Gaussian Ensemble Belief Propagation

Efficient Inference in High-Dimensional Systems

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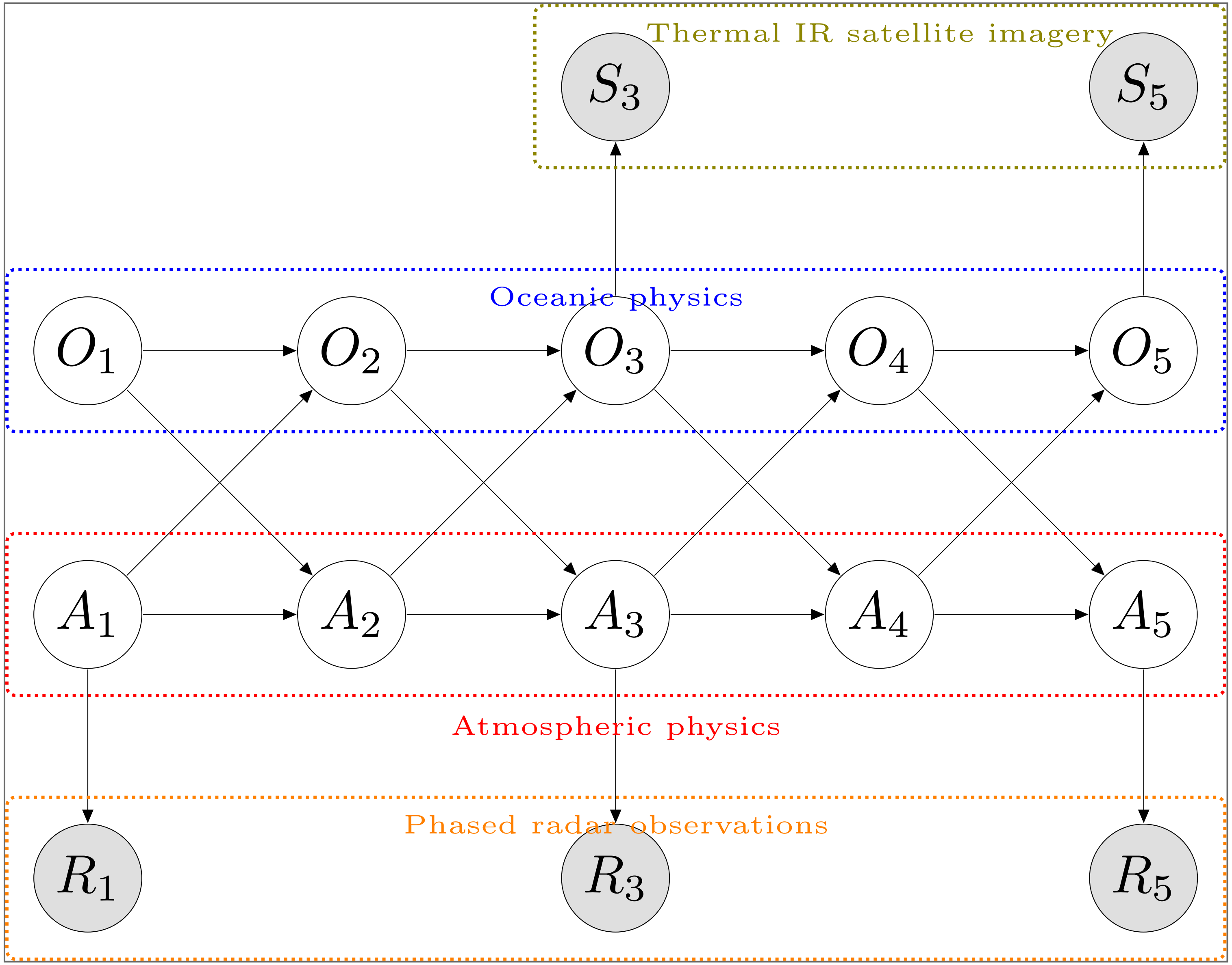
Introduction

