



A PHYSICS-INFORMED APPROACH TO MODEL SOIL-ATMOSPHERE INTERACTION IN SLOPES AFFECTED BY SLOW-MOVING LANDSLIDES

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1 Introduction

Slow-moving landslides represent one of the most insidious categories of natural hazards. Unlike rapid slope failures, which attract immediate attention due to their catastrophic consequences, slow-moving landslides often evolve over long timescales ranging from months to decades. Their progression is subtle, frequently unnoticed until significant deformation has already affected infrastructures and buildings. Despite their slow evolution, the socioeconomic impacts are considerable: they disrupt transportation and distribution networks and damage buildings, hence undermining the resilience of the affected community. A defining characteristic of many slow-moving landslides is their connection with long-term hydrogeological processes, rather than with sudden extreme

rainfall events, particularly in complex geo-hydro-mechanical (GHM) contexts (Cotecchia et al., 2014, 2019). In such cases, rainfall infiltration and groundwater recharge induce fluctuations in piezometric levels within the slope, which in turn reduce the available shear strength along potential or pre-existing shear bands. These processes represent the principal triggers and driving factors of landslide activity. Consequently, understanding and predicting how rainfall translates into piezometric head changes is a prerequisite for any robust early-warning system or risk management strategy. Traditional geotechnical models of groundwater seepage rely on Richards' equation, which governs unsaturated flow in porous media by coupling hydraulic conductivity with soil water retention functions. While powerful, the full nonlinear form of Richards' equation is notoriously challenging to solve numerically. Furthermore, particularly complex GHM scenarios, characterized by high heterogeneity of hydraulic soil properties, and scarcity of field data, hinder the ability to build accurate and detailed numerical models. To address this, researchers often invoke simplifying assumptions. A notable reduction of modelling effort can be achieved when the soil is approximated by constant hydraulic diffusivity, leading to a diffusion equation that still captures the essential dynamics of water redistribution, albeit with less parameter sensitivity. In parallel with advances in hydrogeological modeling, the past decade has witnessed the rise of Physics-Informed Neural Networks (PINNs) as a novel computational paradigm (Raissi et al. 2019; Karniadakis et al. 2021; Cuomo et al. 2022). PINNs embed governing differential equations directly into the loss function of neural networks, thereby unifying data-driven learning with the structure of physical laws. This approach is especially attractive in geosciences, where sparse and noisy data are the norm, but where governing equations provide valuable constraints. PINNs offer the potential to bypass meshing difficulties, adapt to high-dimensional domains, and leverage limited datasets for robust predictions. This work integrates these conceptual and computational strands to tackle the hydrogeological controls on slow-moving landslides in the Pianello hillslope near Bovino (Foggia province, southern Italy) in the Daunia Apennines. The site is a well-documented site affected by a complex basin of slow-moving landslides in clayey flysch soil, subject to recurrent acceleration, apparently related to seasonal rainfall trends. By injecting Richards' equation into the PINN framework, we explore whether neural networks can reliably reconstruct and predict the temporal evolution of piezometric heads at depth given the observed rainfall as an input.

2 Methods

2.1 Governing Equations

Richards' equation for unsaturated flow can be expressed as

$$\frac{\partial \theta}{\partial t} = \nabla \cdot [K(\theta) \nabla (\psi + z)], \quad (1)$$

where θ is volumetric water content, $K(\theta)$ the hydraulic conductivity [LT^{-1}], ψ the pressure head [L], and z the elevation [L]. Under the simplifying assumption of constant diffusivity $D = K(\theta)/C(\psi)$ with $C = \partial\theta/\partial\psi$ this reduces to a diffusion-type partial differential equation (PDE):

$$\frac{\partial \psi}{\partial t} = D \nabla^2 \psi. \quad (2)$$

This PDE allows to describe the evolution of porewater pressure in space and time in the hillslope, while allowing tractable computation and easier embedding into PINNs.

