GRID Newsletter Q1 2026

January 21, 2026

Welcome to the Q1 Newsletter!

Dear readers,
Welcome to the latest edition of the GRID newsletter. The newsletter opens with highlights of Yanjie Song's physics-informed ML talk at BOKU, the launch of a student contest on soil shear parameter prediction and the addition of new partners (OsloMet, Tongji, HPC AG, UniPD, UniSAFE). It features a paper on transfer learning in physics-encoded neural networks, announces grai integration in GGU-CONNECT, and points to updated KPIs, recent publications and upcoming events in Vienna, Berlin and Graz.

Physics-Informed ML Spotlight: Yanjie Song @BOKU

Presentation of Yanjie Song from the University of Leeds (third from the right) at BOKU

During his GRID secondment at BOKU, University of Leeds PhD candidate Yanjie Song advanced collaborative research on physics-informed machine learning for multi-physics PDEs (WP4). Building on his recent work on Loss-Attentional PINNs (LA-PINN), he explored attention-driven weighting schemes that dynamically prioritize hard-to-fit regions, such as stiff points with rapid timescale changes, by learning weights from point-wise squared errors via dedicated loss-attentional networks and adversarial training. This approach demon-strated faster convergence and improved accuracy over vanilla PINNs, particularly in challenging domains. At BOKU, Song shared these findings in his talk, "Loss-Attensional and Time-Attentional AI Model for Solving PDE Problems" and engaged with teams on operator learning and transformers, laying the groundwork for joint experiments, code exchange and future publications in geotechnical applications.

For further info, please see: Y. Song, Loss-attentional physics-informed neural networks.

Join the student contest

6th ICITG

6th International Conference on Information Technology in Geo-Engineering

Are you ready to showcase your skills in Machine Learning? GRID, in collaboration with ISSMGE TC304, TC309, and JTC2, is thrilled to announce a **Student Contest** on Machine Learning algorithms for predicting soil shear parameters.
The **prize ceremony** will be held at ICITG26 in Graz, Austria, from **October 13–16, 2026**.
How to Participate:

- Check out the call details, guidelines, and dataset.

- Form your team and register by contacting Lukas Leibold at BOKU.

Good luck to all participants! We can't wait to see your innovative solutions.

Recent Highlights

New partners: OsloMet, Tongji, HPC, UniPD, UniSafe, Smart-G

New GRID partners

We are excited to welcome new GRID partners: OsloMet (Oslo Metropolitan University, Norway), bringing expertise in applied AI and data-driven engineering; Tongji University, renowned for civil and geotechnical engineering and computational mechanics; HPC AG, a long-standing interdisciplinary engineering company (part of the Ginger Group since March 2025) specializing in soil and groundwater, geotechnics, urban water management, waste management, environmental consulting and infrastructure; University of Padua (UniPD), with strong foundations in geomechanics and numerical modeling; UniSAFE, a technology spinoff advancing sensing, safety and monitoring solutions for infrastructure and geotechnical applications; and Smart-G, another spin-off that bridges academia and industry to develop and deliver advanced ground-improvement design techniques and technologies.

Paper spotlight 1: Practical sparse data-driven constitutive modeling via transfer learning in physics-encoded neural networks
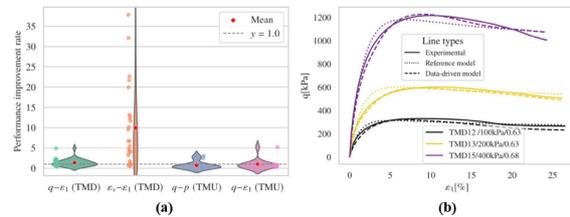

Fig. 8. Results (**a**) overall performance; (**b**) representative results.
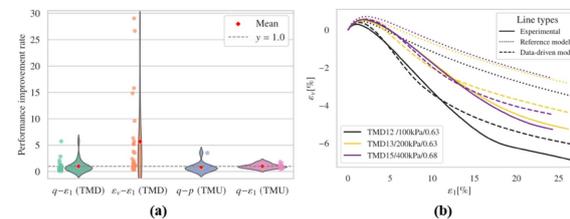

Fig. 9. Results (**a**) overall performance; (**b**) representative results.

Model results in simulating soil material response

This study by Zhihui Wang and Roberto Cudmani of the Technical University of Munich presents a practical pathway for data-driven constitutive modelling when experimental records are scarce. Physics-encoded neural networks (PeNNs) are first pre-trained on synthetic labelled data generated from established constitutive models and then fine-tuned using implicitly labelled, high-fidelity experimental records. By enforcing fundamental mechanical principles during training, the calibrated PeNNs can be directly embedded as user materials in finite element (FEM) software, enabling reliable simulations of drained and undrained triaxial tests.

The results show that transfer learning substantially improves predictive fidelity over synthetic models alone, even with limited experimental data. Model performance is sensitive to the volume and balance of synthetic versus experimental data, as well as fine-tuning configurations such as the architecture of the fine-tuning stage. Overall, the work demonstrates that combining cost-effective synthetic data with curated experiments can yield robust, physics-consistent constitutive models that capture complex stress–strain behavior of geomaterials and integrate smoothly into existing FEM workflows. This contribution aligns with GRID's emphasis on physics-informed AI and operator learning, offering a scalable route to enhance

constitutive modeling under data constraints while preserving physical fidelity and computational efficiency. For further information or collaboration inquiries, please contact the GRID team.

For further info, please see: Wang, Z., Cudmani, R. Practical sparse data-driven constitutive modeling via transfer learning in physics-encoded neural networks.

