

Deep generative modeling of non-stationary sedimentary deposits in 3D

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Subsurface decision-making is hampered by high uncertainties due to sparse data. Embedding geological knowledge into predictive models is therefore essential for robust decisions. Traditional geostatistical methods still struggle to reproduce the architecture and heterogeneity of sedimentary deposits, while recent advances in deep generative models offer a promising alternative, although important challenges remain. The first challenge is obtaining the large number of 3D training images required by such models. To address this, we used a process-based model – the Channel-Hillslope Integrated Landscape Development (CHILD) model – to simulate fluvial evolution over geological timescales (Rongier & Peeters, 2025a). We generated 20,000 simulations of meandering deposits and used them to train a generative adversarial network (GAN). An ablation study shows that techniques developed for generating large 2D images transfer well to 3D fluvial deposits: training remains stable (Figure 2) and the GAN generates diverse, non-stationary deposits with detailed internal structures, without mode collapse or memorization. The second challenge is generating realizations conditioned on well and geophysical data. We evaluated several GAN inversion approaches for fitting well and seismic data and found that the GAN latent space is often entangled, making conditioning difficult (Rongier & Peeters, 2025b). But updating the model's weights during the inversion significantly improves the fit to the data. These results suggest that that we are close to being able to use deep generative models in practical applications. But further work is needed to build geologically plausible and diverse training datasets that support the development of foundational generative models, which can then be fine-tuned to specific case studies and conditioning data.

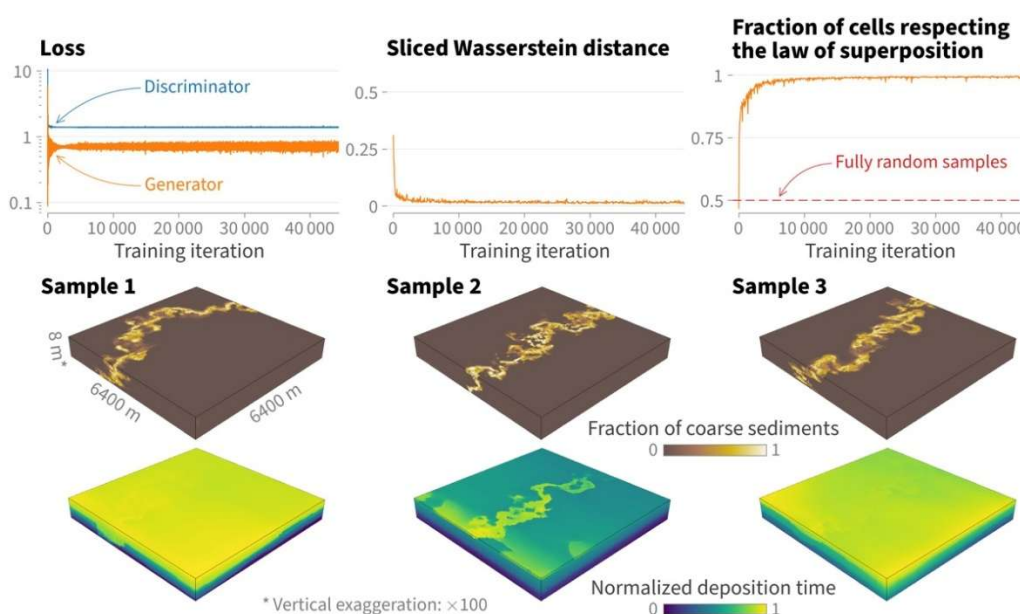


Figure 2. Training a GAN to generate 3D non-stationary fluvial deposits.

Rongier, G., & Peeters, L. (2025a). Towards geological inference with process-based and deep generative modeling, part 1: Training on fluvial deposits (arXiv:2510.14445). arXiv. <https://doi.org/10.48550/arXiv.2510.14445>

Rongier, G., & Peeters, L. (2025b). Towards geological inference with process-based and deep generative modeling, part 2: Inversion of fluvial deposits and latent-space disentanglement (arXiv:2510.17478). arXiv. <https://doi.org/10.48550/arXiv.2510.17478>