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A deep-learning-based Convolutional-LSTM surrogate model for simulating geological CO_2 sequestration with dynamic well controls

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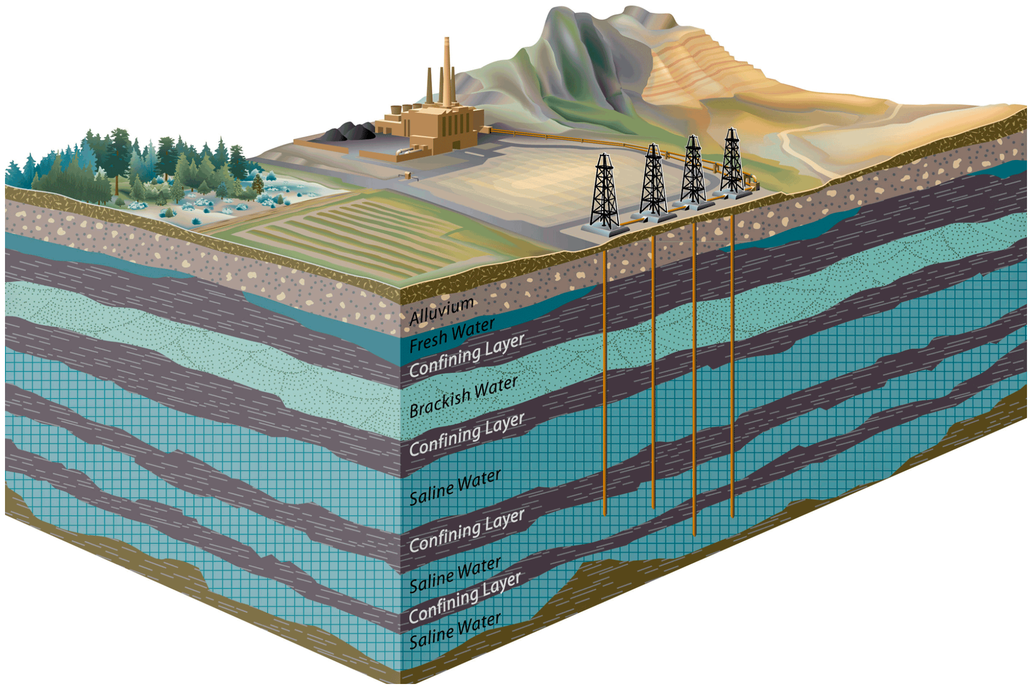
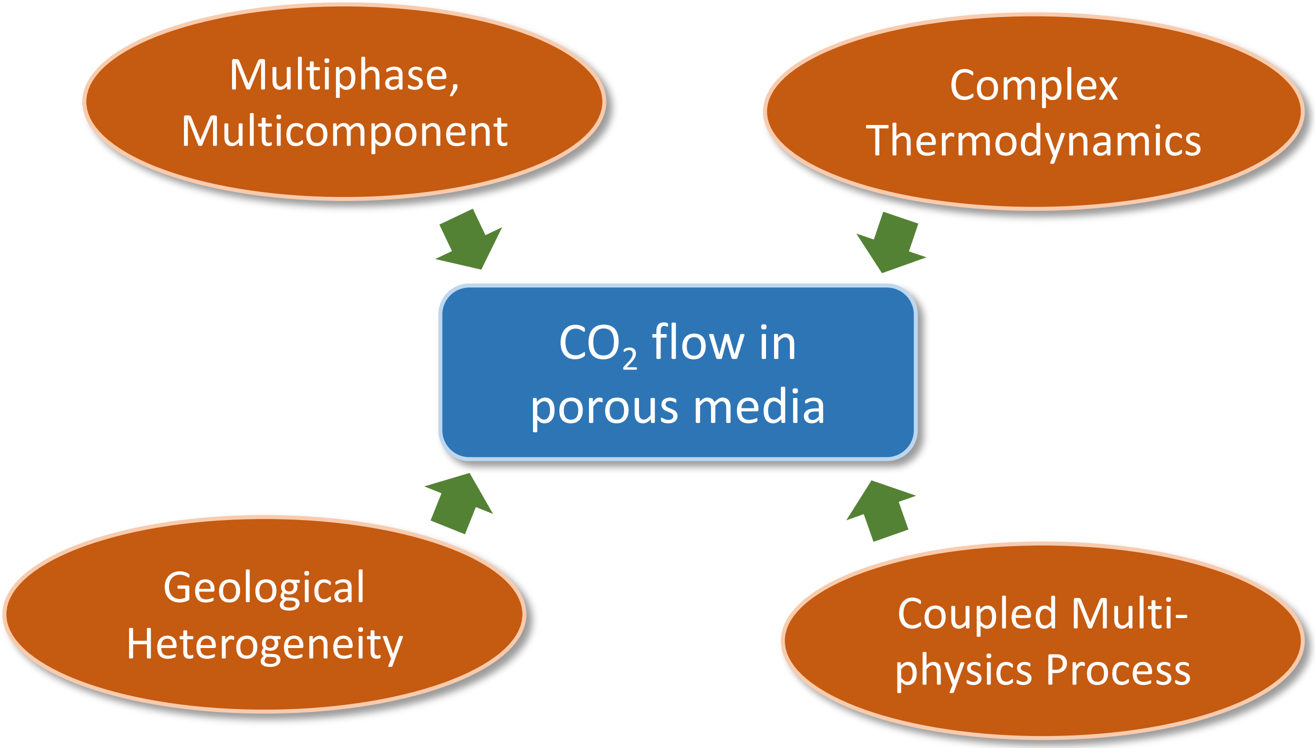
Introduction

Geological Carbon Sequestration (GCS)



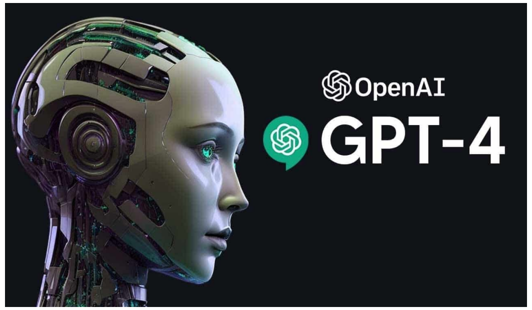


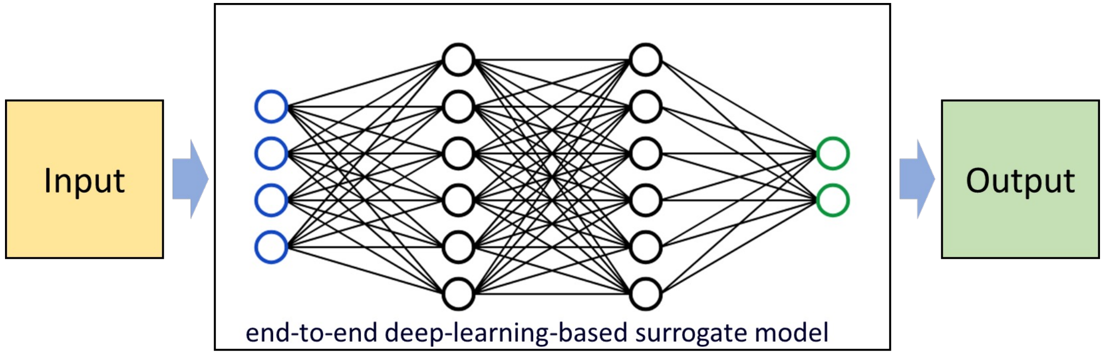
- A promising strategy for mitigating climate warming
- Injection of SC-CO_2 into subsurface reservoirs (e.g. deep saline aquifers)

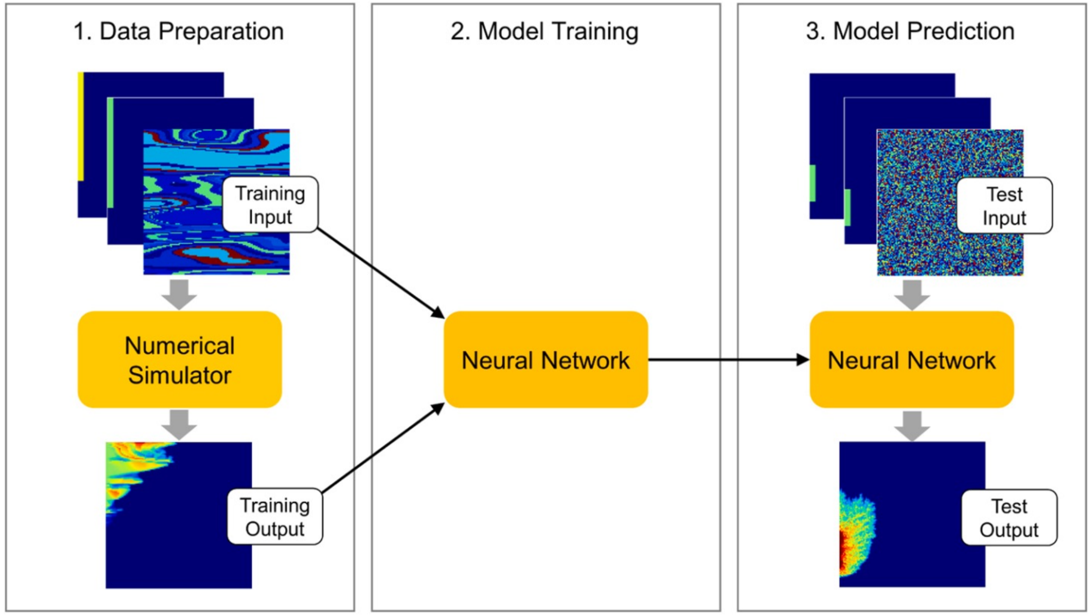
× Challenge to characterize CO_2 migration

