Inference of CO_2 flow patterns – a feasibility study

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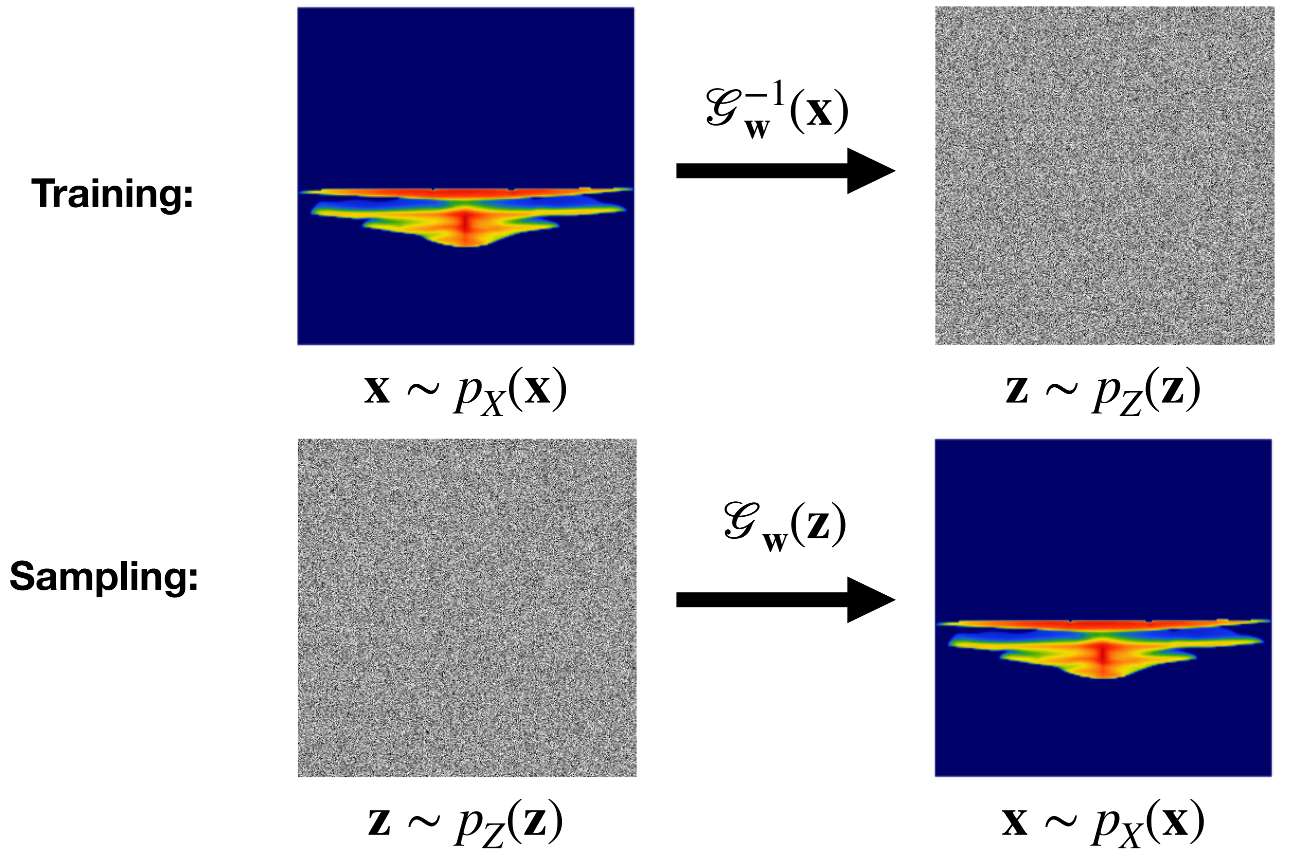
Motivation

CO_2 plume *forecasts* with fluid-flow *simulations* alone are *uncertain*
- can ***not*** expect *precise* predictions of regular & irregular flow
- need to *condition* CO_2 plumes on observed *monitoring* data
- combine *monitoring* data w/ *multiphase flow* models

Calls for *principled* approach using ML & data assimilation to
- incorporate time-lapse well & seismic data *jointly*
- assess *uncertainty* in CO_2 plumes to *inform* policy decisions

