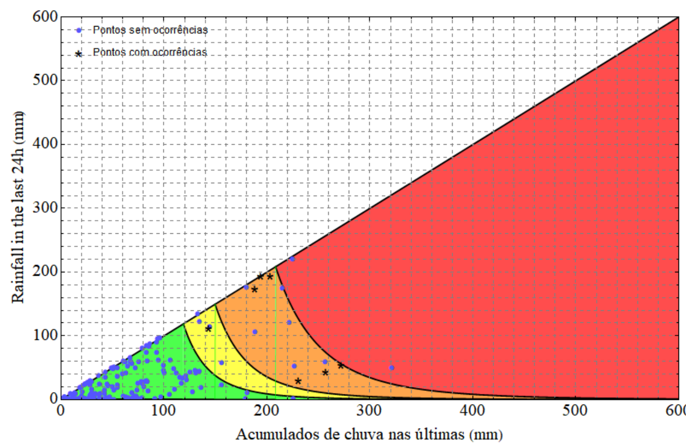

Figure 2. OSPLAN logistic regression curves for landslide susceptibility

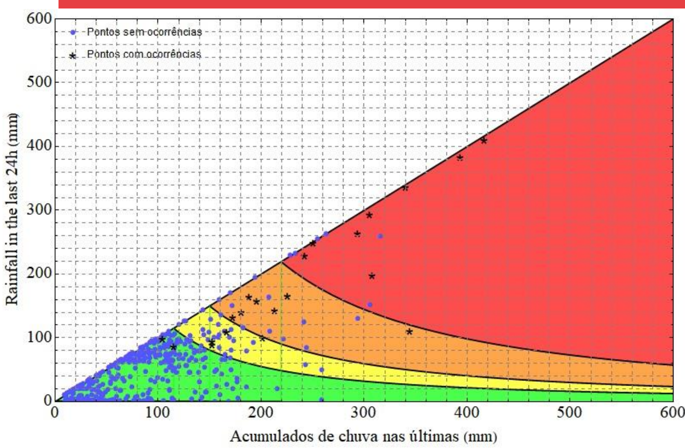

Figure 3. RJMG ROWS logistic regression curves for landslide susceptibility

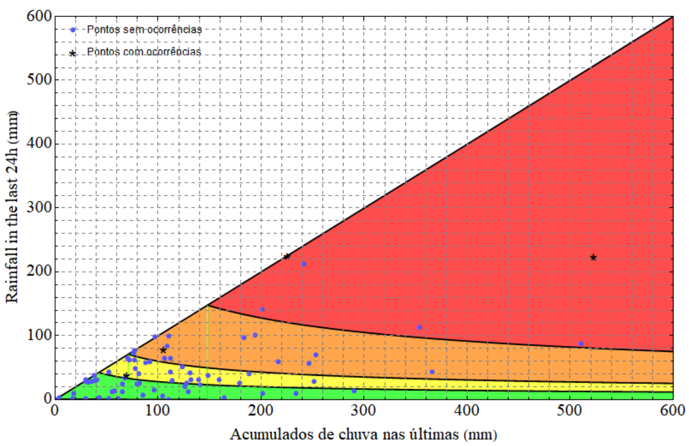

Figure 4. SOUTH region ROWS logistic regression curves for landslide susceptibility

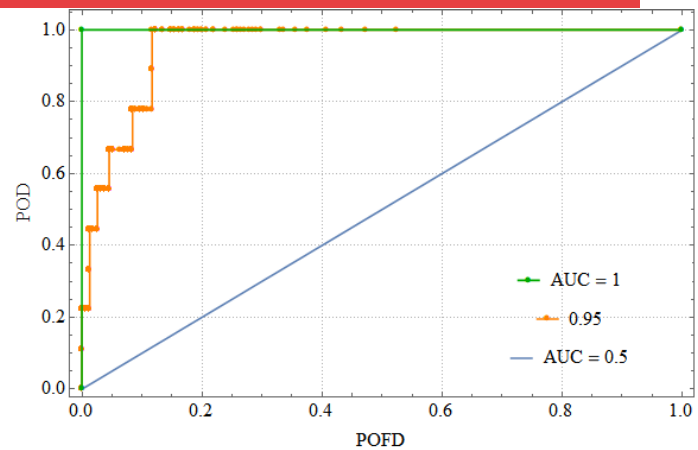

Figure 5. OSBAT ROC curve.

