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OPERATIONAL REGIONAL SCALE LANDSLIDE FORECASTS: PHYSICS-BASED AND DATA-DRIVEN MODELS

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Landslides on natural slopes represent a critical concern in disaster risk management due to the escalating frequency of high-intensity rainfall events. Understanding the mechanisms of slope failure triggered by rainfall or snowmelt, and accurately forecasting slope stability, is challenging due to the inherent complexities involved. At a regional scale, forecasting stability across multiple slopes within predefined boundaries necessitates precise data collection from numerous locations within the region. Implementing a physics-based model for such analysis also requires parameter calibration through back-analysis, followed by forward analysis for slope-stability forecasts.

Geotechnical slope stability models at a regional scale calculate Factor of Safety (FS) values using numerical tools, e.g., infinite slope models, incorporating precipitation data, topographical information, and subsurface characteristics. However, integrating these models into operational slope stability forecasts encounters two primary challenges: firstly, physics-based models often operate independently, making their integration into fully automated workflows utilizing cloud computing challenging; secondly, the complex data collection requirements for these models necessitate frequent updates.

This study addresses these challenges by employing a hybrid approach that combines physics-based and data-driven models for regional-scale slope stability forecasts. A data-driven model predicts the probability of landslides across a large area composed of multiple first-order catchments, for a selected study area in Norway. Additionally, a physics-based model, TRIGRS, predicts pixel-wise FS values within each catchment. Both models operate as cloud services, providing forecasts once daily, and the results are accessible through the Norwegian Geotechnical Institute's (NGI) data platform, NGI Live. The results also show the importance of dividing the large area into smaller zones with more representative geotechnical parameters to improve the overall performance of the model. This research illustrates the practical application of integrating data-driven and physics-based methodologies to develop operational landslide forecasts, a crucial component of effective Landslide Early Warning Systems (LEWS).

Keywords: landslides, early warning, data-driven, dashboards, TRIGRS.

1. Introduction

Landslides pose a significant threat to life, infrastructure, and ecosystems, and result in critical socio-economic setbacks. A basic requirement for efficient landslide risk management, focusing mainly on the preparedness phase, is predicting landslide occurrence. The effective forecasting of slope stability at a regional scale is a complex task, due to the combined effects of precipitation, topography, and subsurface conditions. Traditional slope stability analysis relies on highly detailed physics-based models, but their practical applications at regional scales is often hindered by challenges in data integration and high computational requirements. Recent advances in computational methods and cloud-based platforms have opened up new opportunities for integrating a wide variety of data sources and improving the efficiency of predictive models (Piciullo et al., 2025). Physics-based modelling combined with data-driven approaches can enhance accuracy and operational feasibility for regional slope stability forecasts. These hybrid approaches take advantage of the strengths of physics-based models in detail analysis, while benefiting from the scalability and adaptability of data-driven techniques. This study proposes a new paradigm for operational landslide forecasting in Norway, based on the integration of physics-based and data-driven models to address the challenges of regional slope stability assessment. The research presented highlights the development and actual implementation of a hybrid landslide forecasting system, capable of supporting Landslide Early Warning Systems (LEWS) with reliable and actionable forecasts displayed through Norwegian Geotechnical Institute's (NGI) data platform, NGI Live.

2. Study area

The study area consists of three municipalities in Southeastern Norway (Nord-Fron, Sor-Fron and Sel), belonging to the Innlandet County of Norway (Fig. 1). Several parts of these municipalities have suffered from multiple landslides in 2011 and 2013 (Heyerdahl & Høydal, 2017). In particular, the town of Kvam has significantly suffered from the above-mentioned events, which were triggered due to heavy rainfall and snowmelt. The entire study area is divided into several smaller units, defined based on the register of catchment areas in Norway, by Norway's Directorate of

Water Resources and Energy (NVE, 2020). The study area is thus partitioned into hydro-geomorphological polygons, which provides operational decision support. Catchments smaller than 5 km² were merged with adjacent polygons, and each of these units is called a Pixel Aggregation Unit (PAU). Only catchments entirely within the study area and those containing landslides were included in the analysis, as explained in Liu et al. (2021) and Nocentini et al. (2024). The town that has suffered the most damages, Kvam, is covered by two of such units, and is highlighted in Fig. 1. Major share of the study area is covered by forest lands, followed by exposed bedrock, river, anthropic lands and water bodies. The area is part of a U-shaped valley incised by a river, with steep slopes and valley floors with glacio-fluvial and fluvial deposits (Sletten & Blikra, 2007).

