Seismic monitoring of CO_2 using ensemble Kalman filtering

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Summary

1. We simulate subsurface CO_2 injection into porous rock with seismic measurements,
2. treat the permeability field as a random variable,
3. apply the EnKF to estimate the CO_2 saturation field,
4. compare the EnKF to two baselines, and
5. test the EnKF's performance with different noise parameters.

I. Motivation

A. CO_2 injection

- Carbon-negative strategies are required to mitigate climate change.
- Injecting CO_2 (carbon dioxide) underground is a well-developed technology for the oil industry.
- CO_2 can be injected underground for long-term storage.
- CO_2 storage must be monitored to mitigate risks (e.g., leakage, over-pressure)

B. Monitoring method

- Seismic measurements are non-intrusive and more informative than wells.
- Seismic measurements are noisy and nonlinear.
- Known fluid dynamics can provide additional information.
- Using both sources of information requires data assimilation techniques.

The EnKF is a scalable, mature technique with success on large, nonlinear systems.

II. Background

- Hidden state: $\mathbf{x}$
  - CO_2 saturation field $\mathbf{S}$
  - Pressure field $\mathbf{P}$
  - Permeability $\mathbf{K}$
- Observation: $\mathbf{y}$
  - Seismic data
- Time t indexed by n
- Fluid dynamics: $\mathbf{x}^n = f(\mathbf{x}^{n-1})$
- Seismic imaging: $\mathbf{y}^n = h(\mathbf{x}^n, \nu\boldsymbol{\eta})$, comprised of:
  - noise $\nu\boldsymbol{\eta}$ with signal-to-noise ratio $-20\log\nu$ dB
  - Rock physics model: maps $\mathbf{S}$ to seismic velocity $\mathbf{m}$ and density $\boldsymbol{\rho}$.
  - Seismic model: simulates seismic measurements of $\mathbf{m}$ and $\boldsymbol{\rho}$

Both the observation and transition operators require numerically solving nonlinear PDEs.

A. Data assimilation

- Starting with a priori knowledge $p(\mathbf{x}^0) \equiv p(\mathbf{x}^0 \mid \mathbf{y}^{1:0})$:
- For each new observation $\mathbf{y}^n$:
  - We have a previous posterior: $p(\mathbf{x}^{n-1} \mid \mathbf{y}^{1:n-1})$.
  - Predict: $p(\mathbf{x}^n \mid \mathbf{y}^{1:n-1}) = \int p(\mathbf{x}^n \mid \mathbf{x}^{n-1}) p(\mathbf{x}^{n-1} \mid \mathbf{y}^{1:n-1})\, d\mathbf{x}^{n-1}$
  - Update: $p(\mathbf{x}^n \mid \mathbf{y}^{1:n}) \propto p(\mathbf{y}^n \mid \mathbf{x}^n) p(\mathbf{x}^n \mid \mathbf{y}^{1:n-1})$

Figure 1: Classical data assimilation predict-update loop

- Kalman filter: classical method that assumes linear operators and Gaussian distributions.

$$\boldsymbol{\mu}_a = \boldsymbol{\mu}_f + K(\mathbf{y}^* - h(\boldsymbol{\mu}_f, \mathbf{0})) \qquad K = \operatorname{cov}(\mathbf{x}_f, \mathbf{y}_f)\operatorname{cov}(\mathbf{y}_f)^{-1}$$
$$B_a = (I - KH)B_f$$

- **EnKF**: Monte-Carlo method that represents distributions as samples
  - Transitions each sample individually
  - Observes each sample individually
  - Updates samples based on the measured $\mathbf{y}$ and the sample covariance

$$\mathbf{y}^* = h(\mathbf{x}^*, \underline{\nu^*}\boldsymbol{\eta}^*) \qquad K = \widehat{\operatorname{cov}}(\mathbf{x}_f, \mathbf{y}_f)\left(\widehat{\operatorname{cov}}(h(\mathbf{x}_f, \underline{\alpha\nu}\boldsymbol{\eta})) + R\right)^{-1}$$
$$\mathbf{y}_{f,i} = h(\mathbf{x}_{f,i}, \underline{\nu}\boldsymbol{\eta}_i) \qquad R = \underline{\nu^2\beta^2} I$$
$$\mathbf{x}_{a,i} = \mathbf{x}_{f,i} + K(\mathbf{y}^* - \mathbf{y}_{f,i})$$

- ν^*: true noise scale
- ν: estimated noise scale
- β: regularization scale
- α: 0 or 1 to choose whether noise is used in $\operatorname{cov}(\mathbf{y}_f)$

III. Experiments

We apply EnKF to a seismic monitoring example using scalable, open-source tools (JutulDarcy.jl, JUDI.jl).