2.2 Physics-informed neural network

A neural network for a two-dimensional longitudinal section of the Pianello hillslope, $\psi_\theta(x, y, t)$, is constructed with four hidden layers, each containing 150 neurons and nonlinear activation functions. The loss function combines the following contributions (Raissi et al. 2019; Karniadakis et al. 2021; Cuomo et al. 2022):

- Physics loss: penalizing deviations from the diffusion equation residuals,

$$\mathcal{L}_{PDE} = \|\partial_t \psi_\theta - D \nabla^2 \psi_\theta\|^2, \quad (3)$$

- Initial and boundary conditions: enforcing observed or prescribed conditions at the slope surface, boundaries, and initial state

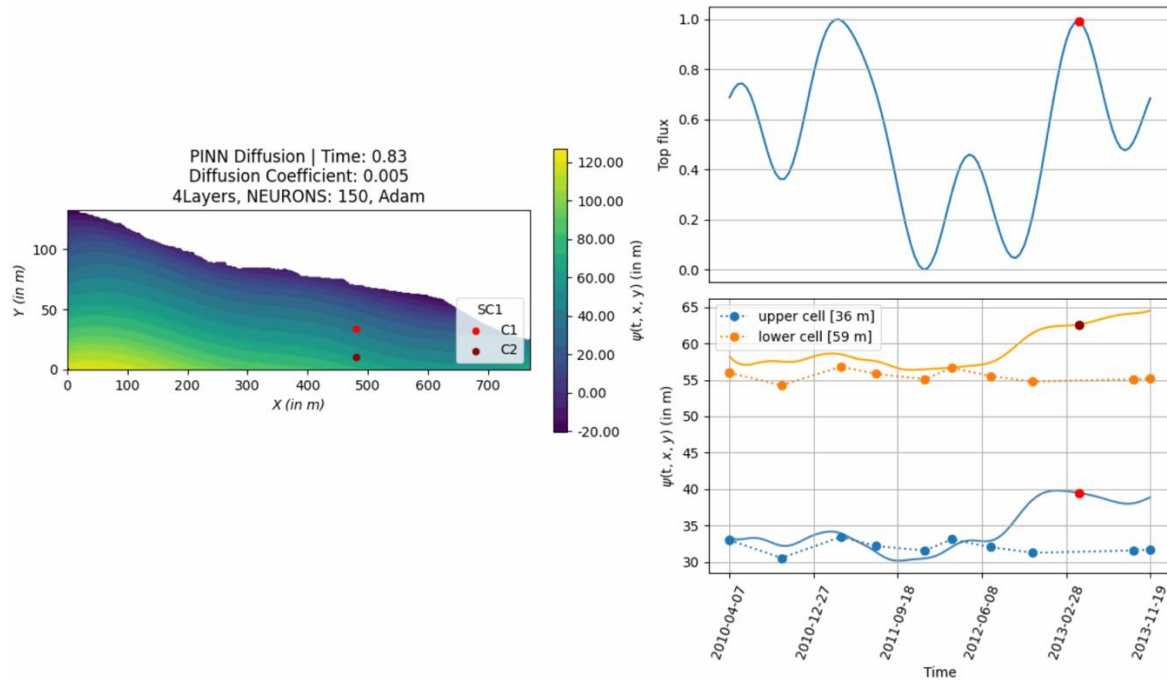


Figure 1. PINN simulation of subsurface flow. Left: Spatial distribution of simulated piezometric head, with monitoring points C1 and C2 indicated. Top right: Temporal evolution of top boundary flux, highlighting the snapshot corresponding to the displayed field. Bottom right: Comparison of simulated and observed piezometric head at two monitoring depths (upper cell C1 at 36 m and lower cell C2 at 59 m), showing optimal matching between PINN predictions and field data.

- Data mismatch: minimizing the difference between network predictions and piezometric head values at monitoring points.

The present work focuses on the physics-constrained component of the PINN loss, while the data mismatch contribution is left aside at this stage. Training is performed using the Adam optimizer, iteratively reducing the composite loss.