× Inefficient to run simulation for optimization/ inverse problems

Deep Learning Techniques and Surrogate Modeling



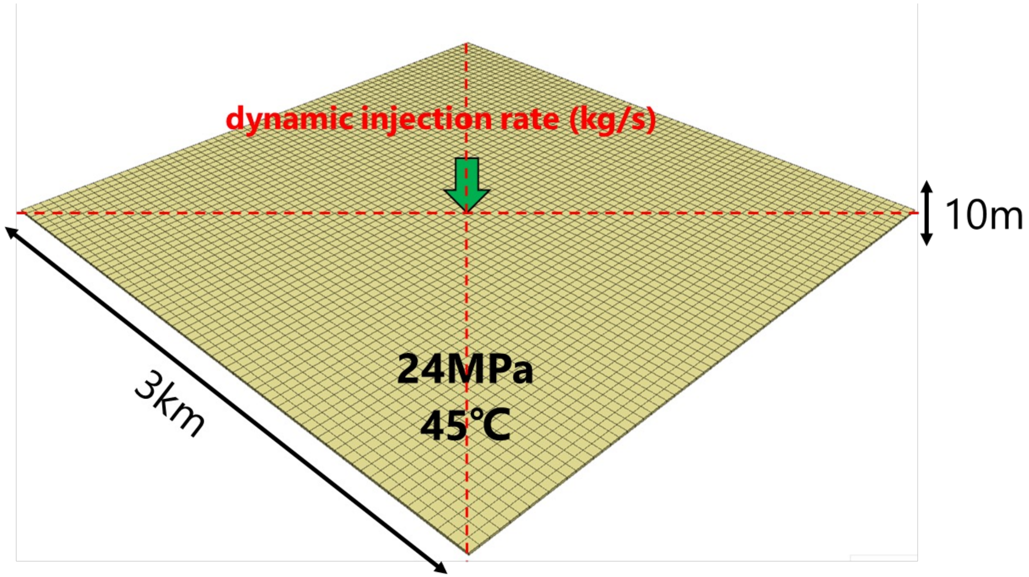




Wen et al., 2021

- ✓ An image-to-image task with end-to-end fashion
- ✓ Fast inference time (within milliseconds)
- ✓ Advantageous in optimization / inverse problems

Methods: numerical simulation



Property	Value
Model Size	3km*3km*10m
Mesh	64*64*1
Boundary Condition	Open Flow
Thermal Effect	Neglected
Relative Permeability	Corey
Capillary Pressure	van Genuchten

- **Mass conservation for each component $\boldsymbol{\kappa}$**

$$\frac{\partial}{\partial t} M^\kappa = -\nabla \cdot \boldsymbol{F}^\kappa + Q^\kappa$$

- **Mass accumulation**

$$M^\kappa = \phi \sum_\beta S_\beta \, \rho_\beta X_\beta^\kappa$$

- **Mass flux**

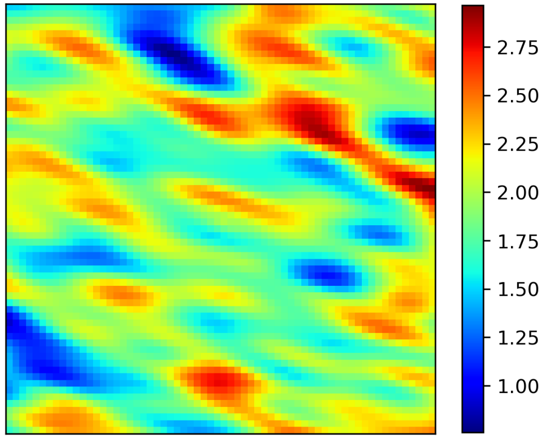
$$\boldsymbol{F}^\kappa = \sum_\beta X_\beta^\kappa \, \boldsymbol{F}_\beta$$

- **Multiphase Darcy's law**

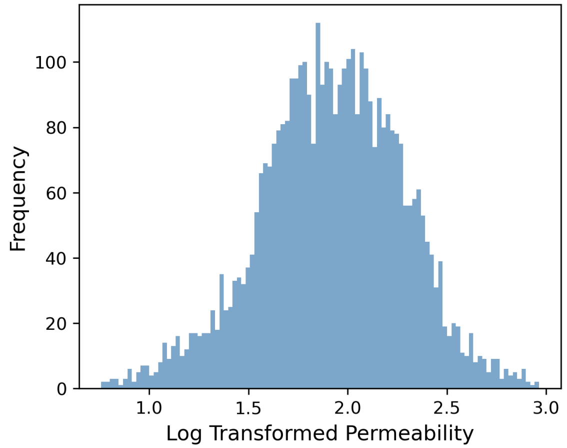
$$\boldsymbol{F}_\beta = -k \frac{k_{r\beta} \rho_\beta}{\mu_\beta} (\nabla p_\beta - \rho_\beta \boldsymbol{g})$$

Methods: heterogeneous field and dataset

Gaussian Random Field



by GSTools

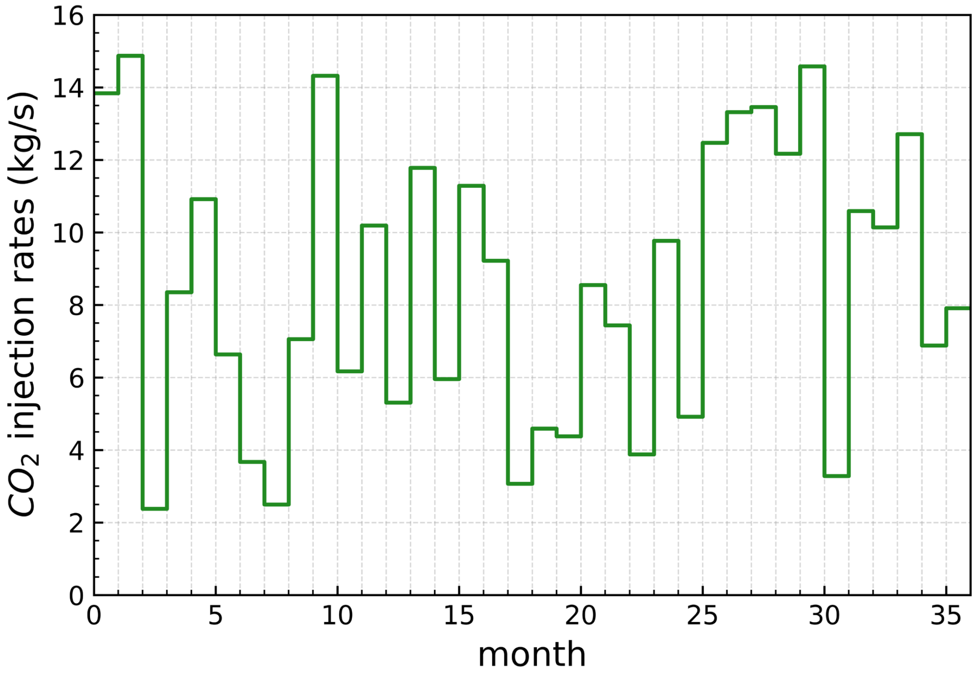


- Permeability follows a log-normal distribution
- Anisotropy permeability fields
- Porosity is correlated to permeability (Zhong et al., 2019):