Simplifying assumptions:

1. All information is known a priori except for $\mathbf{K}$.
2. We can generate 256 samples of possible $\mathbf{K}$.

We compare EnKF to two baselines for estimating $\mathbf{S}$:

- **JustObs**: solely uses $\mathbf{y}$ and observation function
- **NoObs**: solely uses samples of $\mathbf{K}$ and transition function

We also test EnKF performance for modified α, β, ν, and ν^*.

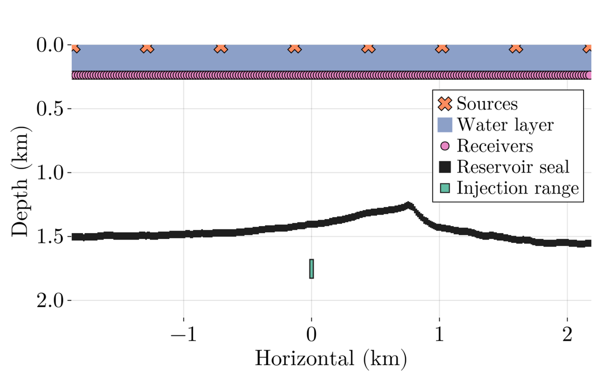


Figure 2: Experimental setup

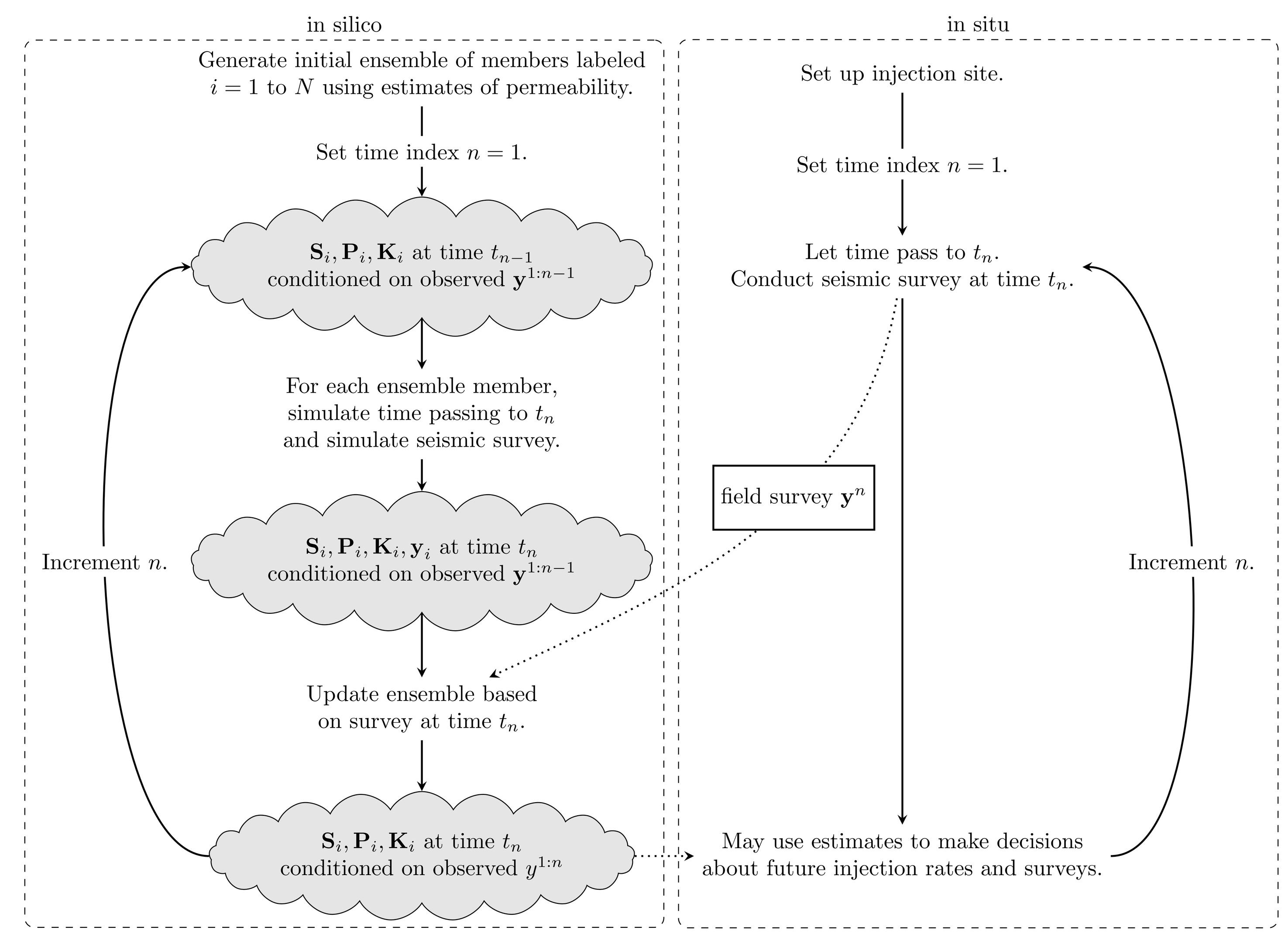
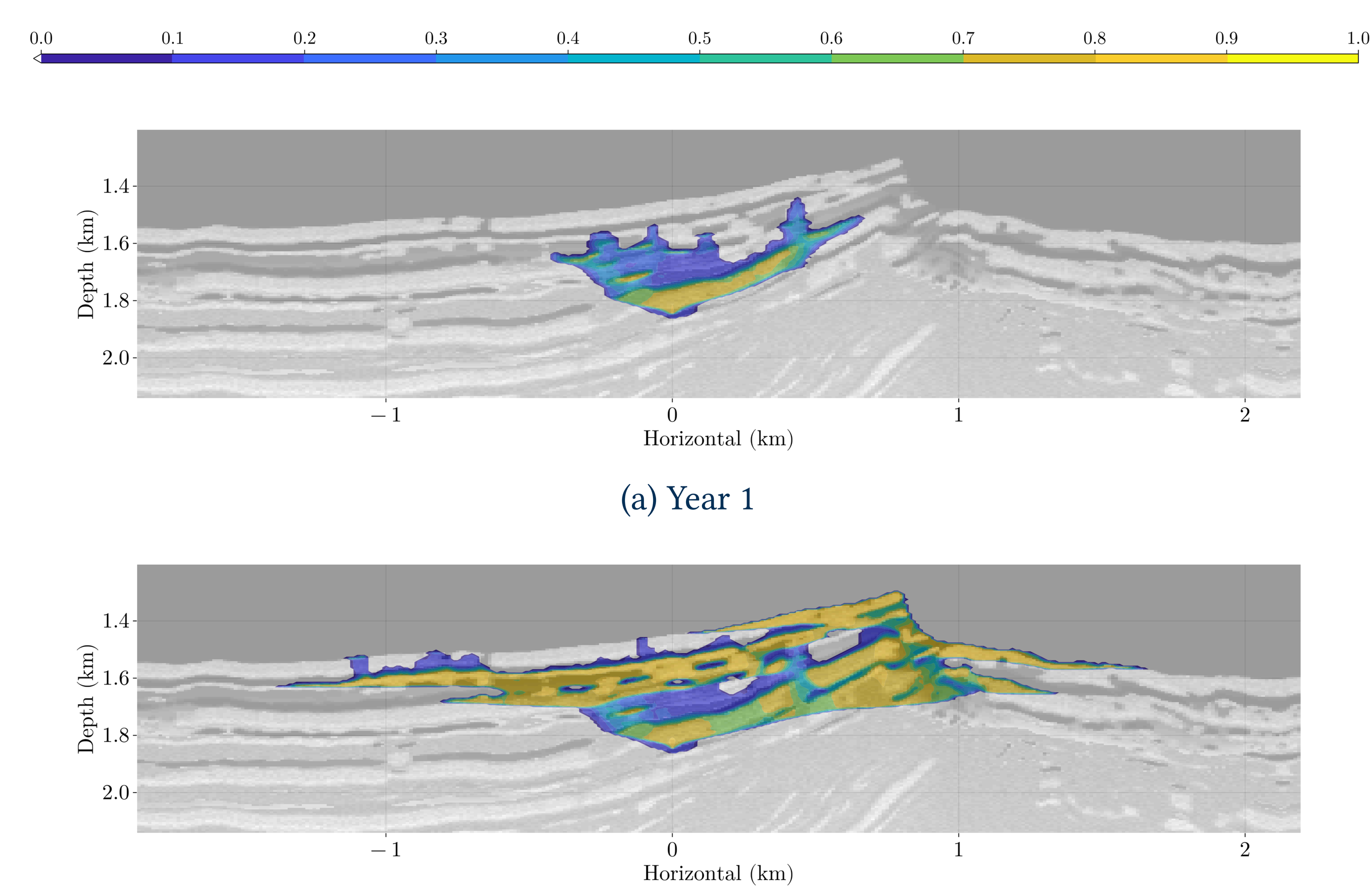


