EGU21-717, updated on 27 Jan 2022
https://doi.org/10.5194/egusphere-egu21-717
EGU General Assembly 2021

Using artificial neural networks with joint muon-gravity datasets for shallow subsurface density prediction at volcanoes

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The ability to accurately and reliably obtain images of shallow subsurface anomalies within the Earth is important for hazard monitoring at many geologic structures, such as volcanic edifices. In recent years, the use of machine learning as a novel, data-driven approach to addressing complex inverse problems in the geosciences has gained increasing attention, particularly in the field of seismology. Here we present a physics-based, machine learning method to integrate disparate geophysical datasets for shallow subsurface imaging. We develop a methodology for imaging static density variations at a volcano with well-characterized topography by pairing synthetic cosmic-ray muon and gravity datasets. We use an artificial neural network (ANN) to interpret noisy synthetic datasets generated using theoretical knowledge of the forward kernels that relate these datasets to density. The deep learning model is trained with synthetic data from a suite of possible anomalous density structures and its accuracy is determined by comparing against the known forward calculation.

In essence, we have converted a traditional inversion problem into a pattern recognition tool, where the ANN learns to predict discrete anomalous patterns within a target structure. Given a comprehensive suite of possible patterns and an appropriate amount of added noise to the synthetic data, the ANN can then interpolate the best-fit anomalous pattern given data it has never seen before, such as those obtained from field measurements. The power of this approach is its generality, and our methodology may be applied to a range of observables, such as seismic travel times and electrical conductivity. Our method relies on physics-based forward kernels that connect observations to physical parameters, such as density, temperature, composition, porosity, and saturation. The key benefit in using a physics-based approach as opposed to a data-driven one is the ability to get accurate predictions in cases where the amount of data may be too sparse or difficult to obtain to reliably train a neural network. We compare our approach to a traditional inversion, where appropriate, and highlight the (dis)advantages of the deep learning model.