$$\phi = 0.05\log_{10}(k) + 0.15.$$

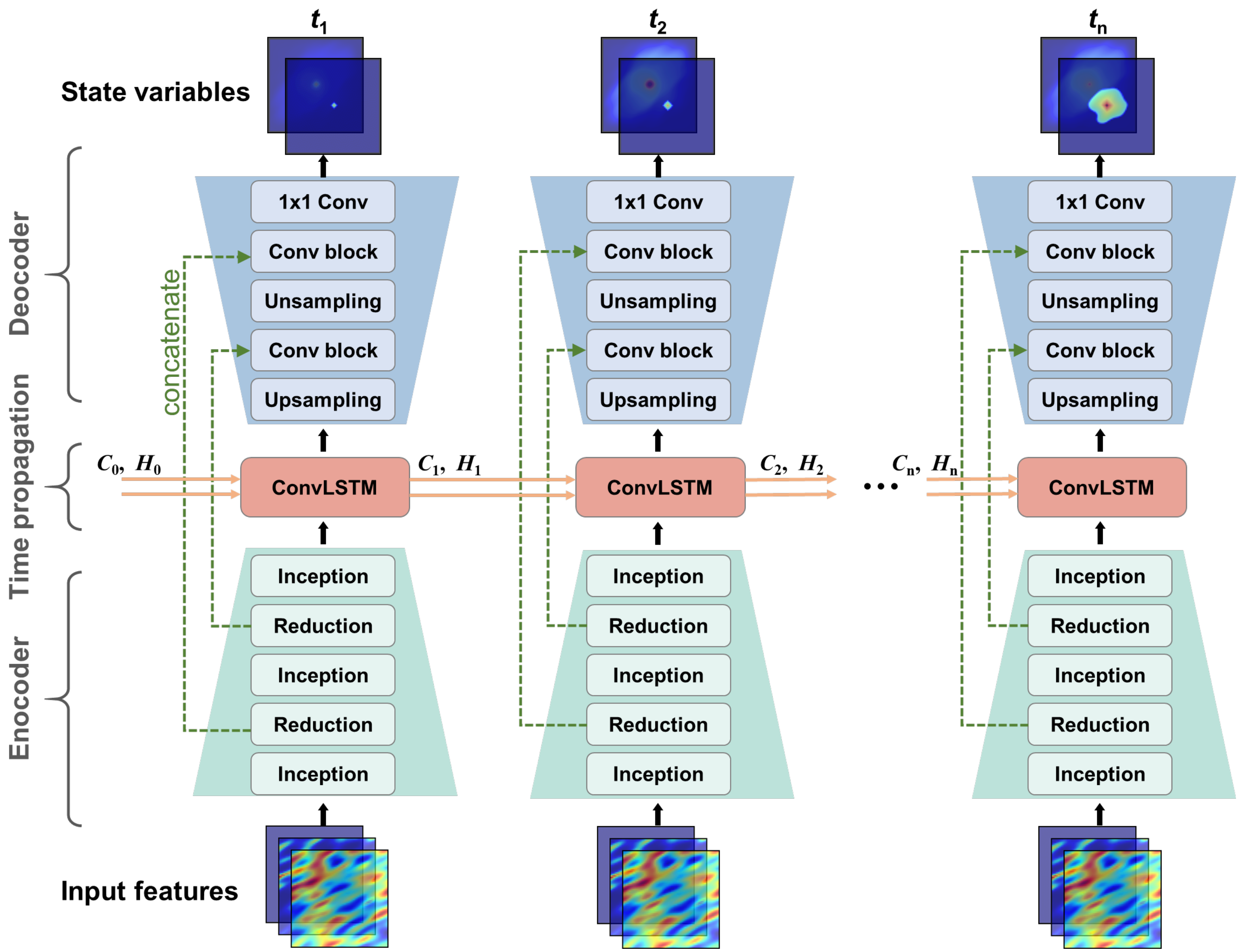
- 5000 cases in total

Dynamic Well Controls

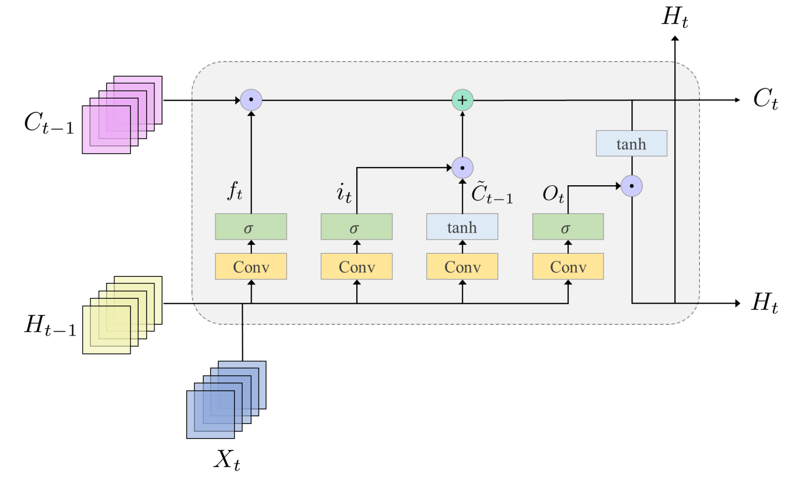


- monthly injection rate sampled via Latin-Hypercube Sampling

Methods: network architecture



Convolution Long Short-Term Memory

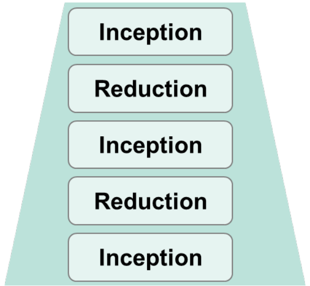


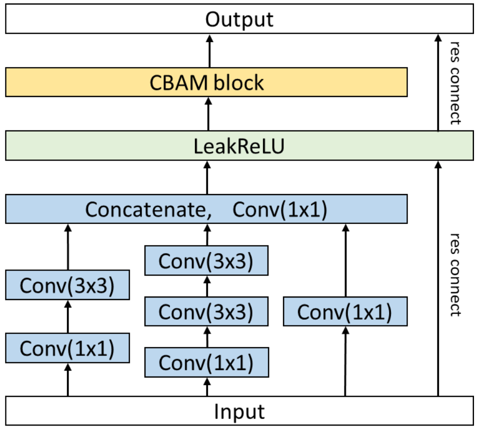
$$
\begin{aligned}
\mathbf{i_t} &= \mathrm{Sigmoid}\left(\mathrm{Conv}\left(\mathbf{x_t};\mathbf{w_{xi}}\right)+\mathrm{Conv}\left(\mathbf{h_{t-1}};\mathbf{w_{hi}}\right)+\mathbf{b_i}\right)\\
\mathbf{f_t} &= \mathrm{Sigmoid}\left(\mathrm{Conv}\left(\mathbf{x_t};\mathbf{w_{xf}}\right)+\mathrm{Conv}\left(\mathbf{h_{t-1}};\mathbf{w_{hf}}\right)+\mathbf{b_f}\right)\\
\mathbf{o_t} &= \mathrm{Sigmoid}\left(\mathrm{Conv}\left(\mathbf{x_t};\mathbf{w_{xo}}\right)+\mathrm{Conv}\left(\mathbf{h_{t-1}};\mathbf{w_{ho}}\right)+\mathbf{b_o}\right)\\
\mathbf{g_t} &= \mathrm{Tanh}\quad\left(\mathrm{Conv}\left(\mathbf{x_t};\mathbf{w_{xg}}\right)+\mathrm{Conv}\left(\mathbf{h_{t-1}};\mathbf{w_{hg}}\right)+\mathbf{b_g}\right),\\
\mathbf{c_t} &= \mathbf{f_t}\odot\mathbf{c_{t-1}}+\mathbf{i_t}\odot\mathbf{g_t}\\
\mathbf{h_t} &= \mathbf{o_t}\odot\mathrm{Tanh}(\mathbf{c_t})
\end{aligned}
$$

- ✓ capturing time-varying features
- ✓ alleviating gradient exploding or vanishing

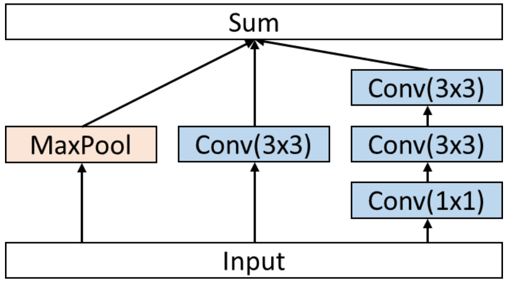
Methods: network architecture

Encoder





Inception block
hierarchical feature

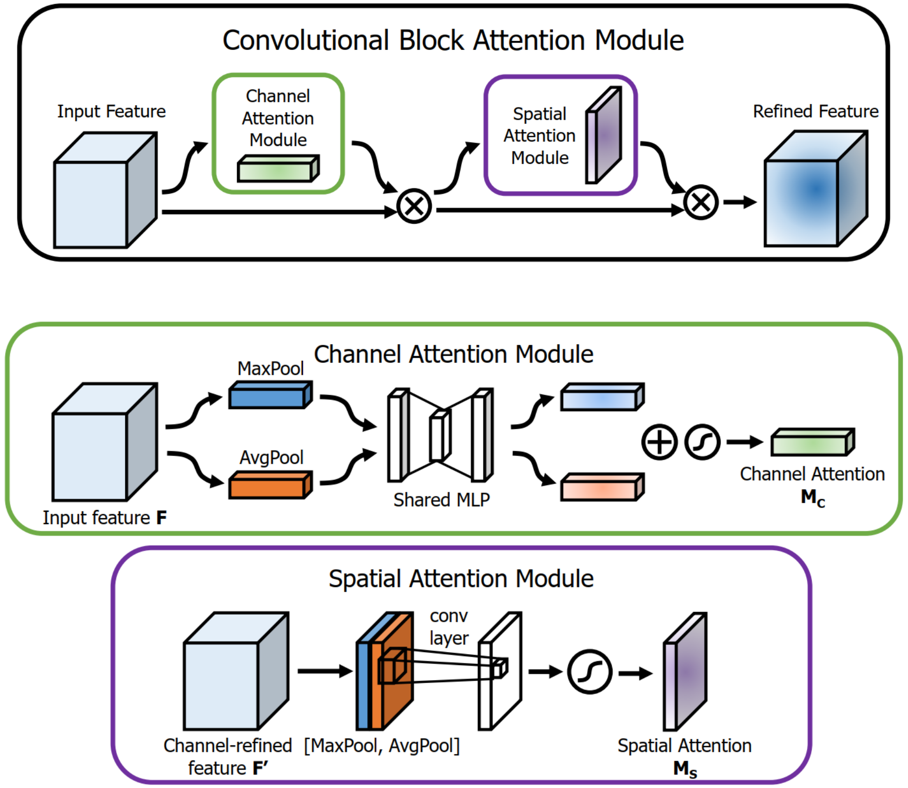


Reduction block
dimension reduced 1/2

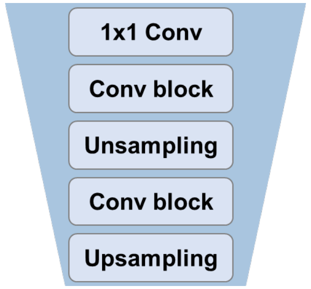
CBAM

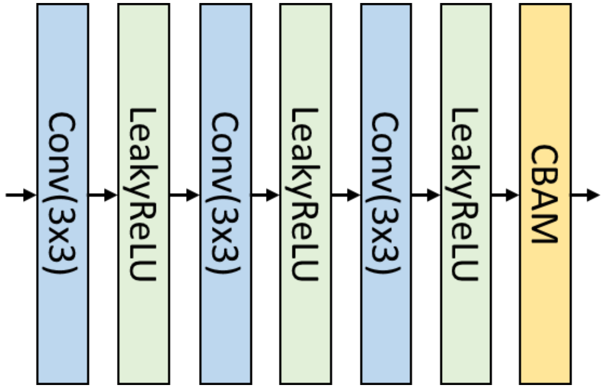
Convolutional Block Attention Module

(Woo et al., 2018)



Decoder





Conv block

Methods: evaluating metrics

Coefficient of determination

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$$

Normalized root mean square error

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad NRMSE = \frac{RMSE}{(y_{max} - y_{min})}$$