Figure 3: Workflow diagram

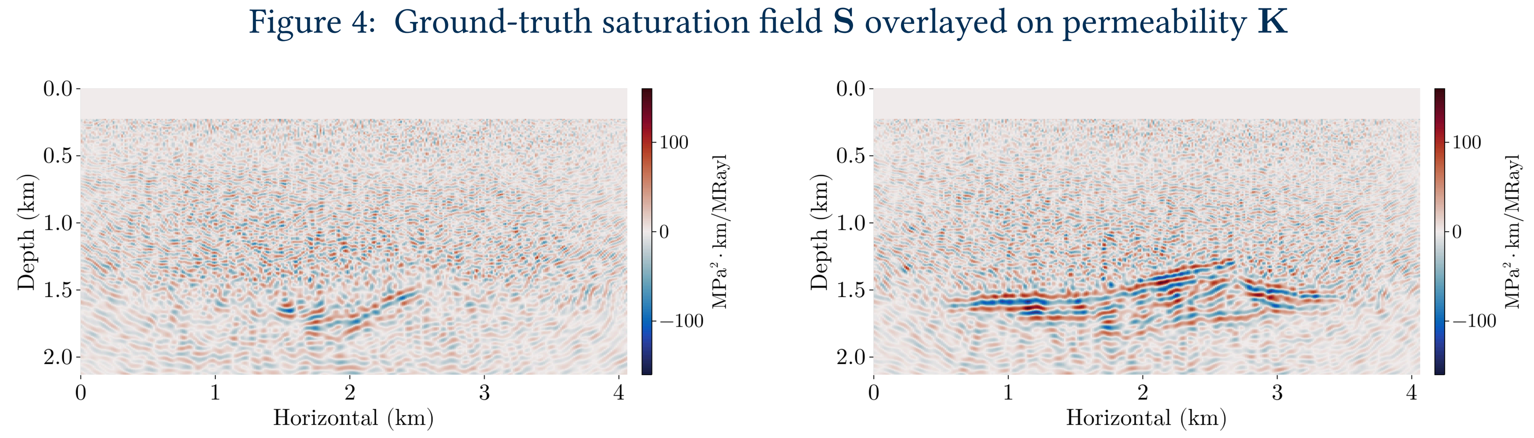
IV. Results



(a) Year 1

(b) Year 5

Figure 4: Ground-truth saturation field $\mathbf{S}$ overlayed on permeability $\mathbf{K}$