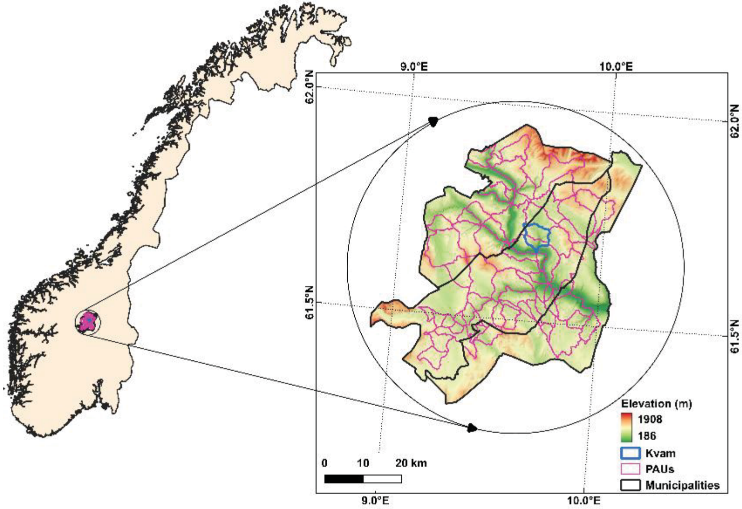

Fig. 1. Details of study area

3. Methodology

The methodology employs two different models applied to the study area, predicting the likelihood of landslides. In the first phase, a daily warning is issued for each PAU, based on a data-driven approach. In the second phase, a physics-based model is used to calculate the Factor of Safety (FS) value for each pixel, using hourly forecasted rainfall data. Both models were developed in previous studies, and the current study focuses on their implementation. The models have several limitations but have resulted in satisfactory and conservative performances as reported in the previous studies. The details are outlined below:

3.1. *Data-driven warning for PAUs*

The data-driven model follows the methodology described in Nocentini et al. (2024), which uses the static landslide susceptibility index (LSI) along with a pre-trained random forest (RF) model to produce dynamic landslide susceptibility maps. The RF model incorporates the effects of rainfall and snowmelt, by considering Cumulative Rainfall (CR) and Cumulative Snowmelt (CS) of various durations. The maps are first prepared on pixels of 100 m resolution, and are further aggregated for each PAU, using a double threshold validation tool (DTVT), considering a critical probability of landslide occurrence and the number of pixels in each PAU exceeding the threshold. The procedures of calculating LSI and training of RF model are explained in detail in Nocentini et al. (2024). This work focuses on automating the methodology developed in Nocentini et al. (2024), to be deployed as an operational landslide forecast. Everyday forecasted rainfall and snowmelt data modelled by the Norwegian Water Resources Directorate (NVE) are retrieved via an Application Programming Interface (API) and used to run the model in real time. The warnings are then uploaded to NGI Live and displayed on a dedicated dashboard.

3.1.1. *Physics-based model for identifying landslide source areas*

An infinite slope stability model, incorporating infiltration and slope stability analysis, through Transient Rainfall Infiltration and Grid-based Regional Slope stability (TRIGRS) analysis (Alvioli & Baum, 2016; Baum et al., 2008), is run once in every three hours using a cloud-based service, using topographic details of 5 m resolution. This work used the data from a previous study (Schilirò et al., 2021), and enhanced model performance by dividing the study area into four different zones based on bedrock geology and soil cover data from the Geological Survey of Norway (NGU). The unit weight, shear strength parameters and hydraulic properties of the study area were classified into four zones, with a major portion covered in till, followed by exposed bedrock, peat and humus and glaciofluvial deposits. The unit weight and shear strength parameters follow a gaussian distribution, and uniform distribution is used for the hydraulic properties. An improved version of the original TRIGRS model (Raia et al., 2014) is used in this study to consider a probability distribution of the material properties instead of a constant value. The gridded rainfall data from openmeteo (Zippenfenig, 2023) via weather forecast API, and the FS values in geotiff format is displayed in NGI Live dashboard. The FS maps for the next three hours are generated in each model run and the model is rerun every three hours, updating the FS maps.

4. Results and Discussion

4.1. *Calibration of TRIGRS model*

The shear strength parameters, cohesion and internal friction angle, for each zone (Fig. 2a) were calibrated using a trial-and-error approach. The FS values calculated using TRIGRS were compared with the source areas of landslides in 2011 (Fig. 2b) for calibration, using a confusion matrix. The calibrated material properties are provided in Table 1. For the parameters which follow normal distribution (Table 1), the standard deviation (SD) is heuristically selected as 10 % of the mean value and mean ± 2.SD were used as the minimum and maximum values.