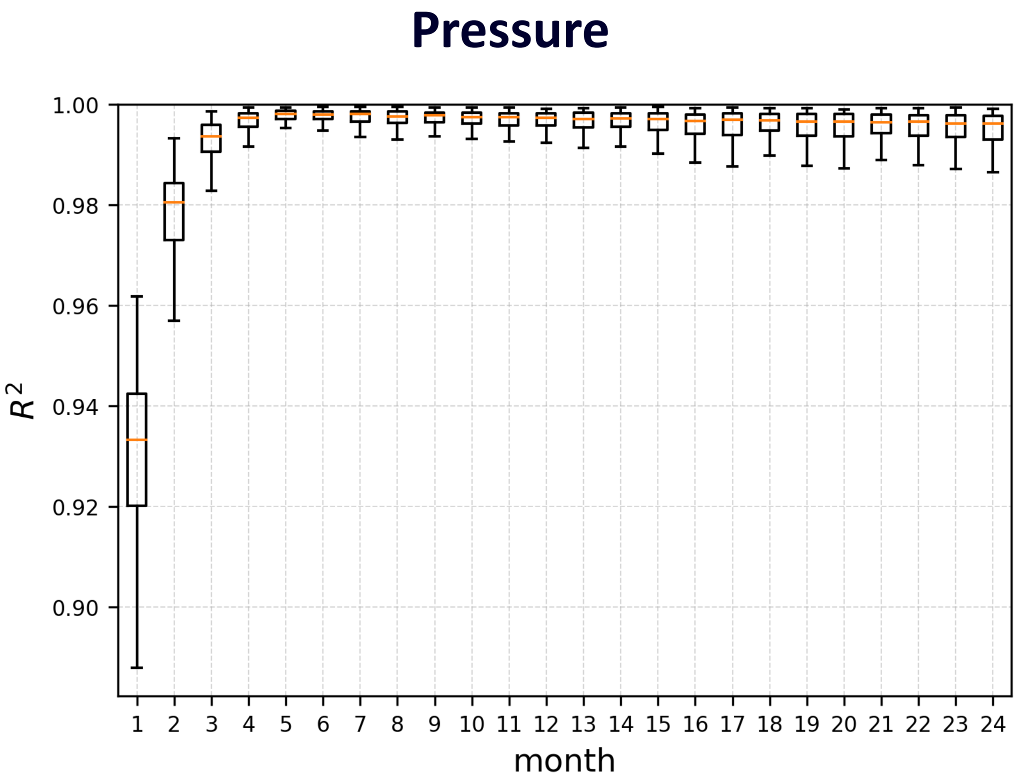
Mean structural similarity index

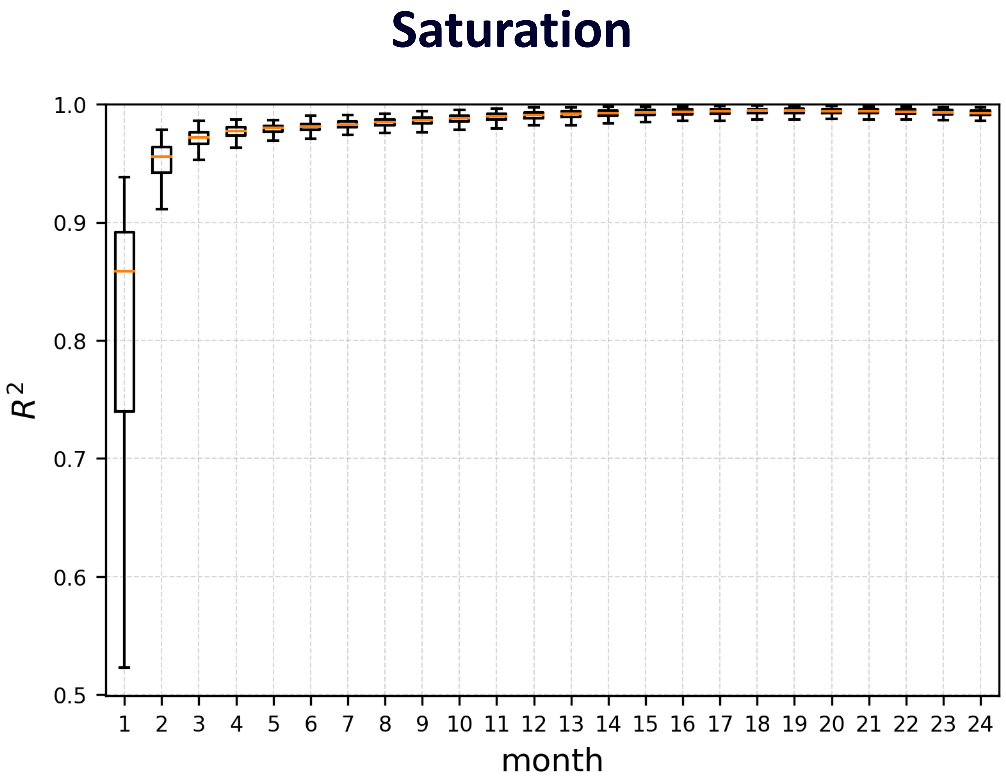
$$SSIM = \frac{1}{M} \sum_{m=1}^{m} \frac{(2\mu_{u,m}\mu_{v,m} + K_1^2)(2\sigma_{uv,m} + K_2^2)}{(\mu_{u,m}^2 + \mu_{v,m}^2 + K_1^2)(\sigma_{u,m}^2 + \sigma_{v,m}^2 + K_2^2)}$$

Normalized absolute percentage error

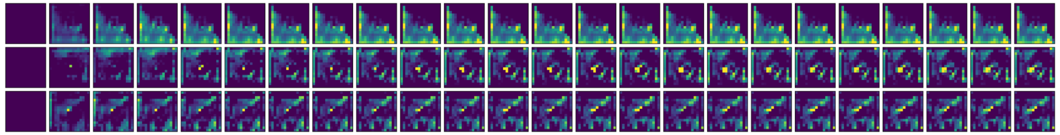
$$NAPE = \frac{||y - \hat{y}||}{y_{max} - y_{min}} * 100$$

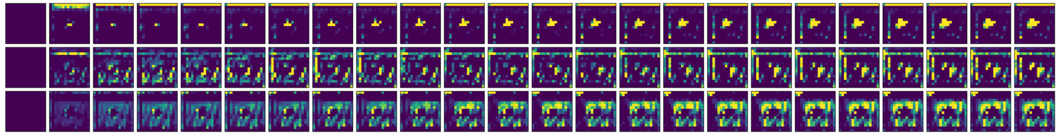
Results: performance through time



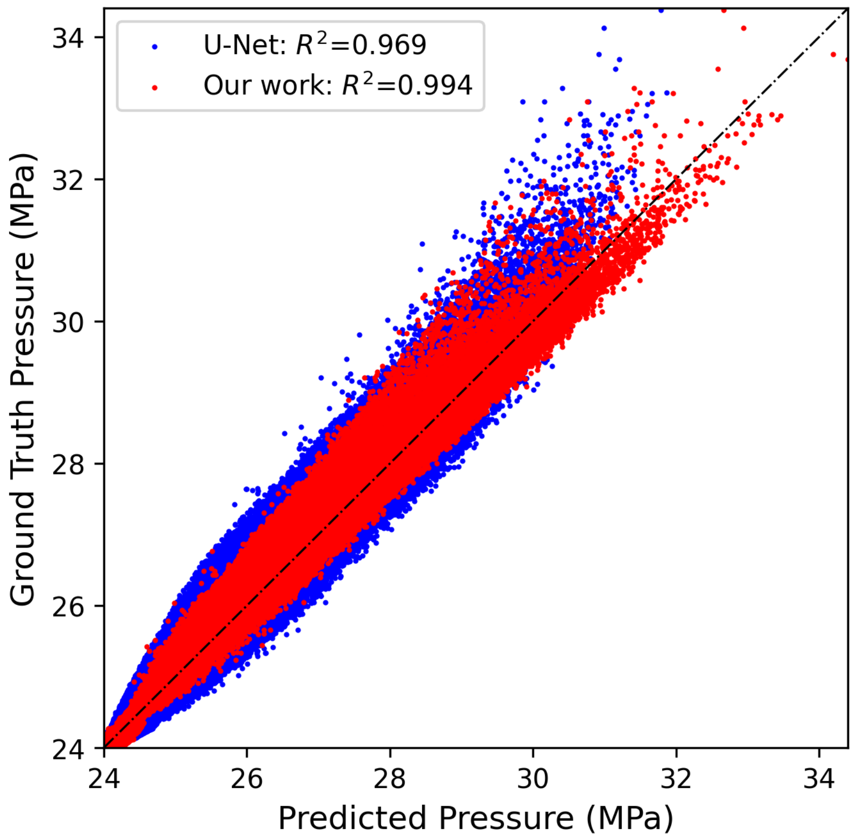


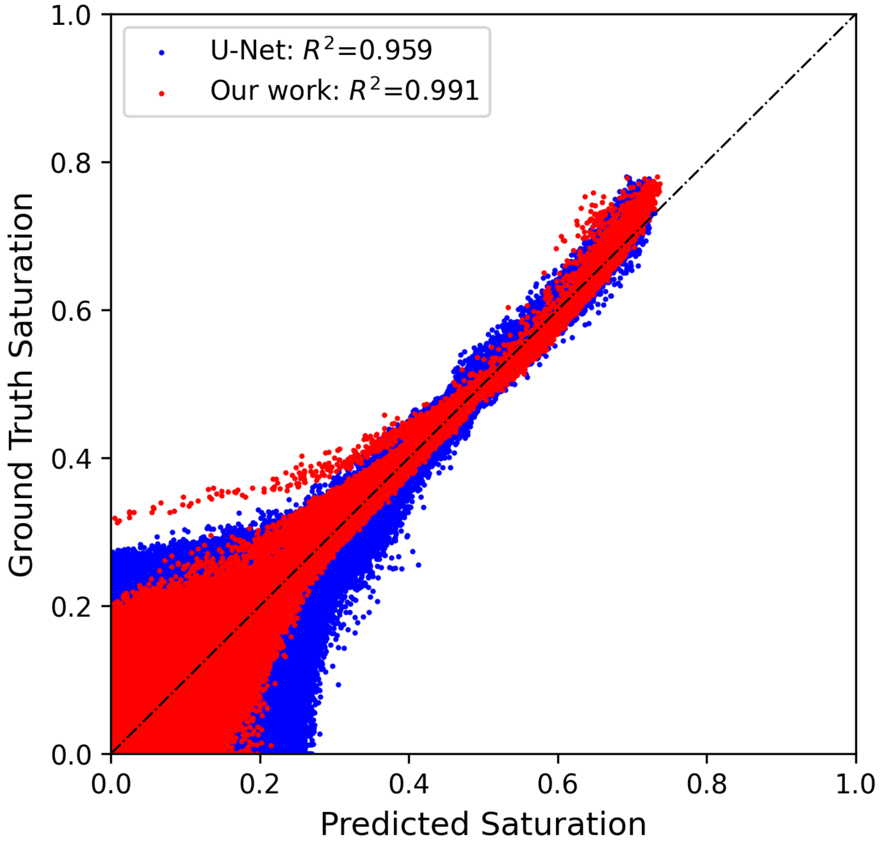
The ConvLSTM gradually captures the hidden states through the time steps:





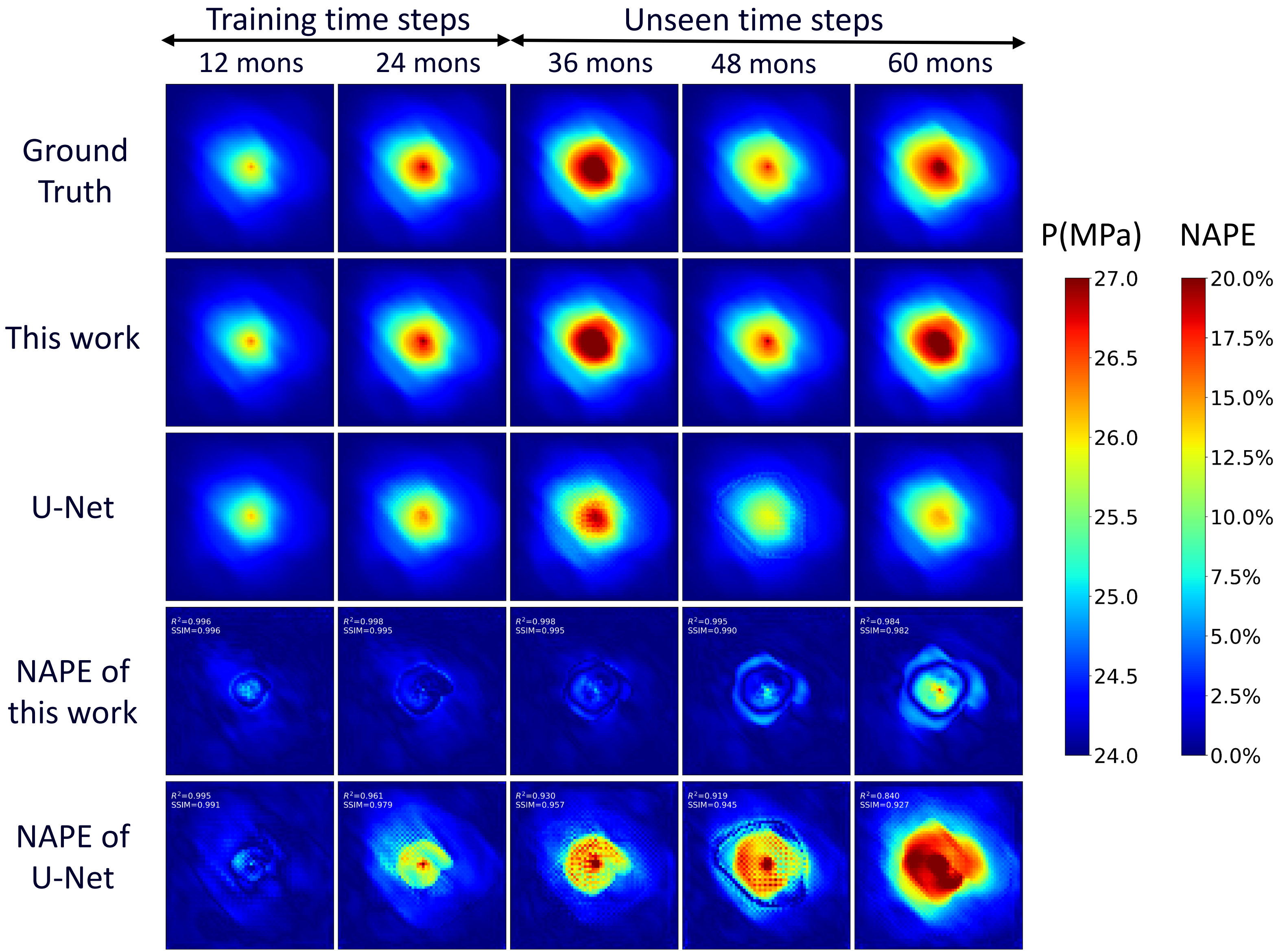
Results: benchmark with U-Net

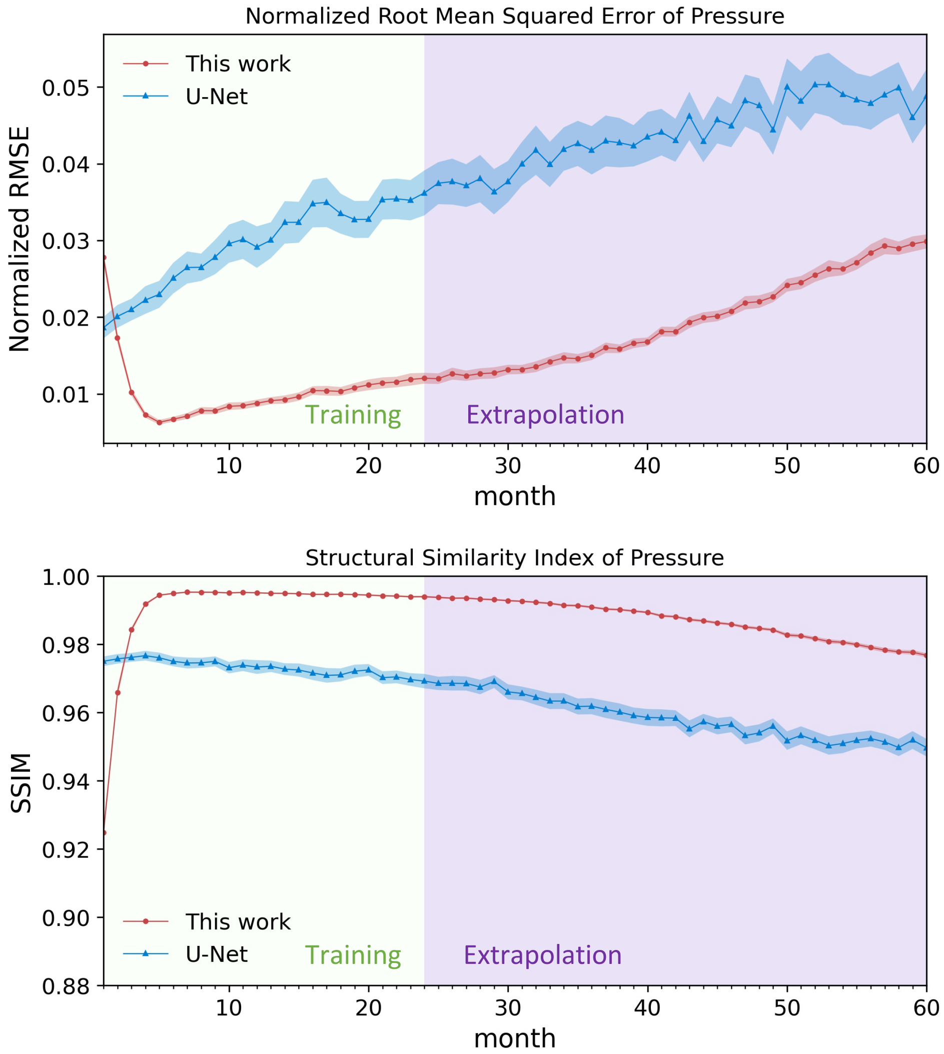




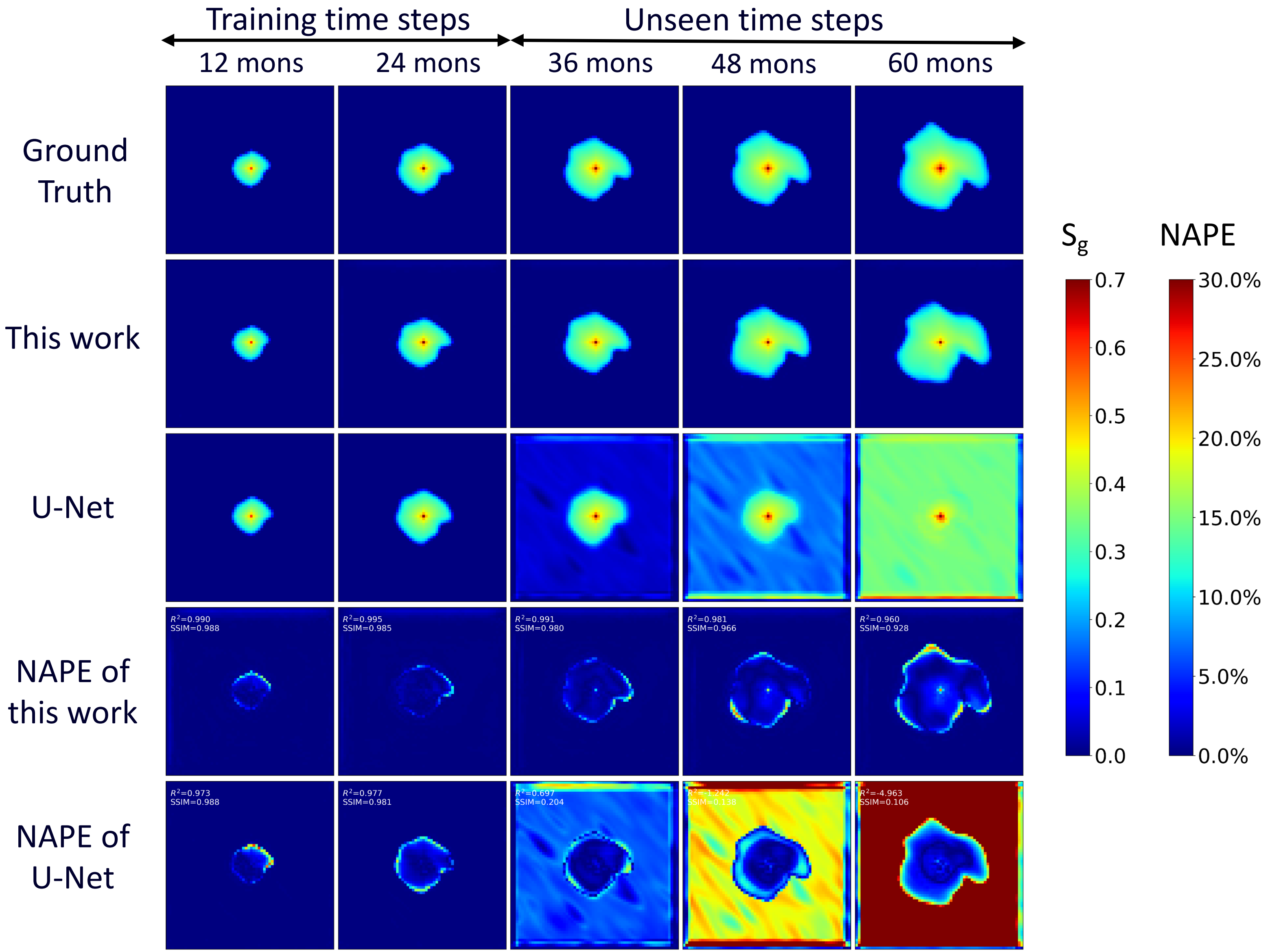
The proposed neural network performs better than U-Net in training time steps (with R^2 larger than **0.99**)