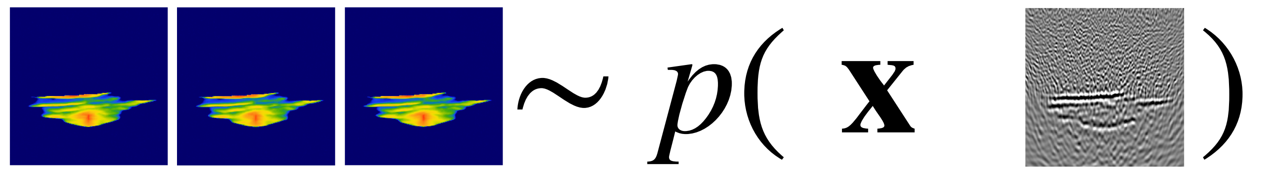
Conditional Normalizing Flows (CNF)



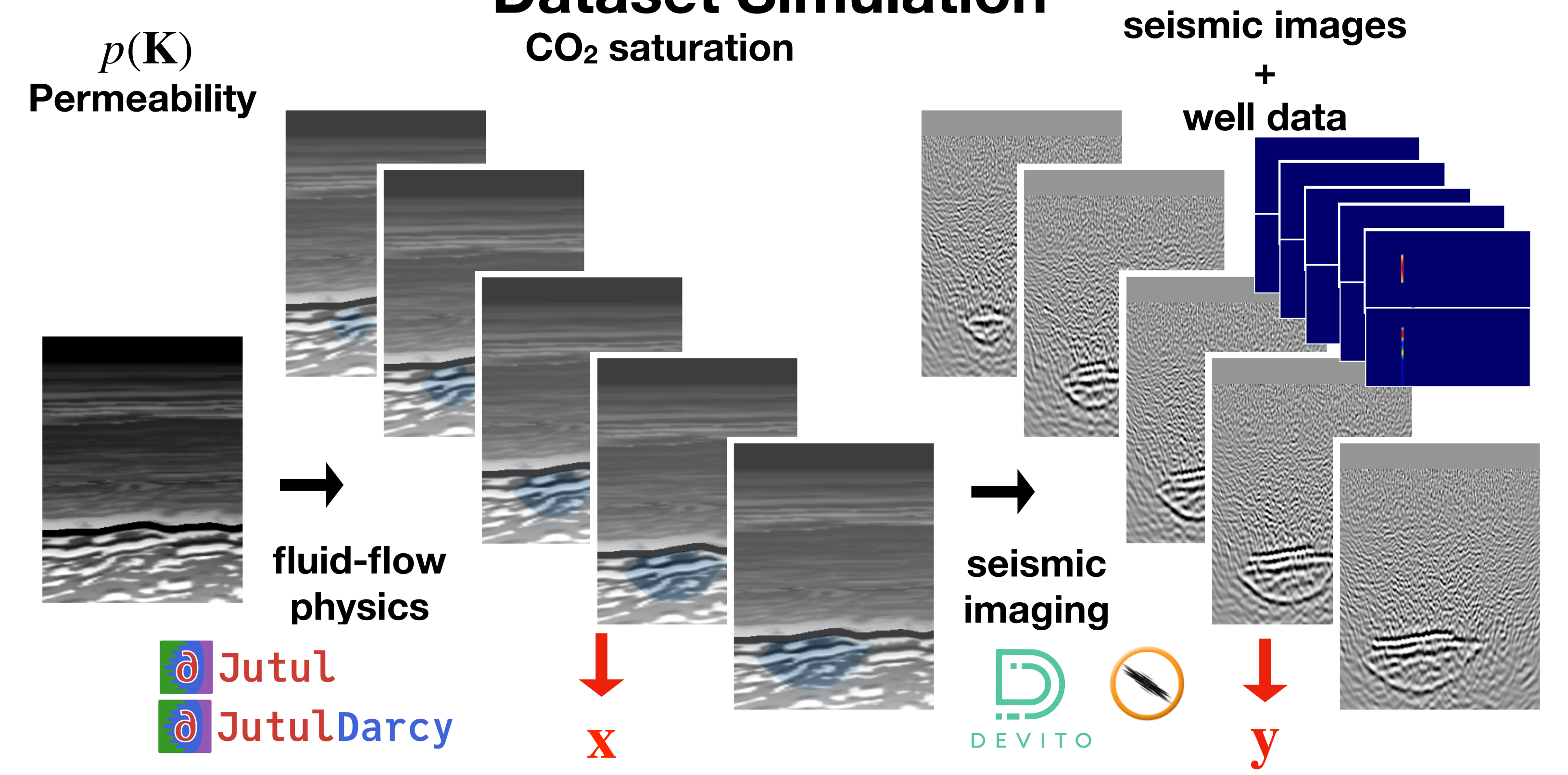
Train CNF on N training pairs $\{\mathbf{x}^{(n)}, \mathbf{y}^{(n)}\}_{n=1}^{N}$ with