Table 1. Calibrated material properties used in TRIGRS

Zone	Cohesion (kPa)	Internal friction angle (degrees)	Unit weight (kN/m^3)	Hydraulic diffusivity (m²/s)	Saturated hydraulic conductivity (m/s)	Saturated moisture content	Residual moisture content
	Mean value, normal distribution			Constant value			
Till	4	35	20	4×10^{-3}	1×10^{-5}	0.40	0.08
Peat and humus	20	5	15	4×10^{-7}	2×10^{-6}	0.50	0.15
Glaciofluvial deposits	3	35	20	4×10^{-3}	1×10^{-4}	0.30	0.03
Bedrock	60	40	26	4×10^{-7}	1×10^{-8}	0.05	0.01

The True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN) were calculated for each trial, using a 3×3 matrix approach. In this approach, if TRIGRS predicts an FS ≤1 for any cell, it is assumed that the cell or any of the eight surrounding cell might fail. This approach significantly reduced FPs compared to the results reported in Schilirò et al. (2021). The number of TN is much higher than the other three attributes, and hence, metrics such as balanced accuracy, Matthews Correlation Coefficient (MCC) and Cohen's Kappa were used for model comparisons (Table 2).

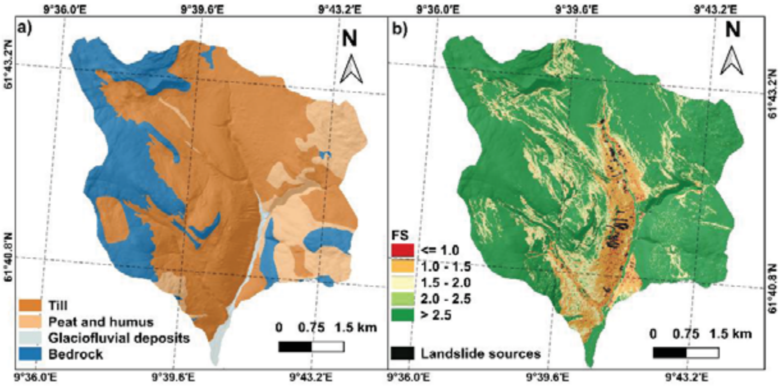

Fig. 2. Maps of Kvam. a) Geological zoning based on quaternary deposits b) FS values from the TRIGRS calculation, at 11 am, 10-06-2011.

Table 2. Statistical comparison of model performance

	Balanced accuracy	MCC	Cohen's Kappa
This work	0.80	0.33	0.27
Schilirò et al., 2021	0.84	0.15	0.06

Dividing the zone area into four and incorporating the 3×3 calibration approach has improved the overall performance of the model. While the balanced accuracy is slightly lower with this method compared to the previous study, improvements in MCC and Cohen's Kappa indicate better overall model performance. Although this approach resulted in a higher number of FNs compared to Schilirò et al. (2021), it did not lead to the complete omission of any landslide source areas, but instead enabled the partial identification of source areas.

4.2. *Deployment in cloud platform*

The deployment setup of the slope stability cloud service, including integrations with weather forecast APIs and NGI Live platform, is depicted in Fig. 3. The prediction models (model runner) run at regular intervals, retrieving updated weather data from weather forecast APIs. Static input data for the models are kept in cloud storage, and keys needed to access the APIs are kept in a cloud secret store. NGI Live serves as a data platform to store and visualize outputs of the prediction models. For the data-driven model, NGI Live is configured with the PAU geometries associated with separate data time series. During each model run, data is ingested into the respective time series using an API. For the physics-based approach, FS maps are uploaded to a cloud database as geotif files for each run. The user can view the latest predictions or historical values on-demand, through the NGI Live dashboards.

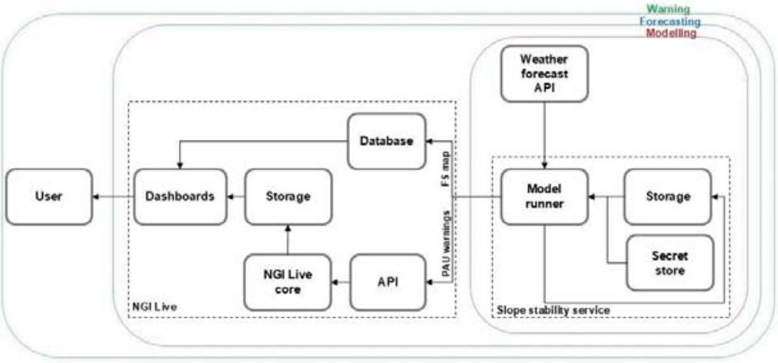

Fig. 3. Architecture of the cloud-based service using NGI Live

The method proposed in this study rely on publicly available data sources and can be exported easily to other study areas, with the support of a cloud-based service like NGI Live.

5. Conclusions

The study presents an operational example of a regional-scale landslide forecasting framework, which can be easily integrated into a LEWS. The combination of data-driven and physics-based approaches ensures a two-level landslide forecast, facilitating significant operational advantages. The first level of alert, for each PAU can be used to issue warning for a large area, while the physics-based model can precisely identify the landslide sources within each PAU. The study demonstrates that the performance of physics-based models can be significantly improved by using precise material properties. Further improvements can be achieved with laboratory tests and instrumentation in the study area. This method can be applied to develop operational LEWS.

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