Numerical simulations of subsurface processes are essential to the success of many geoengineering projects. These simulations often contain significant uncertainties due to imperfect knowledge of material properties and their spatial distribution, boundary conditions, and initial conditions. However, efficient implementations for the quantification of uncertainties for such simulations are big challenges in Computational Geoscience, mainly due to the curse of dimensionality. Process simulations often involve solving high-dimensional Partial Differential Equations (PDE) by using discretization methods such as Finite Difference (FD) or Finite Elements (FE) methods. Although such methods often give good approximations, they are computationally intensive and expensive and therefore infeasible in the applications such as MCMC where thousands of evaluations of the forward simulation are required. Previous work by Degen et.al. (2020) has addressed this problem by using a model order reduction method, the so-called reduced basis (RB) method. However, the method has limitations when considering complex (i.e., hyperbolic and non-linear) PDEs. In this work, we aim to employ the recently developed Fourier Neural Operator (FNO) (Li, 2020) as a tool to implement efficient approximation of PDEs in the application of Geothermal reservoir simulation. FNO involves a Fast Fourier transform to directly learn the mapping from the input function to the output function. FNO has the advantage of being independent of the resolution and complexity of the governing PDE. Our preliminary results show that FNO can provide good approximation results in solving four-dimensional PDEs and thus can be used as a tool for further probability studies of the parameters of interest.