The Challenge: High-Dimensional Inference

- Infer hidden variables in complex physical systems
- Examples: climate, weather, fluid dynamics
- Key difficulties:
  - High-dimensional
  - Noisy observations
  - Complex physics models
  - Hierarchical dependencies

A Real-World Example


Thermal IR satellite imagery
S_3
S_5
Oceanic physics
O_1
O_2
O_3
O_4
O_5
A_1
A_2
A_3
A_4
A_5
Atmospheric physics
Phased radar observations
R_1
R_3
R_5

The Challenge of Scale

- **Planetary-scale systems**
- Weather & climate
- Power grids
- Agriculture
- Flood prediction
- **Computational barriers**
- Expensive simulators
- Sparse observations
- Hidden variables

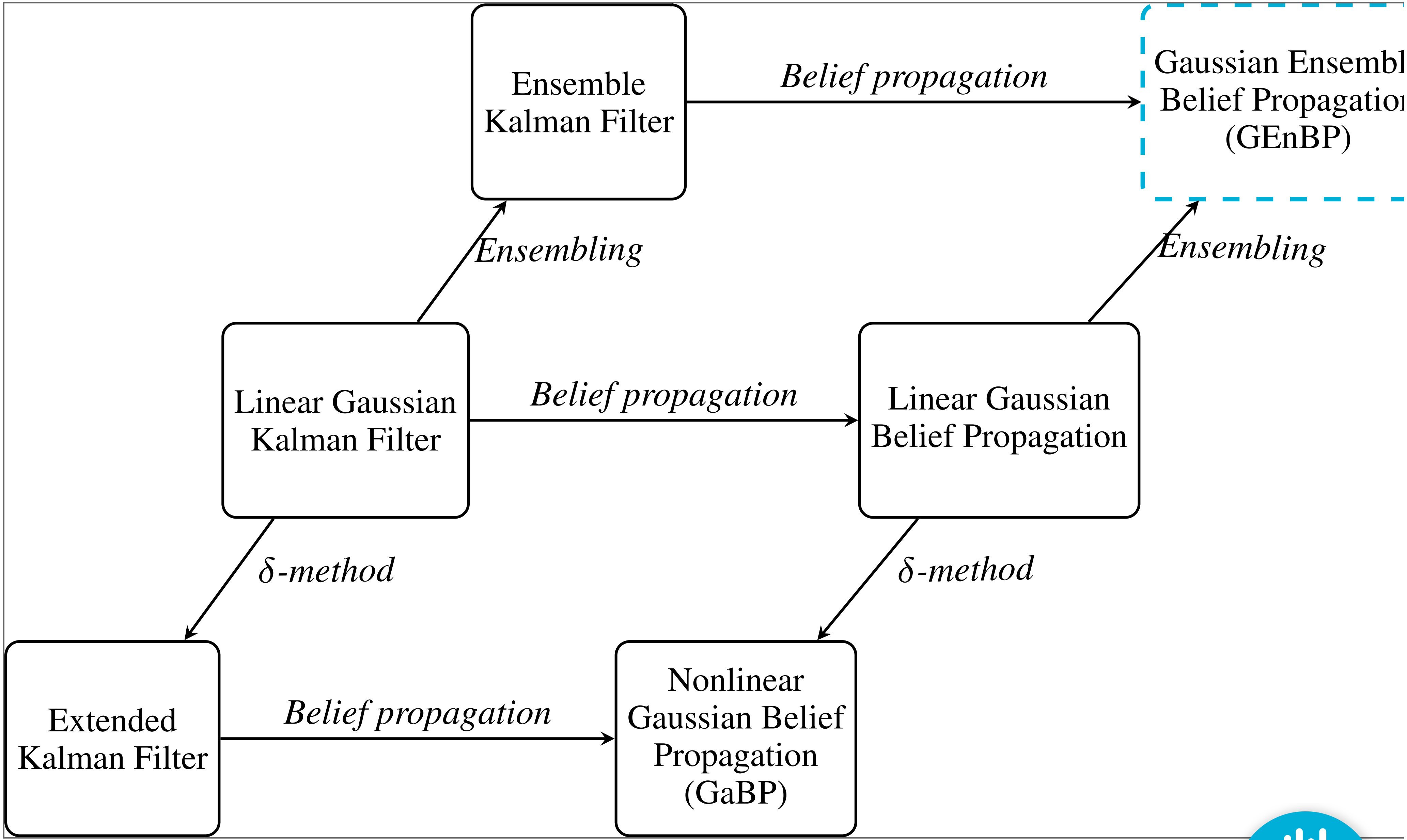
Our Solution: GEnBP

Gaussian Ensemble Belief Propagation:
Belief-propagation + Ensemble Kalman filtering