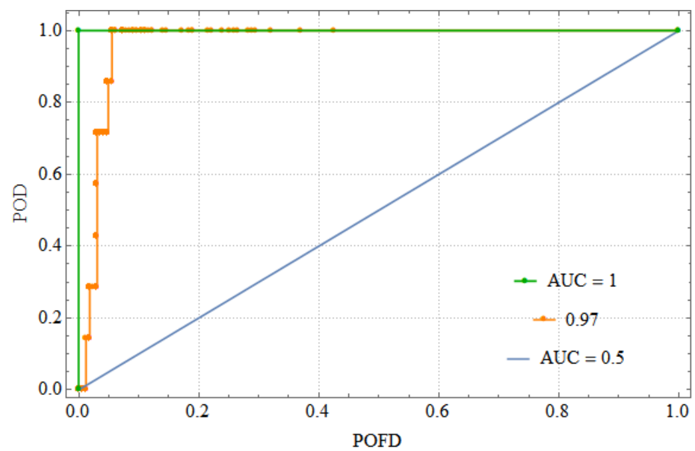

Figure 6. OSPLAN ROC curve.

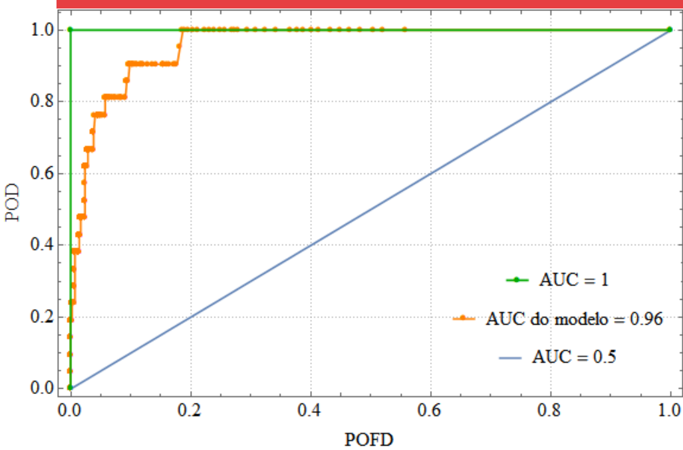

Figure 7. RJMG ROWs ROC curve.

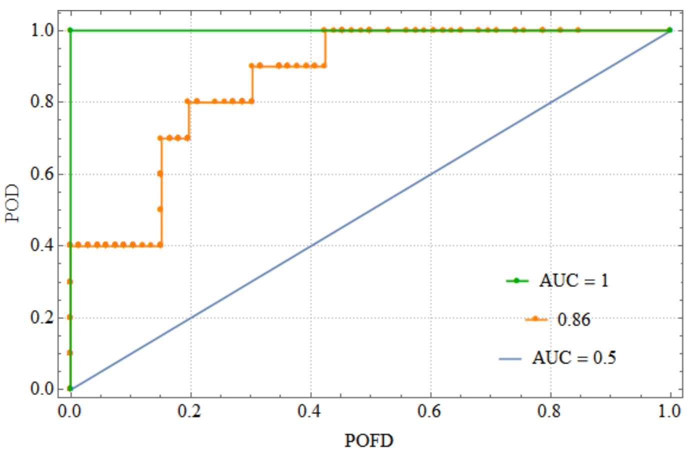

Figure 8. SOUTH region ROWs ROC curve.

The São Paulo (OSPLAN) ROW showed the highest model performance. In contrast, the Southern region exhibited slightly lower predictive accuracy. This could be due to the quality of the data set available for fitting the logistic regression.

From **Table *1*** (OSBAT ROW), The best balance between Probability of Detection (POD) and Probability of False Detection (POFD) occurs at the 5% threshold, where POD is maximum (1.0) and POFD is moderate (0.149). This leads to the highest Hanssen & Kuipers score (HK = 0.85) and the smallest Euclidean distance (δ = 0.149), indicating optimal model performance at this point. At 10%, the model maintains a strong POD (0.777778) with slightly improved POFD (0.09901), but HK decreases (0.685869), and the δ distance increases. From 15% to 35%, POD steadily declines (from 0.666667 to 0.444444), and although POFD also improves, the Hanssen & Kuipers score falls significantly. For instance, at 35%, POD is 0.444444, POFD is 0.019802, but HK drops to 0.4246419, reflecting the diminishing utility of the classifier at higher thresholds. Starting from the 45% threshold, POD drops to 0.333333 and continues decreasing. POFD remains low (as low as 0.00649351), but HK becomes close to or less than 0.2, indicating increased missed detections (FN). From 65% onwards, the model becomes too conservative: POD stabilizes at 0.222222 or lower, and although POFD becomes 0.0, the classifier fails to capture many real events.