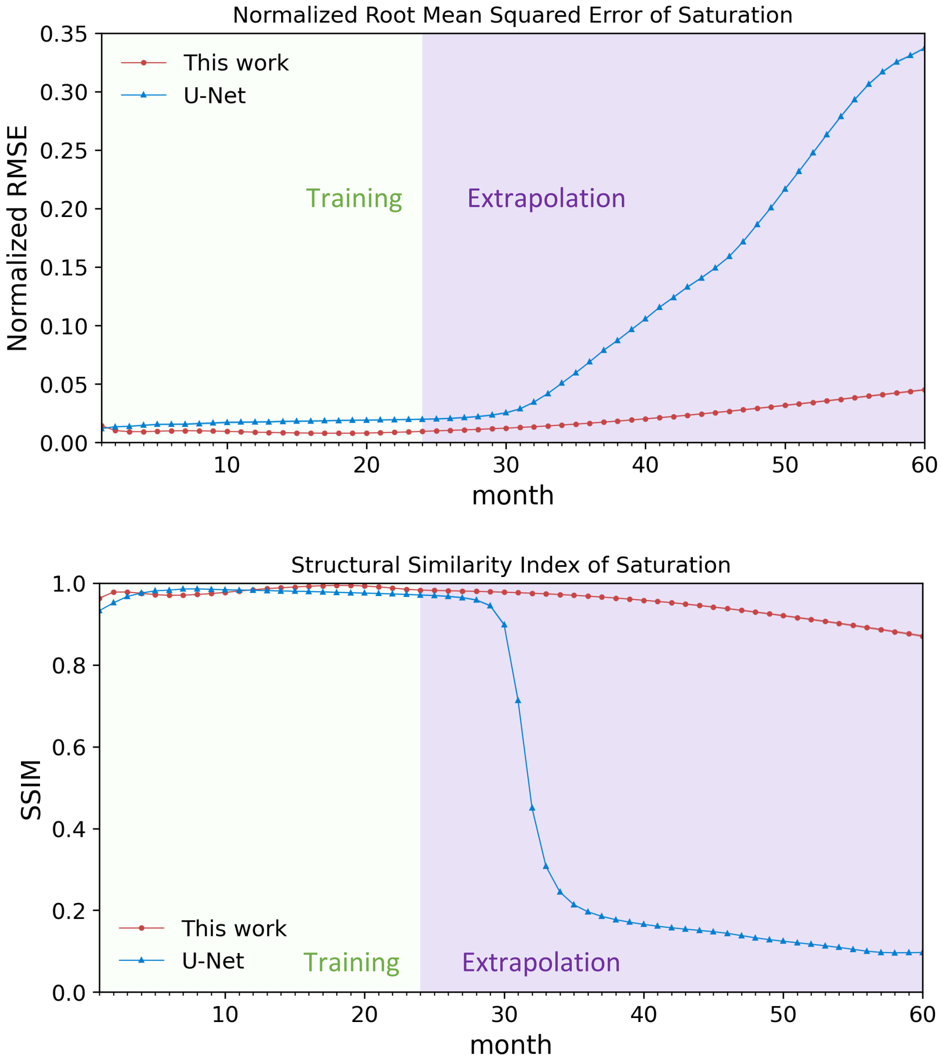
Results: extrapolate to unseen time steps (pressure)





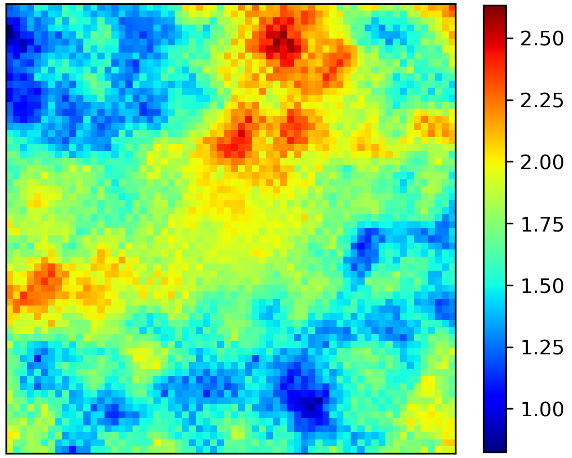
Results: extrapolate to unseen time steps (saturation)

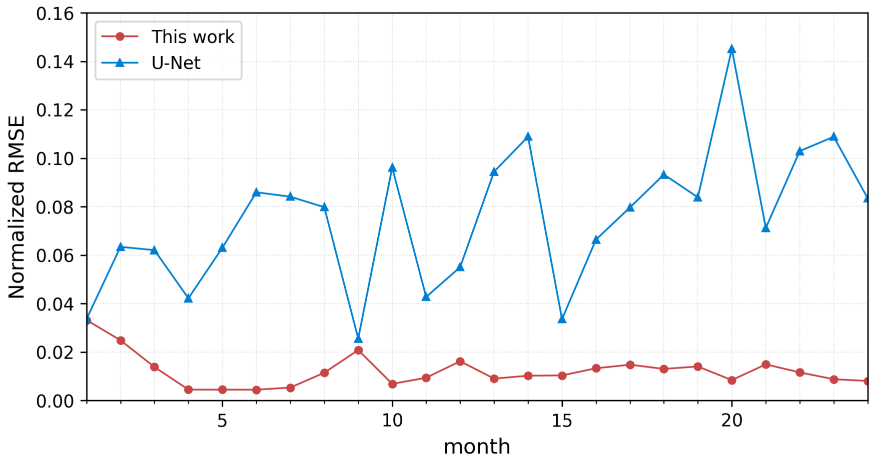


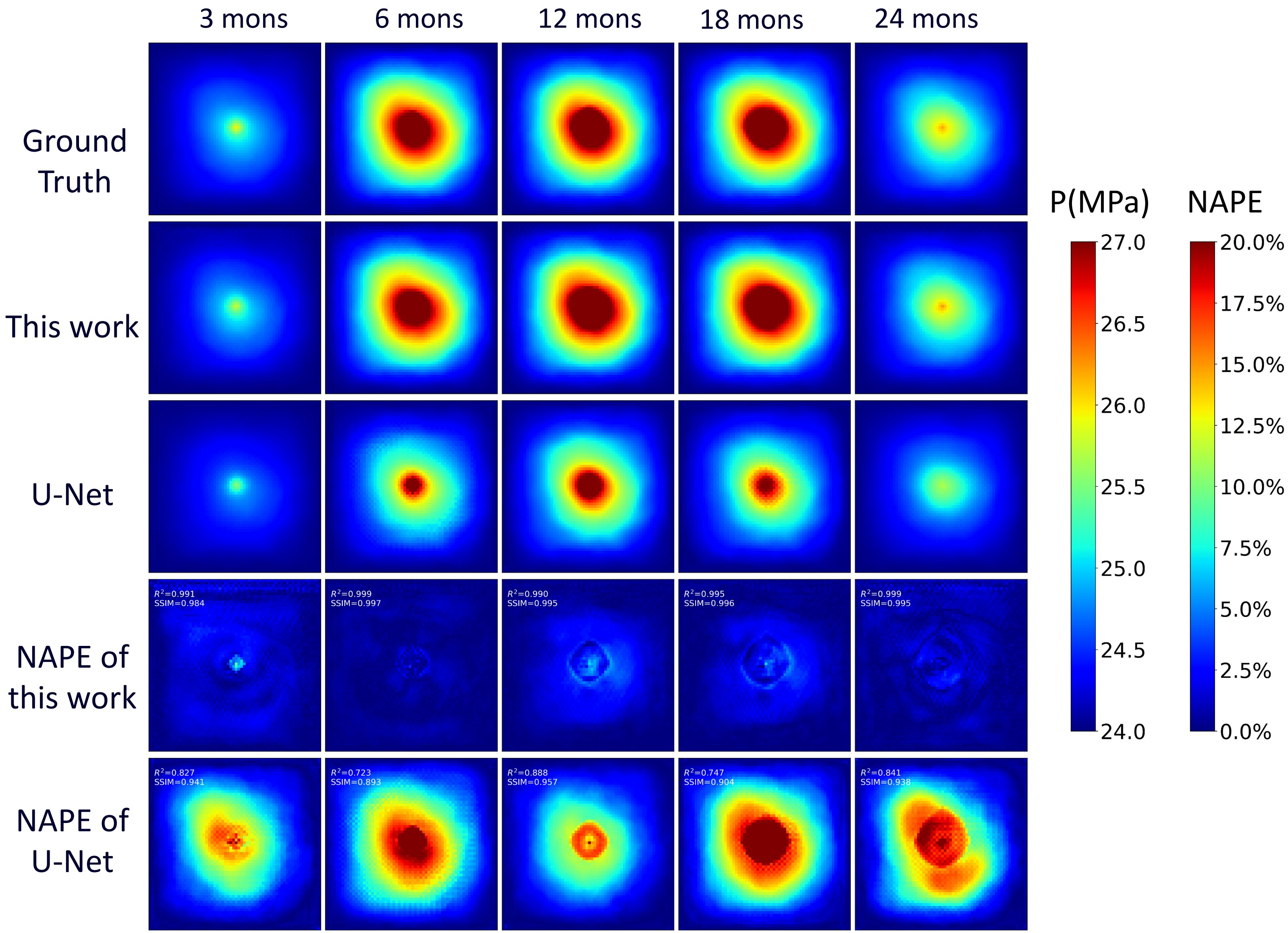


Results: generalize to unseen geological settings (pressure)