(a) Year 1

(b) Year 5

Figure 5: Ground-truth seismic measurements

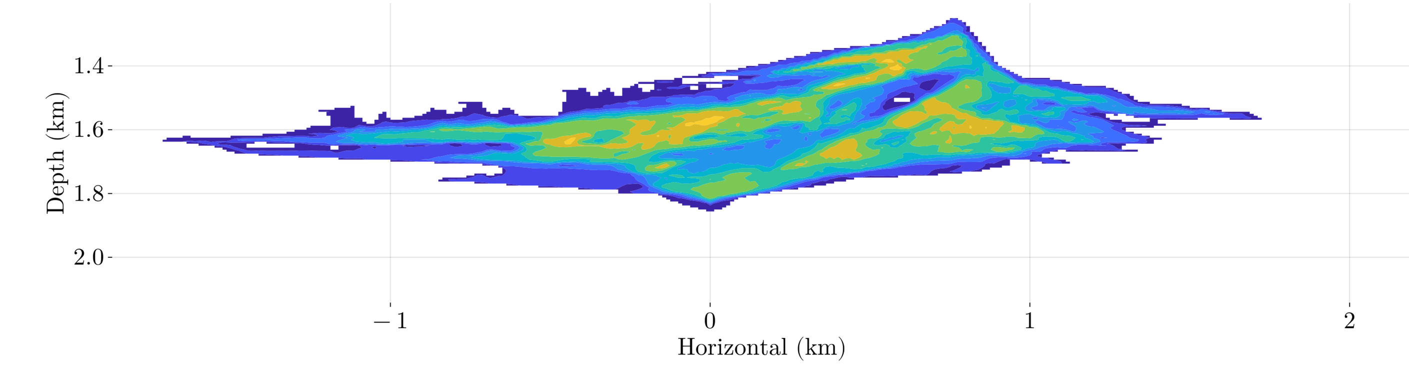


Figure 6: NoObs prediction at year 5

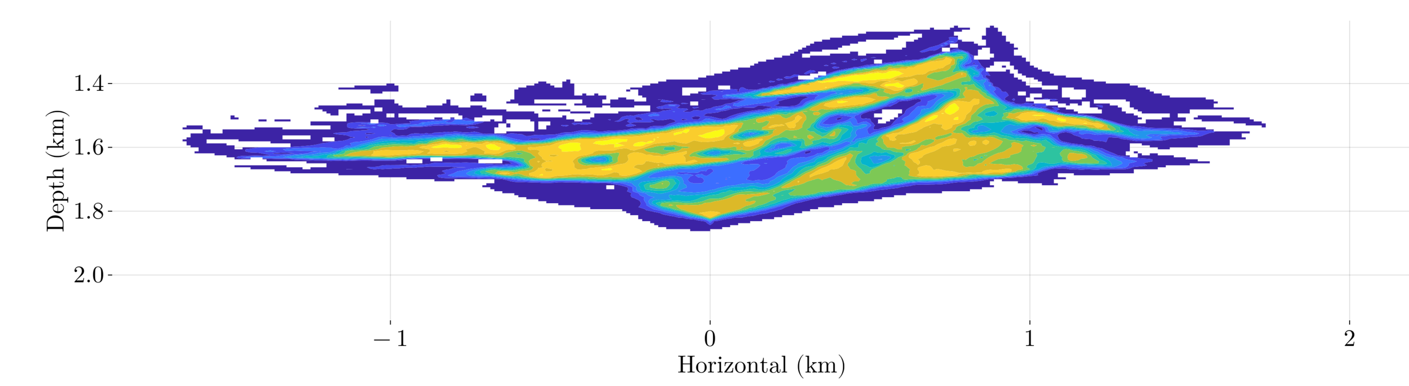


Figure 7: EnKF analysis at year 5

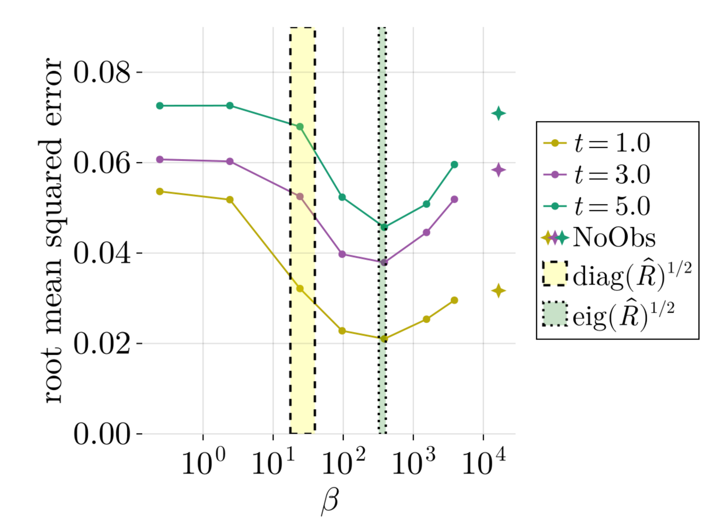


Figure 8: Change β when $\alpha = 0$

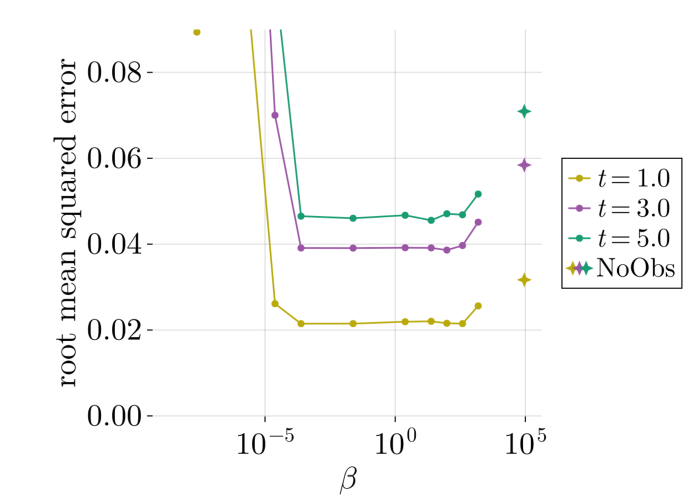


Figure 9: Change β when $\alpha = 1$

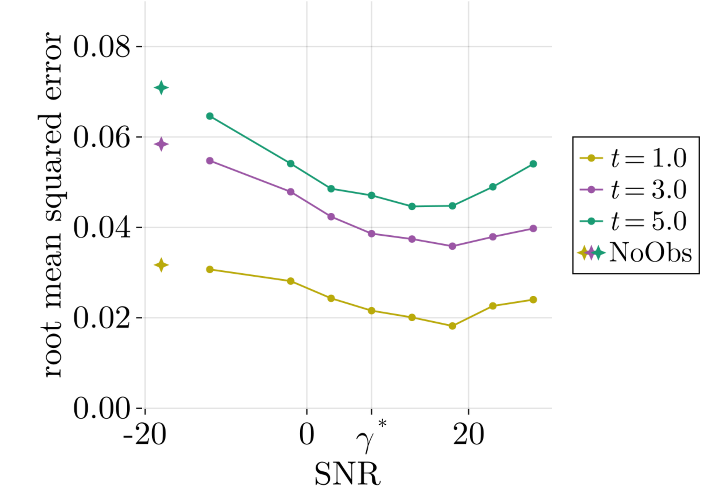


Figure 10: Change ν

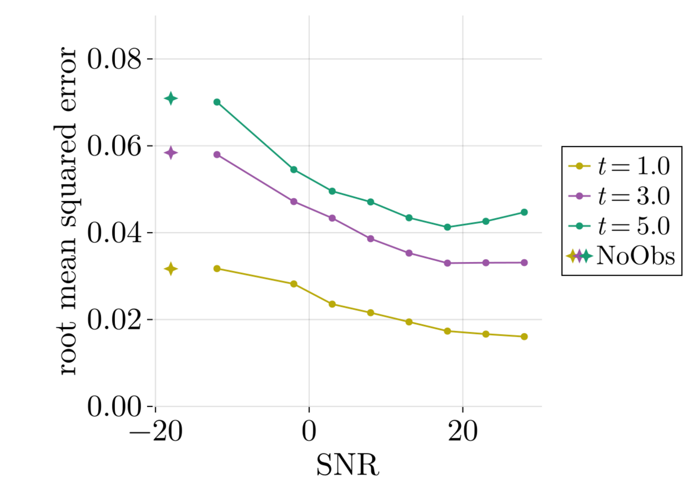


Figure 11: Change ν^*, keeping $\nu = \nu^*$

