Slow-Moving Landslides Modelling using Physics-Informed Neural Networks

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Abstract: Slow moving Landslide dynamics involve complex interactions between geological, hydrological, and mechanical processes that are challenging to model using conventional methods. Physics-Informed Neural Networks (PINNs) provide a promising alternative by embedding governing physical laws into neural network training. This approach allows for the efficient capture of landslide deformation patterns and kinematic evolution, even with sparse observational data. By constraining the learning process with partial differential equations, PINNs ensure physically consistent outputs while maintaining model interpretability. Their ability to incorporate domain knowledge makes them well-suited for modeling slow-moving landslides, offering potential for real-time forecasting and enhancing early warning systems in data-limited environments.

Keywords: ***Landslides, InSAR, Deep Learning, PINN.***

Introduction

Slow-moving landslides pose long-term geohazards in regions with complex geological, hydrological, and mechanical conditions (Lacroix et al., 2020). Their modeling is particularly challenging due to limited observational data, spatial heterogeneity, and the nonlinear behavior of geomaterials under sustained gravitational loading and pore pressure fluctuations (Bontemps et al., 2020). Conventional numerical approaches such as finite element or finite difference methods rely on detailed subsurface information and dense monitoring, which are often unavailable (Dahal and Lombardo, 2025) . In the aftermath of an earthquake often such landslides occurs more often and accelerate causing more damage in the post-earthquake setting (Dahal et al., 2024). On the other hand, data-driven models trained purely on historical deformation signals may fail to capture the underlying physics, reducing their reliability and generalizability. Moreover, to bridge this gap, this study explores the use of Physics-Informed Neural Networks (PINNs) as a robust, hybrid framework for modeling slow-moving landslides under visco-elastoplastic deformation, constrained by the Mohr-Coulomb yield criterion.

Background and Methodology

Landslide deformation is controlled by the balance between internal stress and gravitational forces under quasi-static conditions. The total strain rate consists of elastic and viscoplastic parts, where elastic behavior follows standard linear elasticity, and viscoplasticity accounts for time-dependent, irreversible deformation. Effective stress, which drives failure, is calculated by adjusting total stress for pore pressure influences, incorporating fluid-solid coupling through the Biot coefficient. This framework captures how slopes deform in response to both mechanical loading and fluid pressure changes.

Viscoplastic deformation is governed by a Perzyna-type flow rule, which activates when stresses exceed a material-specific yield threshold defined by the Mohr-Coulomb criterion. This relationship connects shear and normal stress with the soil's friction angle and cohesion and can also be expressed in terms of stress invariants for generalization. Pore pressure evolves through diffusion, influenced by hydraulic conductivity and external sources such as rainfall. These coupled mechanical-hydraulic processes are essential for modeling slow-moving landslides and form the physical foundation for approaches like Physics-Informed Neural Networks.

PINNs embed these physical laws directly into the training objective (Raissi et al., 2019). A neural network approximates displacement $\boldsymbol{u}(\boldsymbol{x}, t)$ and pore pressure $p(\boldsymbol{x}, t)$ across space and time. The total loss function is given by:

$$\mathcal{L}_{total} = \lambda_d \mathcal{L}_{data} \lambda_p \mathcal{L}_{phys} \lambda_b \mathcal{L}_{bc}$$

Where $\mathcal{L}_{\text{data}}$ penalizes errors with observational data, $\mathcal{L}_{\text{phys}}$ enforces PDE constraints, and $\mathcal{L}_{\text{bc}}$ incorporates boundary and initial conditions. The coefficients λ_d, λ_p, and λ_b control the weighting of each term.

The training of PINNs in this study is guided by Interferometric Synthetic Aperture Radar (InSAR) Line-of-Sight (LoS) displacement measurements (Bekaert et al., 2020). InSAR provides high-resolution surface deformation data projected along the radar viewing direction, offering dense spatial coverage even in remote areas. Although these measurements represent only one component of the 3D surface deformation vector, their integration within the physics-informed framework enables the network to infer full-field displacement and subsurface states by reconciling the data with governing equations. PINN minimizes the difference between the predicted LoS displacement and observed InSAR values while satisfying mechanical and hydraulic constraints. This approach allows for physically plausible reconstructions of hidden variables such as internal slip and pore pressure distribution, even with limited and indirect observations.

Application to Creeping Landslides

We apply the PINN framework to simulate and analyze several slow-moving landslide sites, one of which occurred in Turkey in the post-earthquake scenario of 2023 earthquake (Görüm et al., 2023) is presented here. These sites exhibit long-term creep behavior with observable surface displacement fields, but with limited access to subsurface measurements. The primary objectives of our models is to reconstruct spatio-temporal displacement fields from sparse surface data through deep learning model which incorporates the failure mechanism (Dahal and Lombardo, 2025).

