**Convolutional-Recurrent Proxy Model for Spatiotemporal CO2 Monitoring**

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**Abstract**

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**Keywords**: Spatiotemporal forecasting, Convolutional neural network, Recurrent neural network, Proxy model

1. **Introduction**

Geologic CO2 sequestration (GCS) is a proven technology to reduce anthropogenic greenhouse gas emissions to the atmosphere [citation]. This has become increasingly popular worldwide due to the need to meet international climate protection agreements [citation]. In order to accurately forecast and monitor subsurface multiphase flow, numerical simulation is required. However, these numerical simulations are computationally intensive and time-consuming since they require iterative solutions of large-scale nonlinear systems of equations [citation]. Similarly, due to the large degree of uncertainty in subsurface data collection, inherent uncertainty in the spatial distribution of the properties of heterogeneous porous media require a robust, probabilistic assessment for improved engineering decision-making [citation]. In order to capture the fine-scale multiphase flow behavior given an uncertain spatial distribution of subsurface properties, a large number of forward numerical simulation runs are required, leading to very high computational costs [citation]. To overcome this, machine learning techniques have emerged as candidate reduced-order models for efficient parameterization and prediction of subsurface flow and transport behavior [citation].

1. **Methodology**
   1. Reservoir model description
   2. Reservoir simulation
   3. Model architecture
      1. Spatial structure
      2. Temporal structure
2. **Results and Discussion**
   1. Training performance
   2. Prediction results
   3. Cumulative co2 as a proxy for PVI
3. **Conclusions**