Comparison of Groundwater Modeling Approaches including Groundwater Heat Pumps

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Groundwater heat pumps are a promising renewable energy technology. The installation of new heat pumps is constrained by already existing heat pumps and regulations on groundwater temperature fluctuations. Hence, a fast and reliable quantification of the impact on groundwater temperature is required.

In our work, we start with simplified box-examples and scale to complex multiscale-scenarios like groundwater flow in the region of Munich (geoKW project [1]). In each step we compare analytical, numerical and machine learning approaches, analyze their limitations and improve these methods further if possible.

So far, a simplified two-dimensional stationary and isotropic benchmark problem with varying quantities of permeability and Darcy velocity is defined. The comparison includes an analytical model (LAHM) [4], a numerical simulation (Pflotran [3]) and a data-driven neural network (e.g. CNN).

The real-world scenario is a large, three-dimensional domain, with limited data availability, and effects not modelled by simulation software like Pflotran, such as thermal recycling and groundwater temperature that varies with season and depth. The goal of our work is a multiscale, multilevel neural network that incorporates physics (PINN [5]) and super-resolution approaches (PICNNSR [2]) to balance the missing data and to model effects not previously included in simulation software while quantifying the uncertainty of its results.

References

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