Exponential Random Fields







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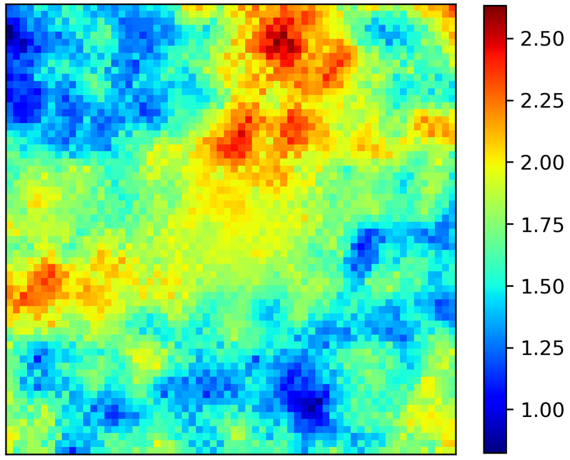
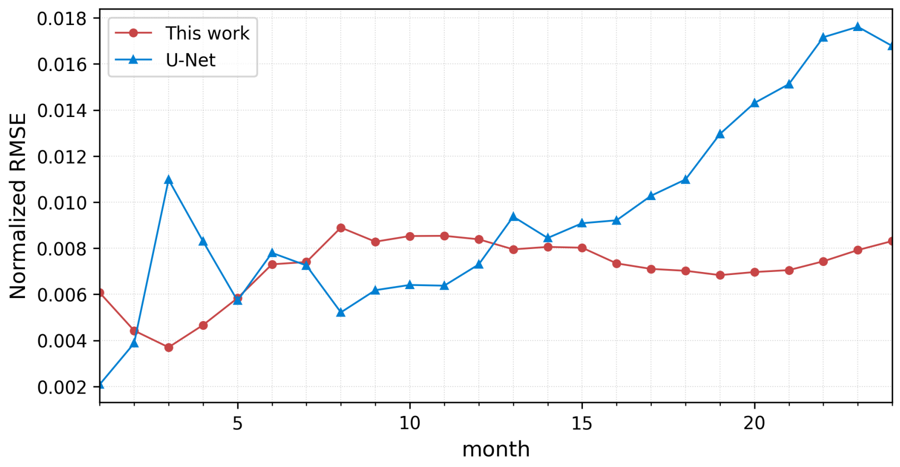
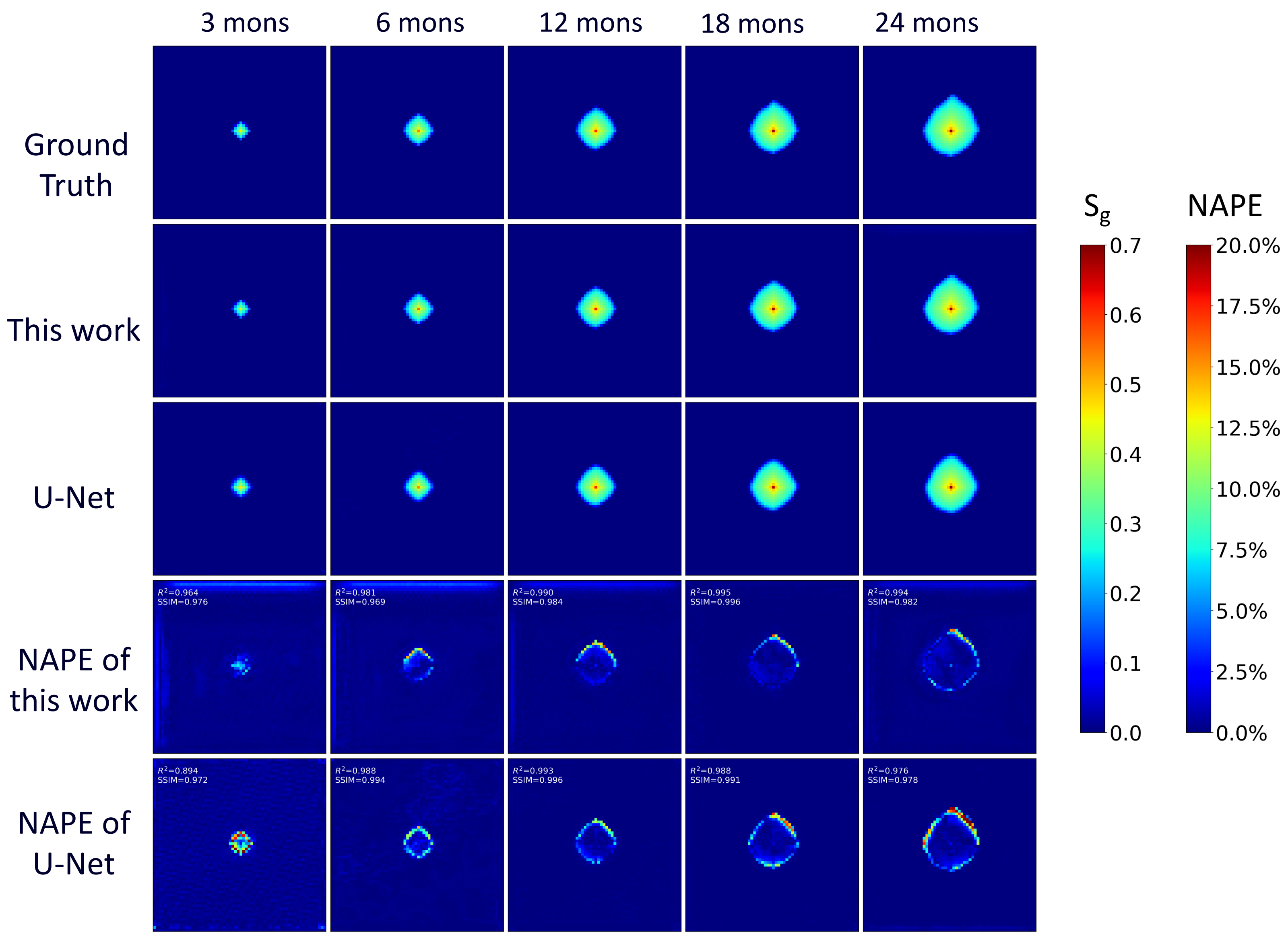
Exponential Random Fields







Results: generalize to unseen geological settings (pressure)

