

# Surrogate modeling with convolutional neural networks to evaluate CO<sub>2</sub> storage under geological uncertainty

JAEHWAN OH<sup>1</sup>, PROF. CHANGHYUP PARK, PHD<sup>1</sup> AND SURYEOM JO<sup>2</sup>

<sup>1</sup>Kangwon National University

<sup>2</sup>Korea Institute of Geoscience and Mineral Resources

Presenting Author: [changhyup@kangwon.ac.kr](mailto:changhyup@kangwon.ac.kr)

This study presents a noble methodology based on a deep-learning framework to estimate CO<sub>2</sub> sequestration in heterogeneous saline aquifers with geological uncertainty. The geological uncertainty, made by the lack of accurate information, limits quantitative analyses of subsurface flow. The high computation cost hinders to implement available heterogeneous geo-models on designing CO<sub>2</sub> storage and thus geological uncertainty has been limited to proper decision-making. This study develops a convolutional neural network (CNN)-based surrogate model including spatial distribution of aquifer properties, i.e., permeability and porosity, of available geo-models, statistical parameters to construct aquifer models and the operation conditions, i.e., injection rate of CO<sub>2</sub> and the maximum bottom hole pressure (operation pressure of injecting facilities). The statistical parameters are such as mean permeability, mean porosity, shale volume ratio, salinity, and temperature. CNN reduces the dimensionality of spatial properties, i.e., permeability and porosity, and then a fully-connected network integrates these extracted features (the latent codes flatten) with the statistical parameters and the operational conditions. The output layer consists of the volume of structural CO<sub>2</sub> trapping amount, of dissolved trapping, and the CO<sub>2</sub> injection volume at the given operation condition. The heterogeneous 1200 geo-models are generated geostatistically that are used on training, validating, and testing the deep-learning architecture. The performances of surrogate modeling are evaluated with the output values compared with those by time-consuming compositional simulations. The testing set shows that the developed deep-learning architecture estimates the trapping volumes accurately; the correlation coefficients of testing set are 0.85 for structural trapping volume, 0.98 for dissolved trapping volume, and 0.91 for the injected CO<sub>2</sub> amount, respectively. The workflow can replace the time-consuming compositional simulations considering the inputs and the outputs linked non-linearly.