2.3 Study Site and Data

The Pianello hillslope in Bovino consists predominantly of clayey flysch deposits (Faeto Flysch, Losacco et al., 2021), highly plastic and characterized by remarkably low shear strength parameters. Many ground investigation and monitoring campaigns have been conducted on the hillslope since the 1980s. In particular, data from Casagrande cells installed along one vertical (at 36 m and 59 m b.g.l.) have been employed in this preliminary study as a reference, showing piezometric head fluctuations in the monitoring period 2010–2013 (Cotecchia et al. 2016; Losacco et al., 2025). For the same time interval, daily rainfall data have been acquired from the regional Civil Protection database. Previous studies showed that peaks of piezometric head in the reference period are synchronous with the 180-day cumulative rainfall, which in turn correlate well with the landslide acceleration inferred from inclinometer measurement.

3 Results

3.1 General PINN Performance

The PINN successfully reproduced the spatiotemporal dynamics of the pressure head within the two-dimensional hillslope domain during the time period April 2010–June 2012, while an overestimation is observed in the time interval June 2012–November 2013. The contour plot in Figure 1, left panel, illustrates the distribution of $\psi(x, y, t)$, in meters, at normalized analysis time $t = 0.83$, corresponding to April 2013 (time is normalized with respect to the length of the observation interval, i.e. 1323 days). Higher heads are concentrated upslope, while diffusion gradients propagate downslope, consistent with expected patterns. The chosen neural network architecture, four layers with 150 neurons, proved sufficient to capture both spatial variability and temporal oscillations. The dimensionless diffusion coefficient $D = 0.005$ provided the best balance between capturing observed trends and maintaining computational stability. D is calculated in the dimensionless computation lattice scaled in space and time with respect to the longitudinal dimension of the hillslope section (700 m) and the total observation time span (1323 days).

3.2 Matching with Observed Piezometric Heads

A crucial validation step involved comparing PINN predictions with observed piezometric heads at the two monitoring depths. The right-hand panels of Figure 1 present this comparison.

- 180-day cumulative rainfall in top-right panel, normalized to vary in the [0,1] interval: the blue curve shows the rainfall collected flux through the slope top boundary as a function of time. For this study, cumulative rainfall data have been smoothed through a Fourier filter. Notably, a peak is recorded in April 2013, highlighted by a red marker, coincident with a relatively sharp peak of cumulative rainfall. The result appears reasonable, although no field data are available for validation in the interval November 2012 – September 2013.
- Upper and lower cell piezometric heads in bottom-right panel: PINN predictions (solid lines) are plotted against field data (dotted lines with markers). The PINN captures the amplitude of seasonal oscillations of pressure head for both the upper (blue) and lower (orange) piezometric cells. Phase matching emerges as well, since the timing of peaks and troughs in the PINN simulations aligns with observed data. This is particularly important to capture the timing of induced landslide activations.

The matching between measured data and preliminary numerical results suggests that PINNs represent a promising tool to capture subsurface hydrogeological processes despite data sparsity and simplifying assumptions. Figure 1 collectively illustrates the central achievement of this study: physics-informed learning allows to capture both spatial distribution and temporal dynamics of porewater pressure as an effect of rainfall infiltration. The red points emphasize the predictive capability of the proposed approach and the ability to fill the gaps in available data.

4 Discussion

The successful reproduction of piezometric head fluctuations at different depths has several implications:

- Hydrogeological realism under reduced parametrization: By formulating the problem in terms of a constant-diffusion model, the PINN framework was able to reproduce the essential features of piezometric head dynamics. This indicates that even with a compact representation of subsurface processes, machine learning can effectively model complex hydrogeological responses, if boundary conditions are consistently integrated into the training.
- Strength of physics-informed learning: By directly constraining the solution with diffusion physics, the PINN framework produced stable and interpretable predictions. This integration of physical laws into the learning process is particularly suited to geotechnical contexts, where measurement campaigns are limited by cost and accessibility.
- Temporal predictability: Correctly reproducing seasonal oscillations indicates that PINNs can serve as forecasting tools for slope stability analysis. By integrating rainfall forecasts, the trained network could simulate future piezometric responses, thereby identifying periods of elevated landslide risk.
- Spatial insights: The spatial distribution of pressure head informs slope hydrodynamics beyond point measurements. This could guide the placement of new monitoring instruments, optimize drainage strategies, or support the design of mitigation measures.