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{N}\sum_{n=1}^{N}\left(\|f_{\theta}(\mathbf{x}^{(n)};\mathbf{y}^{(n)})\|_2^2 - \log\left|\det \mathbf{J}_{f_\theta}\right|\right)$$

Trained *invertible* network $p_{\hat{\theta}}(\mathbf{x}\ \ \mathbf{y}) \approx p(\mathbf{x}\ \ \mathbf{y})$ and turn, conditioned on any $\mathbf{y}$,
- samples of $\mathbf{x}$ into noise – i.e., $f_{\hat{\theta}}(\mathbf{x};\mathbf{y}) \sim N(0,I)$
- noise samples $\mathbf{z} \sim N(0,I)$ into samples $\mathbf{x} \sim p_{\hat{\theta}}(\mathbf{x}\ \ \mathbf{y}^{\mathrm{obs}})$ where $\mathbf{x} = f_{\hat{\theta}}^{-1}(\mathbf{z};\mathbf{y}^{\mathrm{obs}})$

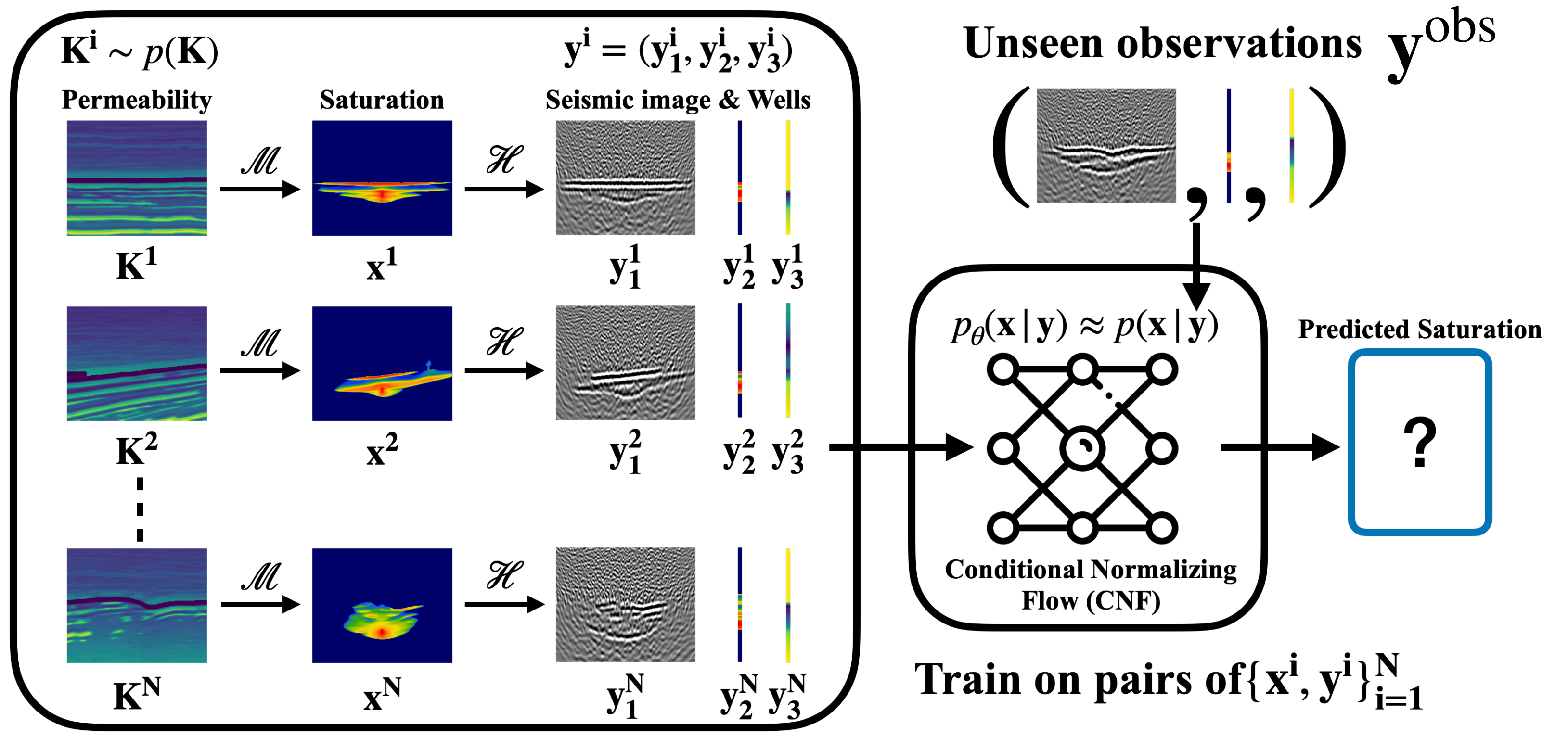


Dataset Simulation



CO_2 plume simulations:
- draw permeability realization $\mathbf{K} \sim p(\mathbf{K})$
- inject 1.2 MT CO_2 annually
- simulations output every 80 days

Monitoring:
- saturation & pressure data collected at injection & production wells
- time-lapse seismic images from 200 receivers (20m) & 8 sources (500m)

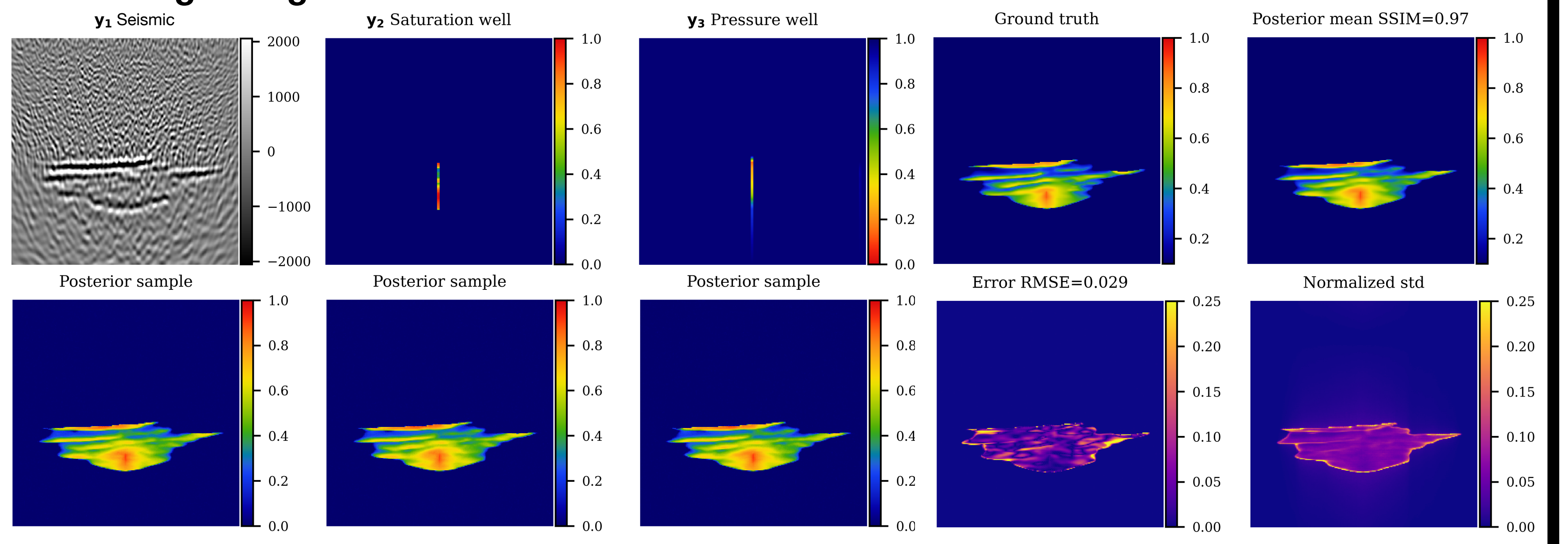


$\mathcal{M}$ – dynamics operator $\mathcal{H}$ – observation operator K– permeability model $\mathbf{y}^{\mathrm{obs}}$ – time-lapse observations