Gaussian Ensemble Belief Propagation

- **Key innovation:** Combines Ensemble Kalman Filter with Gaussian Belief Propagation
- **Core principles:**
- Use existing simulators with random noise inputs
- Update guesses with local information
- Iteratively improve estimates
- Maintain ensemble of estimates to quantify uncertainty

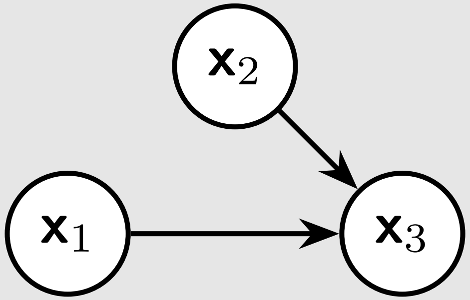
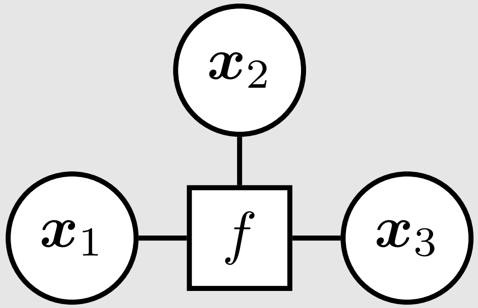
Relation to existing methods



Ensemble Kalman Filter
Belief propagation
Gaussian Ensembl
Belief Propagatio
(GEnBP)
Ensembling
Ensembling
Linear Gaussian Kalman Filter
Belief propagation
Linear Gaussian Belief Propagation
δ-method
δ-method
Extended Kalman Filter
Belief propagation
Nonlinear Gaussian Belief Propagation (GaBP)