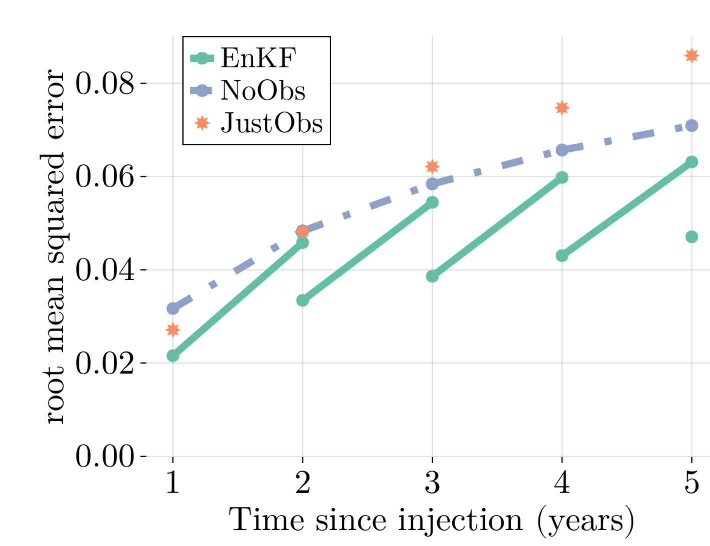


Figure 12: RMSE for 3 methods over time

V. Conclusions

- EnKF error < JustObs error and NoObs error.
- For $\alpha = 0$,
  - sensitive to noise parameters
  - best results using noise eigenvalues
- For $\alpha = 1$,
  - insensitive over large range
  - similar error to lowest $\alpha = 0$ error

EnKF is a promising data assimilation method for monitoring subsurface CO_2 with seismic measurements.

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