5 Conclusions and Outlook

This study demonstrates the feasibility and value of PINNs for modeling slope hydrology in landslide-prone areas. Specifically:

- A diffusion-based PINN framework was implemented for the Pianello hillslope, embedding simplified Richards' physics into a neural network trained on long-term rainfall.
- The network accurately reproduced both spatial distributions of pressure head and temporal fluctuations at monitoring depths, with fair agreement to observed piezometric heads.
- Figure 1 illustrates this success by showing the close match between measured and simulated values, validating the good matching capability of PINNs.

Beyond its methodological novelty, this work underscores the broader promise of physics-informed learning in natural hazard contexts. By blending mechanistic understanding with flexible neural architectures, it is possible to achieve predictive power even in data-limited settings. This is crucial for advancing landslide risk assessment in a changing climate. Future work will extend the present study in several directions:

- Incorporating heterogeneity: Introducing spatially variable diffusivity and soil retention functions to capture the heterogeneous flysch formation more realistically.

- Three-dimensional modeling: Extending the current two-dimensional framework to fully three-dimensional geometries, explicitly accounting for soil layering, anisotropy, and lateral groundwater flow, to achieve more realistic reconstructions of slope hydrogeology.
- Integration of field measurements: Future work will incorporate piezometric head observations directly into the PINN training process. By assimilating these sparse monitoring data, the model will gain the ability to “fill the gap” across the domain, providing a continuous spatio-temporal reconstruction of subsurface hydrodynamics from limited measurements. This will not only enhance validation but also improve predictive reliability for slope stability assessment.

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7 References

- Cotecchia F., Pedone G., Bottiglieri O., Santaloia F., Vitone C. (2014). Slope-atmosphere interaction in a tectonized clayey slope: A case study. *Rivista Italiana di Geotecnica* 48
- Cotecchia F., Vitone C., Petti R., Soriano I., Santaloia F., Lollino P. (2016). Slow landslides in urbanised clayey slopes: An emblematic case from the south of Italy. In: *Landslides and Engineered Slopes. Experience, Theory and Practice*. <https://doi.org/10.1201/b21520-79>
- Cotecchia F., Tagarelli V., Pedone, G., Ruggieri, G., Guglielmi, S., Santaloia, F. (2019). Analysis of climate-driven processes in clayey slopes for early warning system design. *Proceedings of the Institution of Civil Engineers - Geotechnical Engineering* 172, 465–480. <https://doi.org/10.1680/jgeen.18.00217>
- Cuomo S., Di Cola V. S., Giampaolo F., Rozza G., Raissi M., Piccialli F. (2022). Scientific Machine Learning Through Physics-Informed Neural Networks: Where we are and What's Next. *J. Sci. Comput.* 92, 88. <https://doi.org/10.1007/s10915-022-01939-z>
- Karniadakis G. E., Kevrekidis I. G., Lu L., Perdikaris P., Wang S., Yang L. (2021). Physics-informed machine learning. *Nat Rev Phys* 3, 422–440. <https://doi.org/10.1038/s42254-021-00314-5>
- Losacco N., Bottiglieri O., Santaloia F., Vitone C., Cotecchia F. (2021). The geo-hydro-mechanical properties of a turbiditic formation as internal factors of slope failure processes. *Geosciences (Switzerland)* 11. <https://doi.org/10.3390/geosciences11100429>
- Losacco N., Cotecchia F., Santaloia F., Vitone C., Palladino G. (2025). Multi-source data analysis for conceptual modelling of slow landslide mechanisms: Application to the Pianello hillslope in the Daunia Apennines. *Engineering Geology*, 355, 108255, <https://doi.org/10.1016/j.enggeo.2025.108255>
- Raissi M., Perdikaris P., Karniadakis G. E. (2019). Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J. Comput. Phys.* 378, 686–707. <https://doi.org/10.1016/j.jcp.2018.10.045>