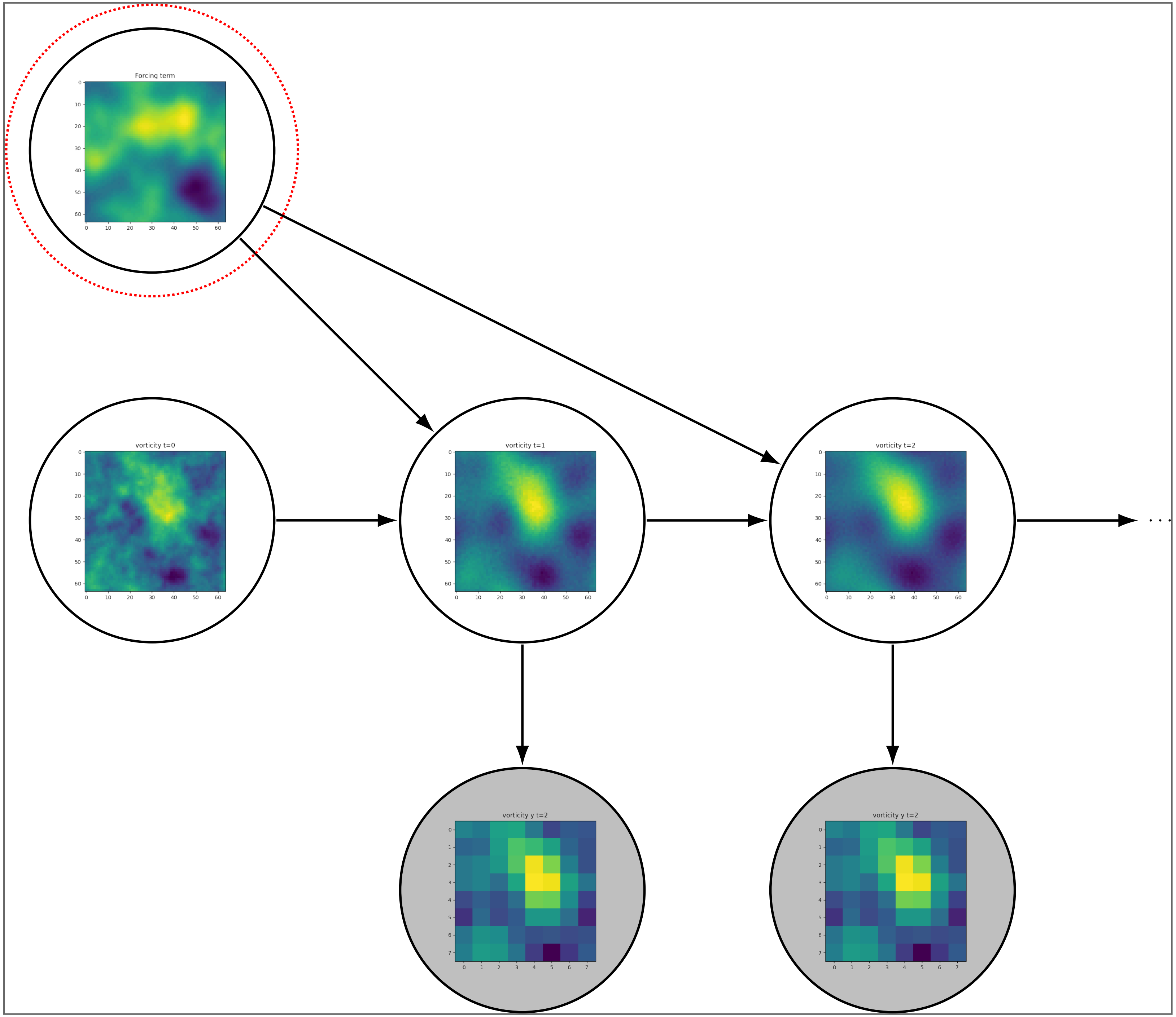
The process

Empirical statistics →

	Generative	**Density-based**
Operations	• Sample • Condition	• Propagate
Graph type	Directed 	Factor 
Decomposition	$\mathbf{x}_3 = \mathcal{P}(\mathbf{x}_1, \mathbf{x}_2)$	$f(x_1, x_2, x_3)$
Node Parameters	Empirical moments $\boldsymbol{m}$, K	Canonical parameters $\boldsymbol{n}$, P

← Ensemble recovery

Test Case: System Identification


Forcing term
vorticity t=0
vorticity t=1
vorticity t=2
vorticity y t=2
vorticity y t=2

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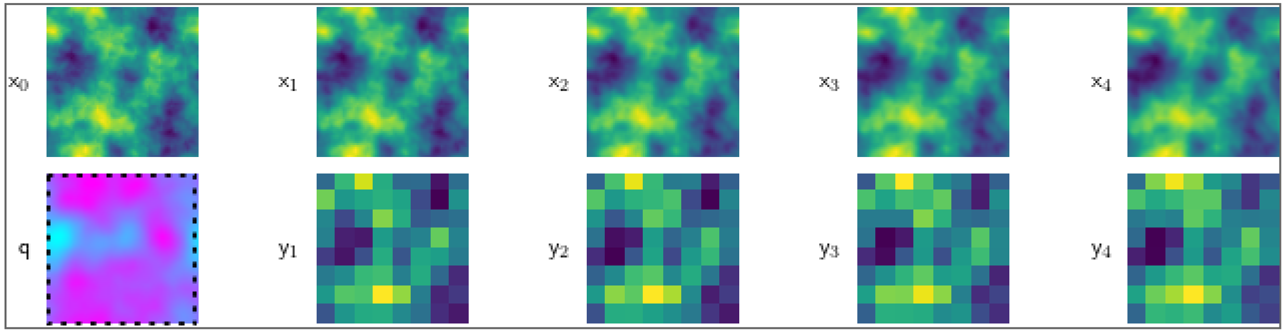

