

Towards integrated seismic characterisation of fluvial geothermal reservoirs with deep learning

B. S. I. Gesbert¹, D.J. Verschuur¹, G. Song¹, H. A. Abels¹, S. Geiger¹

¹ Geoscience and Engineering Department, Delft University of Technology

Geothermal developments require a high success rate because of their challenging finances. This usually restricts seismic data acquisition to 2D lines (Rehling et al., 2023), which are impractical for accurately interpreting 3D channelised reservoir connectivity (Posamentier et al., 2022), posing considerable uncertainty to geothermal production estimates and well drilling decisions. Given data scarcity and constrained budgets, it is key in geothermal projects to explore a wide range of geological uncertainties and to exploit available seismic data without excessive computational costs.

We build a comprehensive deep-learning-based framework that couples geological scenario modelling with seismic forward modelling and impedance inversion for efficient seismic characterisation of fluvial geothermal systems. The Rapid Reservoir Modelling software is employed, enabling quick probabilistic construction of numerous different 3D sandstone-shale reservoir models (Jacquemyn et al., 2021; Song et al., 2025). A finite-difference modelling workflow leads to a diverse deep learning dataset of 2D seismic depth images, which are inverted for underlying acoustic impedance distributions by training a conventional U-Net architecture (Ronneberger et al., 2015).

Inference of the trained U-Net on various unseen reservoir scenarios shows good inversion outcomes that are remarkably similar between seismic images filtered to high (112 Hz) and low maximum frequencies (40 Hz; Fig. 1). Additionally, applying random seismic noise seems to not matter much above an overall signal-to-noise ratio of around 1 in the image domain, reflecting substantial image distortion. Next steps include further increasing random noise and geological complexity, as well as evaluating how deep-learning inversion predictions affect geothermal flow simulation.

Jacquemyn, C., et al. (2021). Sketch-based interface and modelling of stratigraphy and structure in three dimensions. *Journal of the Geological Society*, 178(4), jgs2020-187.
 Posamentier, H. W., Paumard, V., & Lang, S. C. (2022). Principles of seismic stratigraphy and seismic geomorphology I: Extracting geologic insights from seismic data. *Earth-Science Reviews*, 228, 103963.
 Rehling, J., et al. (2023). The Dutch SCAN Geothermal Exploration Programme—The first three years of 2D seismic acquisition and (re) processing. *First Break*, 41(1), 33-43.
 Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Cham: Springer international publishing.
 Song, G., Geiger, S., Voskov, D., Abels, H. A., & Vardon, P. J. (2025). Scenario-based data assimilation framework to improve production estimates for geologically complex geothermal reservoirs. *Authorea Preprints*.

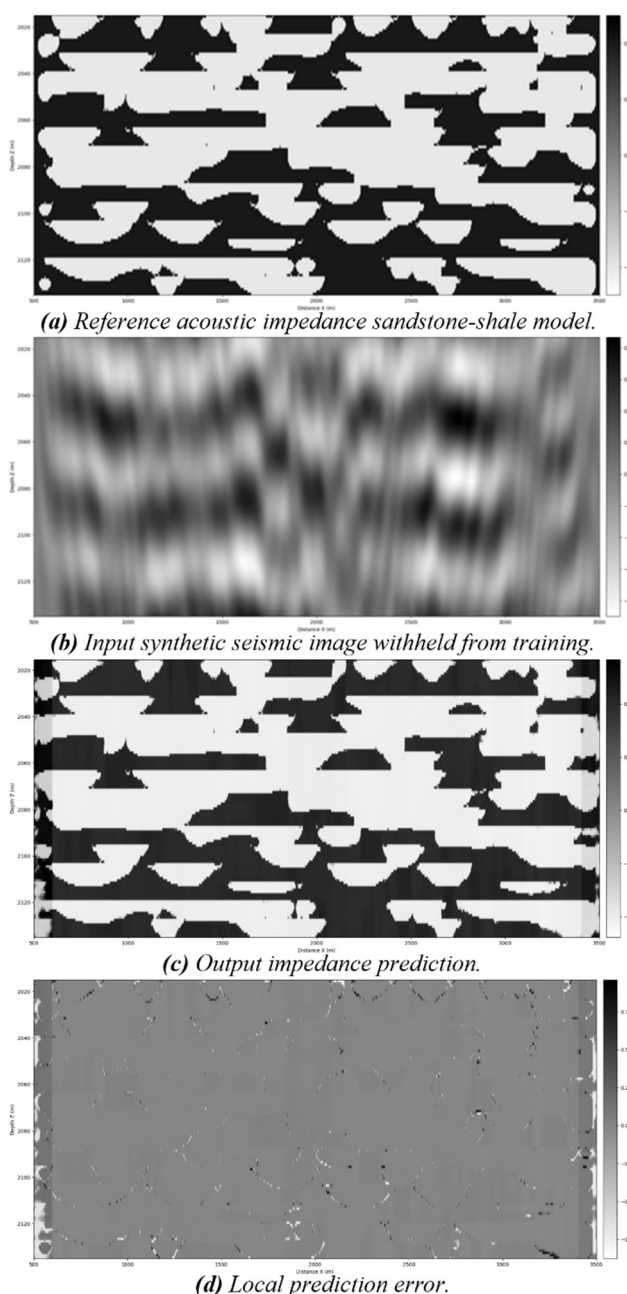


Fig 1. Convolutional neural network (U-Net) inversion results on a synthetic sandstone-shale reservoir test case. The simulated seismic image has been filtered to 40 Hz at maximum, after which it has been perturbed with random noise.