Paper spotlight 2: Real-Time 3D Consolidation Prediction with Physics-Informed Neural Networks
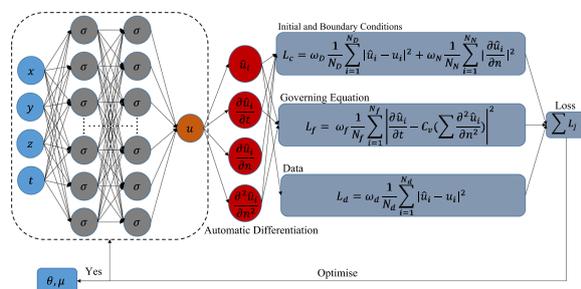

Architecture of the PINN

This study introduces a different paradigm—a physics‐informed neural network (PINN) tailored to three-dimensional consolidation that embeds the governing laws directly into learning, enabling swift, physically consistent predictions of pore pressure dissipation and settlement across space and time . By incorporating directional regularisation along x, y and z, the framework explicitly represents anisotropic behaviour and monitors geotechnical displacements with greater precision in complex domains .

The training procedure is equally deliberate: a two‐stage strategy first concentrates samples where the physics are hardest to approximate via importance‐probability resampling, then balances competing objectives through loss‐based adaptive weighting to stabilise convergence and improve fidelity. In comprehensive tests, the PINN achieved over 98% accuracy in both forward and inverse settings while demonstrating robustness to noise and overfitting—performance supported by physics‐guided regularisation and adaptive loss formulation. It also reproduced non‐uniform consolidation under spatially variable loading with strong agreement to reference solutions,

reinforcing its applicability to heterogeneous field conditions.

For further info, please see: Biao, Y., Heitor, A., Wang, H., Chen, X., Physics-Informed Neural Networks for Fast 3D Consolidation Prediction: A Surrogate Modelling Application

grai in GGU-CONNECT
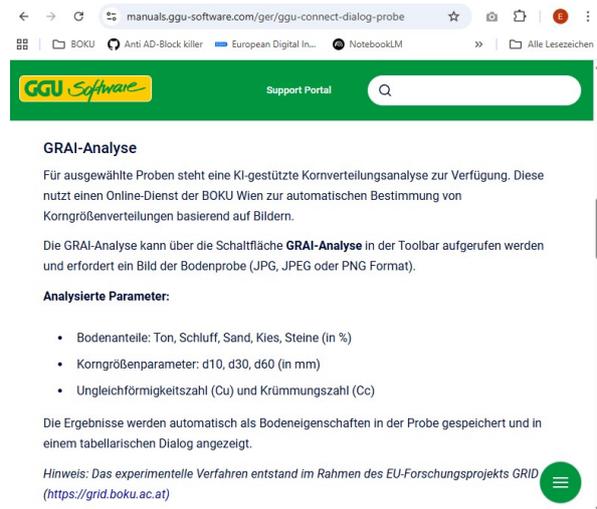
Screenshot of the GGU-Connect manual featuring the grai analysis

GGU-CONNECT now offers native integration with the grai service, streamlining AI-assisted prediction of the particle size distribution from soil images. The release introduces a grai-analysis button directly in the sample log, enabling one-click submission of dataset entries for analysis.

To support smooth data exchange with grai pipelines, this version also adds import and export menu entries for key test parameters.

For further info, please see: Soranzo, E., Guardiani, C. and Wu, W., Convolutional neural network prediction of the particle size distribution of soil from close-range images and Soranzo, E., Machine learning prediction of soil particle size distribution from smartphone images.

Upcoming Events

Catch up with GRID at these upcoming events:

Vienna: June 14–19, 2026

Berlin: September 22–25, 2026

Graz: October 13–16, 2026

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Spotlight on Research
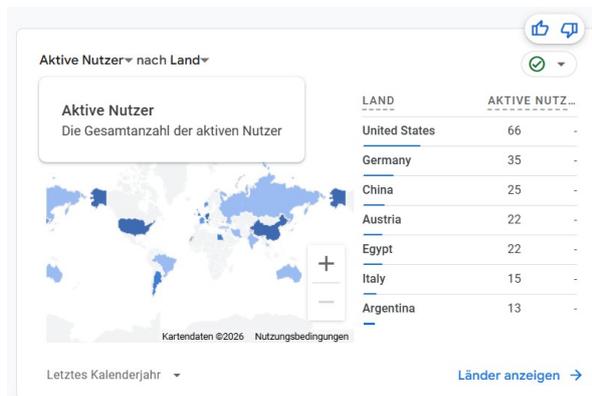
Our recent publications include:

Large language models for automated grading in geotechnics ▶

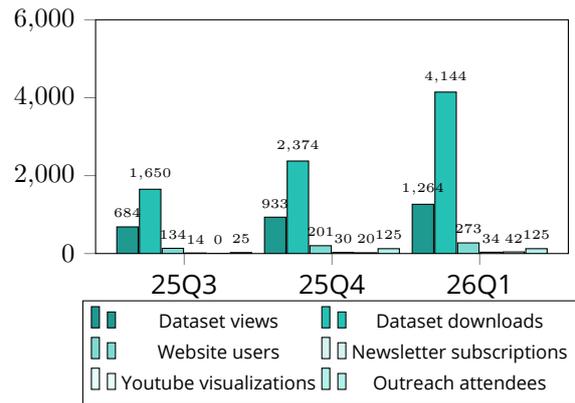Predictive modeling of pore pressure build-up in vibratory pile driving through machine learning ▶

Practical sparse data-driven constitutive modeling via transfer learning in physics-encoded neural networks ▶

Physics-Informed Neural Networks for Fast 3D Consolidation Prediction: A Surrogate Modelling Application ▶

Communication KPIs of the GRID project

Engaging the Community

Number of active users of website and their geographical distribution according to Google Analytics

Get Involved

Join us in revolutionizing geotechnics and AI. Visit our website at grid.boku.ac.at.

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