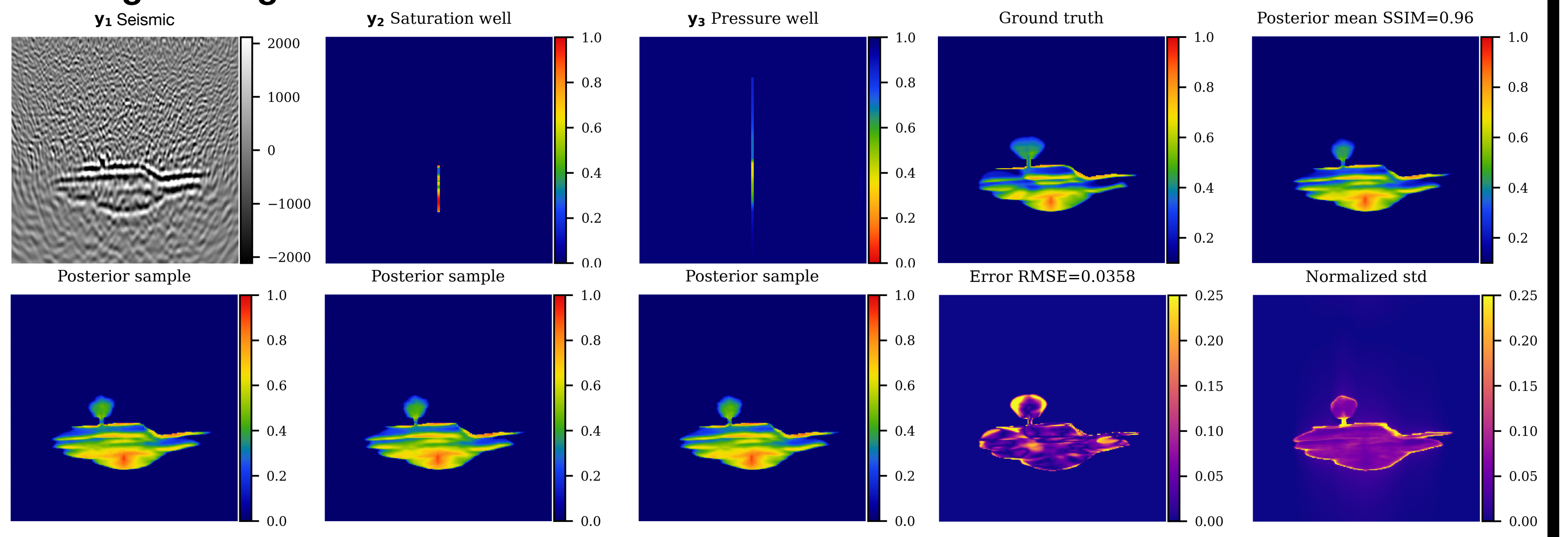
Training & inference:
- CNF is trained on simulated pairs CO_2 saturation $\mathbf{x}$ & time-lapse data $\mathbf{y}$
- $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_3, \mathbf{y}_3)$ w/ seismic surface & saturation/pressure data at well
- At inference, CNF generates CO_2 plume predictions $\mathbf{x} \sim p(\,\cdot\,;\mathbf{y}^{\mathrm{obs}})$

Results

No-leakage – regular flow



Leakage – irregular flow



Observations:
- conditional mean remains close to ground truth – high SSIM & low RMSE
- uncertainty (normalized std) is higher in geologically complex areas
  – top of the plume – fracture zone where CO_2 leaks
- uncertainty correlates well w/ errors compared to ground truth

Conclusions

Inference framework:
- robust w.r.t to noise & uncertainties in permeability
- capable of predicting leakage w/ observed time-lapse data

Future work:
- perform sequential Bayesian inference
- assimilate time-lapse observations & monitor for early leakage

References

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