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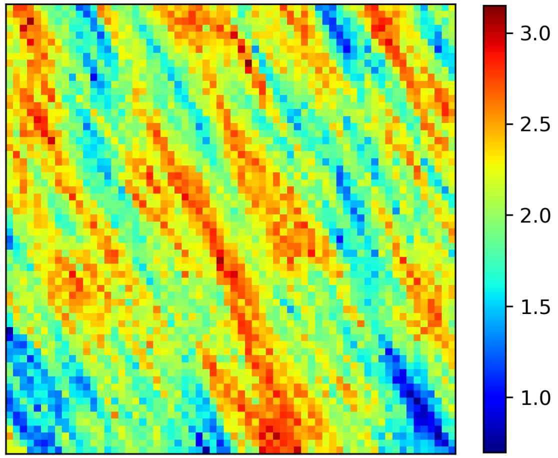
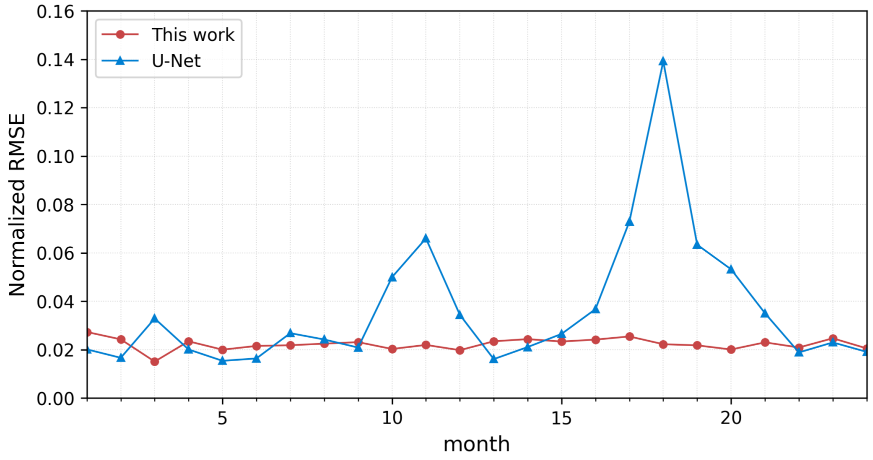
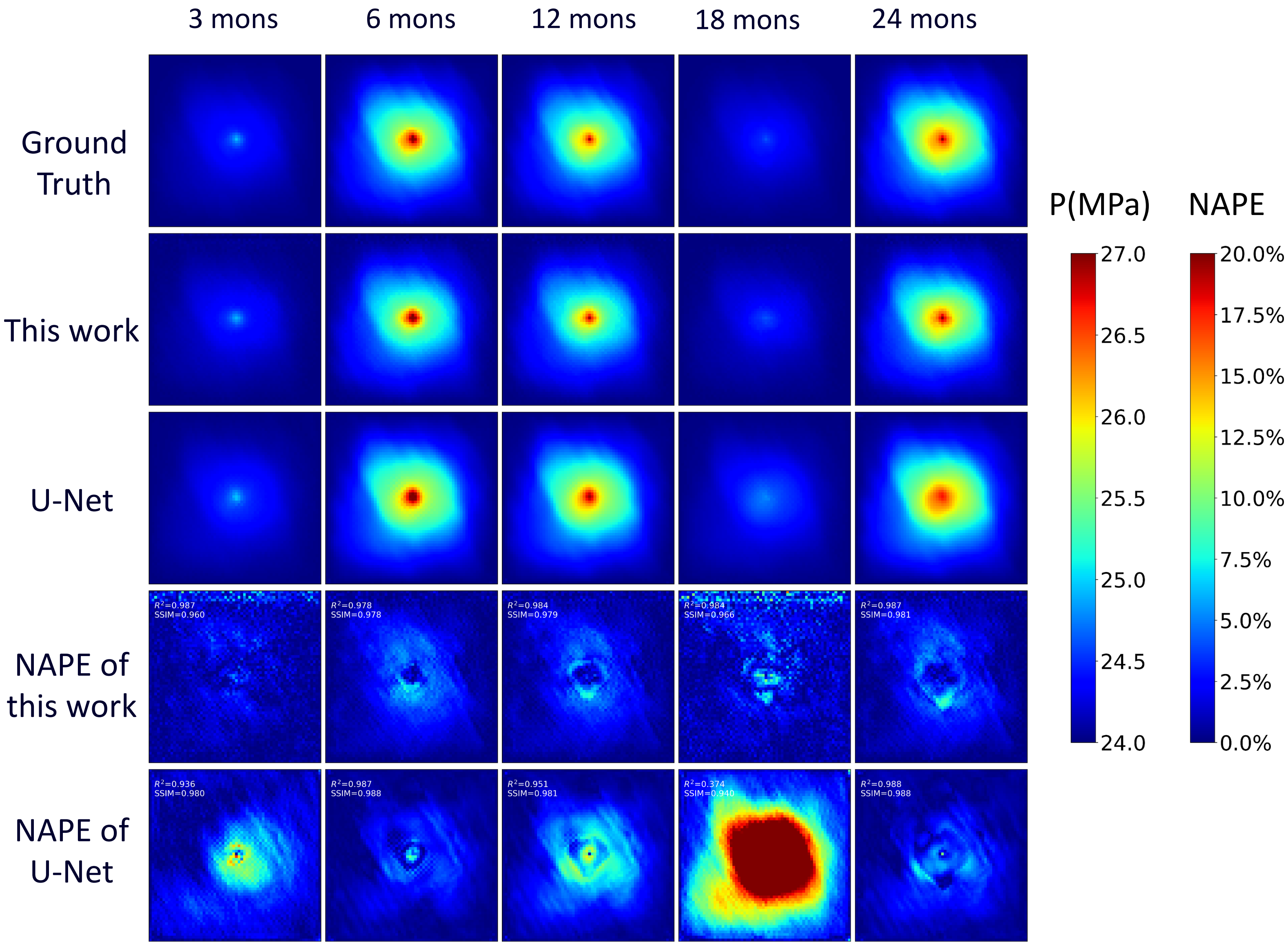
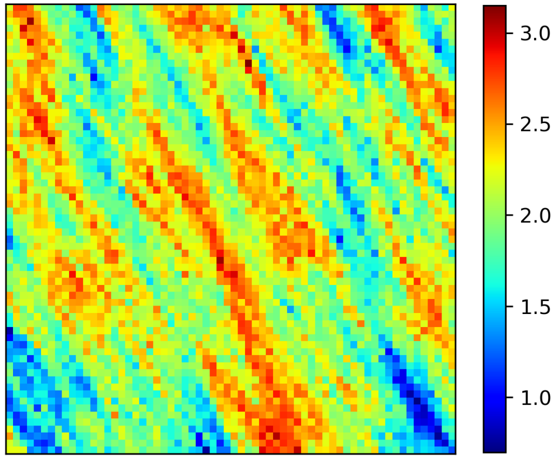
Exponential Random Fields (with anisotropy)

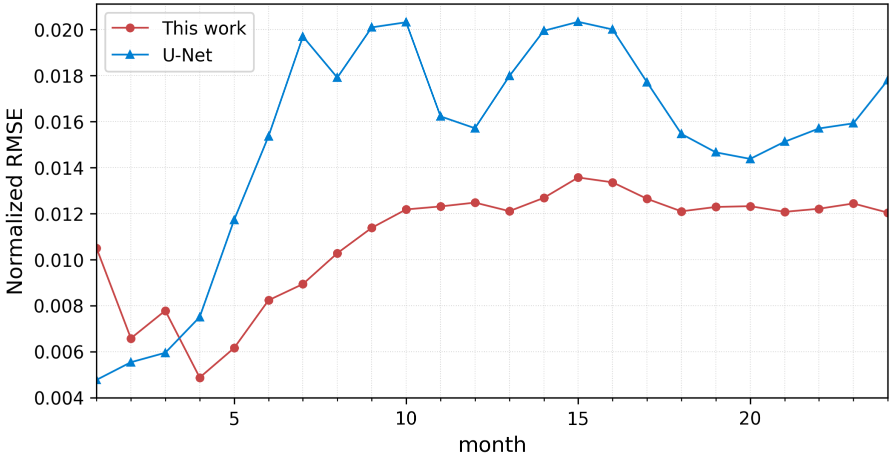


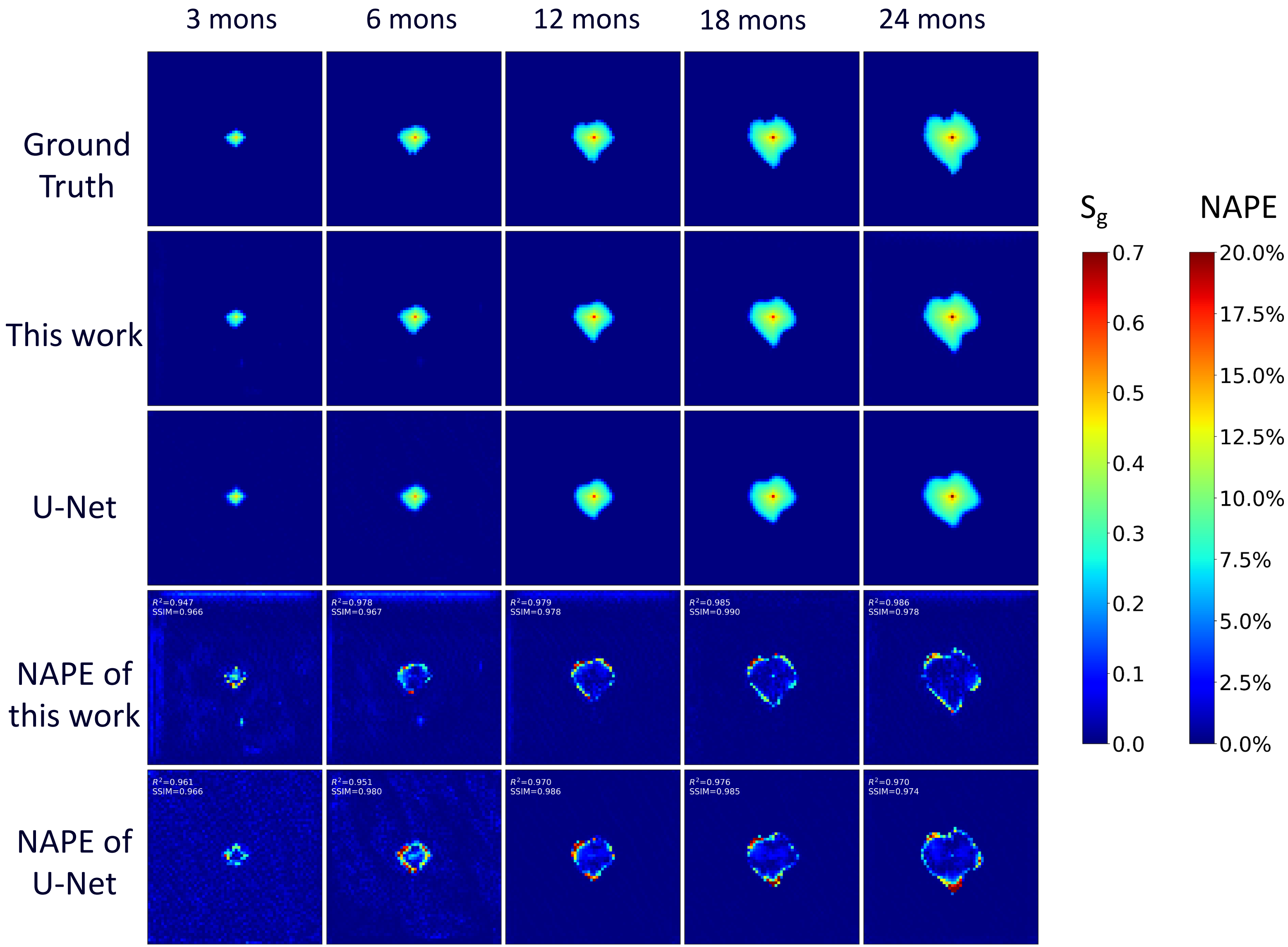




Exponential Random Fields (with anisotropy)







Conclusions & Remarks

Conclusions:

1. A data-driven surrogate model for GCS with dynamic well controls is proposed based on an encoder-decoder convolutional-LSTM architecture. It is able to make more decent predictions compared with U-Net.
2. Thanks to the convolutional-LSTM backbone, the model is capable of extrapolating to unseen time steps.
3. The powerful feature extraction blocks enables the model to generalize well to unseen geological settings.

Remarks:

1. Pre-training, refining time steps and proper initialization might help alleviate the relative large errors at initial stages.
2. Realistic 3D reservoirs with multiple wells is the focus of the following research.

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Thank you !

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