By solving the inverse problem using PINNs, we are able to infer physically plausible internal deformation structures that are not directly observable. The model is validated by comparing predicted displacements against the withheld time steps used as test dataset (30%).

Results and Insights

Initial results demonstrate that PINNs can model the deformation behavior in the landslide body and the overall RMSE of the model output is 15.67 mm whereas the Pearsons correlation coefficient between the true LoS displacement and observed LoS displacement is 0.60, which is not exceptionally great result, but it shows a significant correlation between the two. The overall result is present in Figure 1.

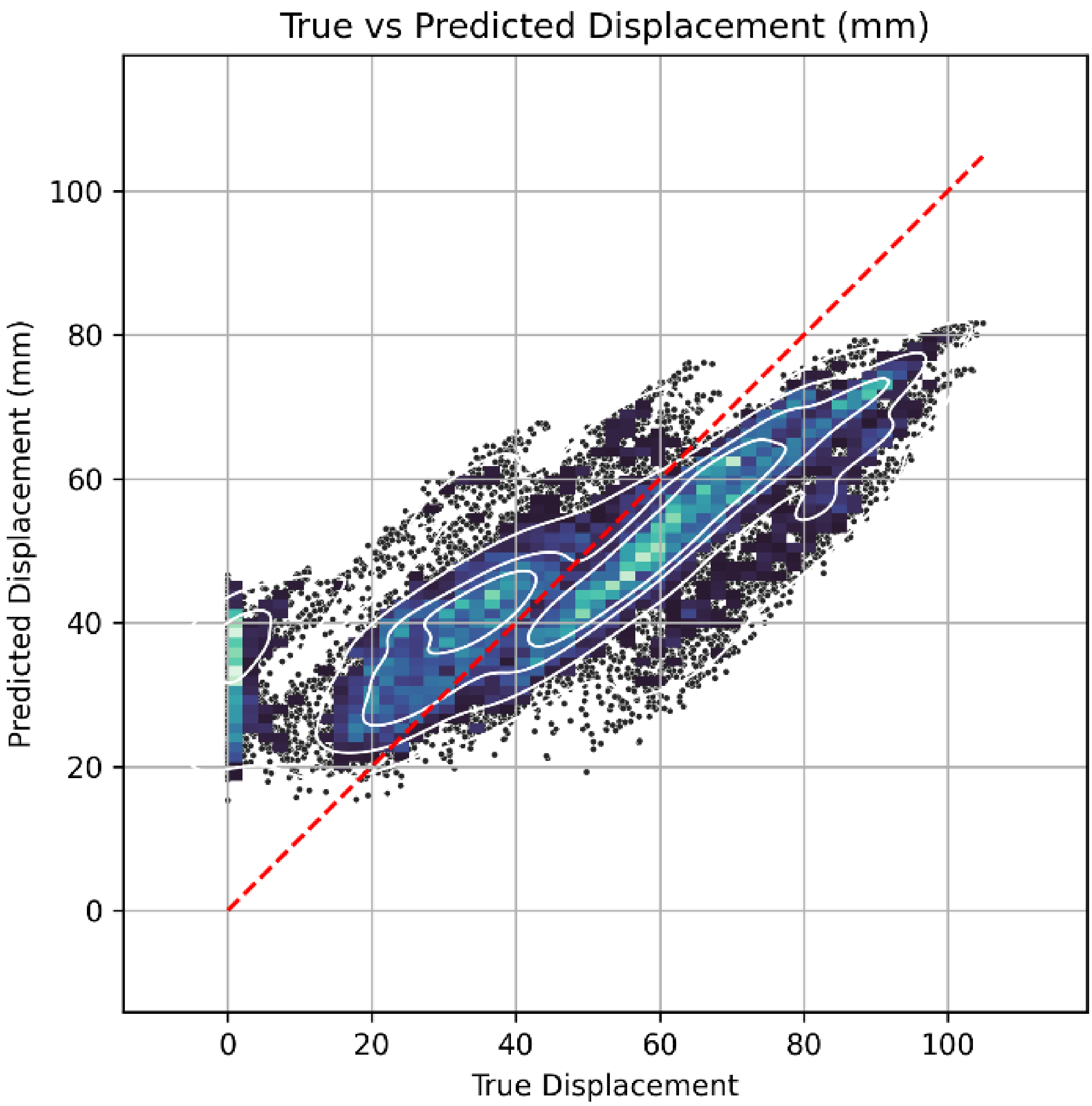

Figure 1, Correlation plot of the observed vs predicted landslide deformation for all observation nodes.