From **Table *2*** (OSPLAN), At the 10% threshold, the classifier achieves its best overall balance. This threshold represents the optimal operating point, balancing high sensitivity with low false detection. At the 5% threshold, although the model still detects all true positives (POD = 1.0), the false positive rate increases slightly (POFD = 0.074074), resulting in a slightly lower HK = 0.925926. Between 15% and 25%, the model maintains high detection rates (POD = 0.8571) and moderate POFD values (ranging from 0.03 to 0.07), indicating the model still performs well, but with gradually declining effectiveness. Beyond the 30% threshold, POD begins to drop noticeably, and HK also declines — reflecting a growing number of missed events. At thresholds above 55%, POD approaches zero, and POFD also drops to zero, which indicates that the model makes almost no positive predictions, and it fails to detect true events (TP = 0 from 55% onward). Efficiency (Ef) remains above 0.94 in almost all thresholds, but this metric alone can be misleading since it is affected by the large number of TNs and does not fully capture the cost of missed landslide detections. The efficiency indicator (Ef) remains consistently high (above 0.90) across thresholds between 25% and 80%, showing that the model maintains strong general performance even with reduced sensitivity.

From **Table *3***, the 5% threshold yields the highest POD (0.904762) and the highest Hanssen & Kuipers score (HK = 0.79445). Although the POFD is 0.110312, the model maintains the best balance between detecting true events and avoiding false alarms. Additionally, this threshold also has the lowest δ value (0.145736), confirming its proximity to the behavior of a perfect classifier. As the threshold increases, POD steadily decreases (from 0.81 at 10% down to 0.09 at 90%), POFD improves (approaching 0), but this comes at the cost of higher false negatives (undetected landslide events). Furthermore, HK drops sharply beyond 15–20%, reaching zero at 95%, indicating loss of discriminative power as the threshold increases.

From **Table *4***, at 5% the model achieves the maximum POD (1.0), but at the cost of a high POFD (0.47) and moderate HK (0.53). δ = 1.0 confirms it is distant from optimal balance. The optimal threshold in this configuration appears to be 10%. Thresholds between 15–25% maintain moderate POD (0.6–0.7) with improved POFD (0.10–0.20), but HK is slightly lower than at 10%. For intermediate thresholds (30–50%), the balance begins to shift: POD stabilizes at 0.4 from 30% to 50%, indicating increasing false negatives; the POFD improves continuously, dropping to just 0.03 at 50%; the HK score gradually rises to 0.366997 at 50%, but it's still below the peak observed at 10%; and Ef reaches its maximum at 50% (0.894737), yet this is largely influenced by the high number of TNs and does not reflect sensitivity performance. From 65% upward, the classifier effectively stops identifying any true positives. At this range of probability, TP = 0, POD = 0, HK = 0, Ef remains high (~0.86–0.88) only because of the overwhelming TNs. POFD and POFA = 0, but this is because no alerts are issued at all, including for true events. Results are labeled "Indeterminate" for Ef and HK in this region, reinforcing that these thresholds are not viable for operational use.

4. Conclusions

This paper showed an application of the logistic regression model that successfully improved a rainfall-threshold model for landslide triggers. The results confirm that logistic regression is a robust and valuable methodology for defining dynamic, probabilistic rainfall thresholds in support of risk-based decision-making

The proposed methodology concerns with the continuous update and reassessment of the susceptibility curves. This guarantees diligence in actions intending to enhance overall resilience and efficiency of pipeline operations in landslide-prone areas.

The proposed logistic regression model exhibited a consistent and interpretable performance along all operational regions to where it was applied. The classifiers performed better in low probability instead of high probability threshold, mostly around 10%, where sensitivity was maximized, false detection rates remained within acceptable limits, and the balance between detection and specificity was optimal, as indicated by the highest HK scores and the lowest Euclidean distances to the perfect classifier.

As probability thresholds increased, classifier performance decreased progressively. Although false alarms decreased, the true positive rate decreased as well, which is negative for operational safety. For thresholds above 60%, the classifiers failed to identify any relevant events, although they presented high efficiency values, which is explained by the prevalence of true negatives

The conclusion to these observations points to the fact that either adopting overly conservative or non-conservative thresholds leads to operational safety problems. In practice, this is solved by combining 4 different threshold curves with different response actions.

While the logistic models have shown strong performance, one should still be concerned with limitations to the method:

- The models depend on the quality and completeness of reported landslide data. The lack of these qualities makes the application of logistic-regression unfeasible.
- The logistic regression model is a dynamic tool for susceptibility mapping, and it does not take terrain-specific variables (e.g., slope angle, land use, lithology) into account, which are instead addressed indirectly via static susceptibility maps.
- As new data is inserted into the database, the threshold must be reevaluated periodically, especially considering that the pattern of extreme events is changing.

Future works will test ensemble learning methods, physics informed susceptibility maps, dynamic rainfall-triggering indicators derived from remote sensing, and integration with soil moisture sensor data.

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