Figure 1: Low viscosity

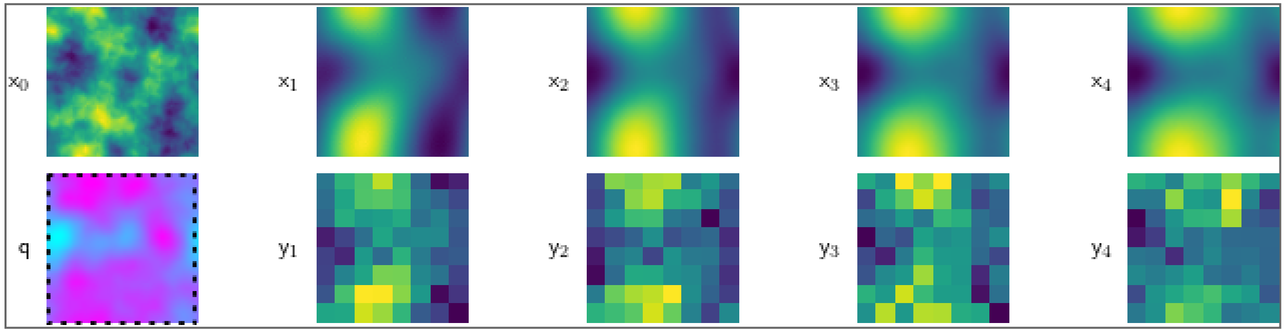

Figure 2: Medium viscosity

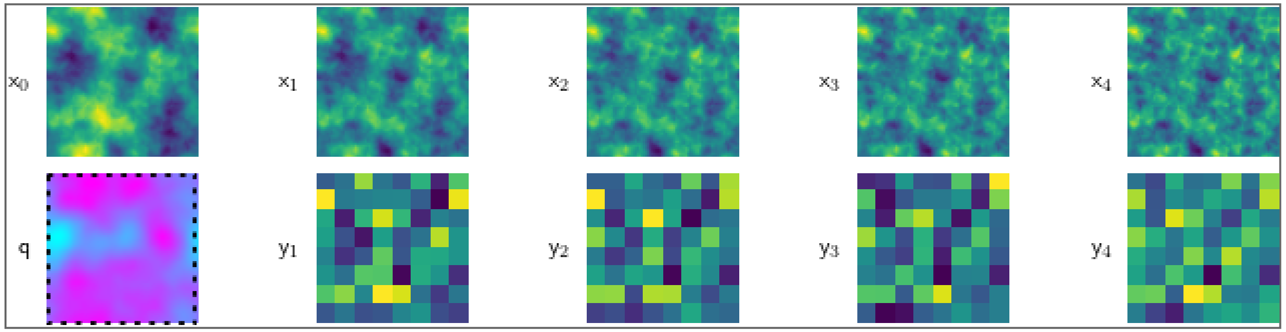

Figure 3: High viscosity

Results

Performance Comparison

Classic GaBP

Our GEnBP

Scaling to Larger Problems

Handling Different Fluid Types

Advanced Application: Reality Gap

Neural Network Emulation

Emulator Performance

Conclusion

Key Advantages

- **Scalable**: Handles millions of dimensions vs. thousands for GaBP
- **Efficient**: Better computational complexity
- **Versatile**: Works with existing simulators
- **Accurate**: Better posterior estimates in many cases
- **Innovative**: Bridges the gap between two research communities

Try It Yourself

- Code: **github.com/danmackinlay/GEnBP**
- Paper: **arxiv.org/abs/2402.08193** (**MacKinlay et al. 2025**)
- Supported by CSIRO Machine Learning and Artificial Intelligence Future Science Platform

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Bonus time

Extra images

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acKinlay, Tsuchida, Pagendam, et al. 2025. "**Gaussian Ensemble Belief Propagation for Efficient Inference in High-Dimensional Systems**." In *Proceedings of the International Conference on Learning Representations (ICLR)*.

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Speaker notes