The models maintain high fidelity in capturing key deformation features such as acceleration phases and kinematic shifts without requiring large training datasets. Additionally, the embedded physics constraints make predictions more interpretable and less prone to overfitting compared to traditional black-box neural networks. The overall velocity dynamics of the landslide body is shown in the Figure 2. Where we can observe that the crest of the landslide has highest velocity whereas the middle pard of the landslide body slows down and the tail of the landslide has much lower moving velocity.

One notable advantage is the model's flexibility forecasting the future deformation scenario given the current scenario: often known in the deep learning literature as recurrent learning. This recurrent learning approach is suitable for slow moving landslides as it is possible to forecast the failure in future days given the current scenario and projected precipitation (Fang et al., 2023). This approach allows this model to be used for early warning systems. Moreover, given the lightweight nature of the model it can be run in small computing instruments locally to build on-site early warning systems.

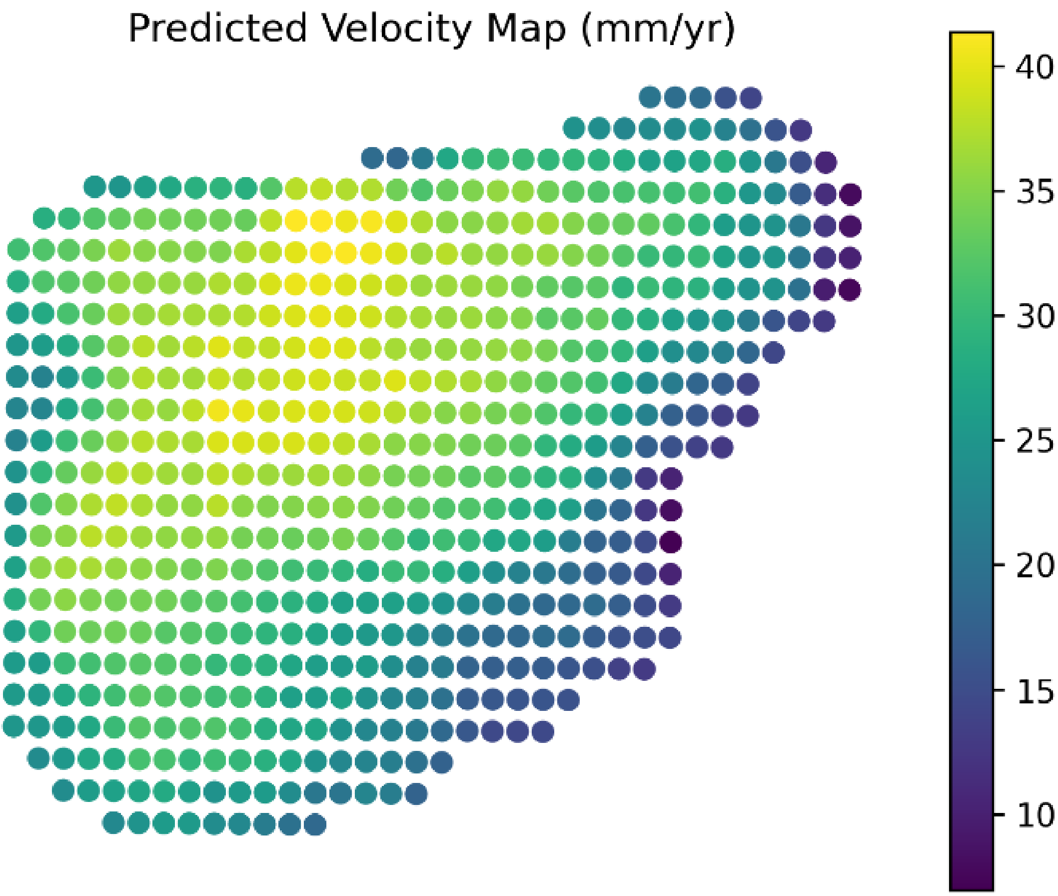

Figure 2, Annual velocity observed at each observation node.

Conclusion

Physics-Informed Neural Networks offer a powerful and flexible framework for modeling the dynamics of slow-moving landslides in data-scarce environments. By embedding physical laws within neural architectures, PINNs provide a principled approach to learning from limited observations while maintaining interpretability and generalizability. Our results suggest that PINNs are well-suited for both forward and inverse modeling tasks, offering new opportunities for landslide forecasting, hazard assessment, and infrastructure planning.

Future work will focus on extending the framework to fully three-dimensional domains, improving training efficiency, and exploring hybrid models that incorporate both data-driven surrogates and traditional numerical solvers. PINNs represent a promising step toward unifying theoretical geomechanics with practical, real-time geohazard monitoring and mitigation.

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