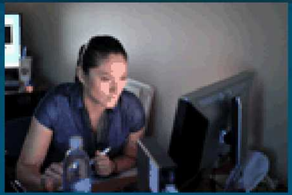
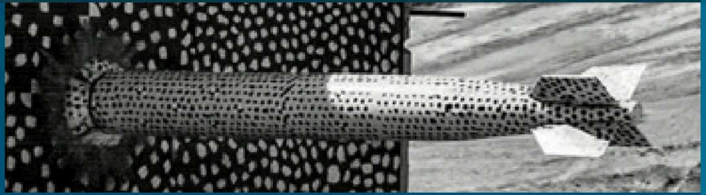
SAND2019-1775PE

Coupled Machine Learning and Reservoir Simulations to Forecast Marine Sediment Properties





PRESENTED BY

Michael Nole

U.S. NAVAL RESEARCH LABORATORY

Team

Sandia National Laboratories

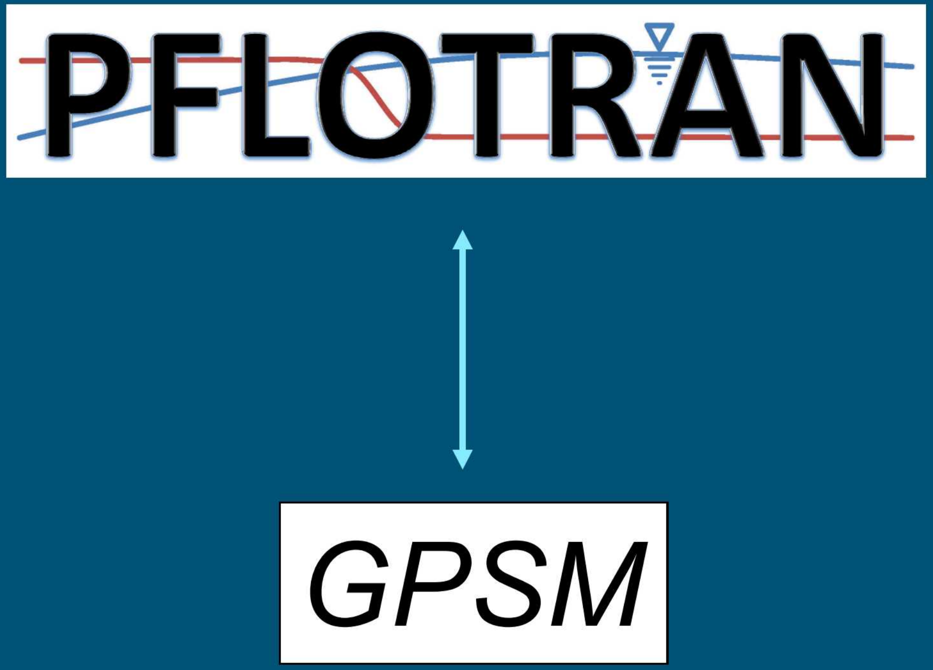
- PI: Jenn Frederick (geosciences, code development)
- Michael Nole (geosciences, code development)
- Ken Sale (methanogenesis)
- Hongkyu Yoon (geomechanics)
- Brian Young (geophysics)

Naval Research Laboratory

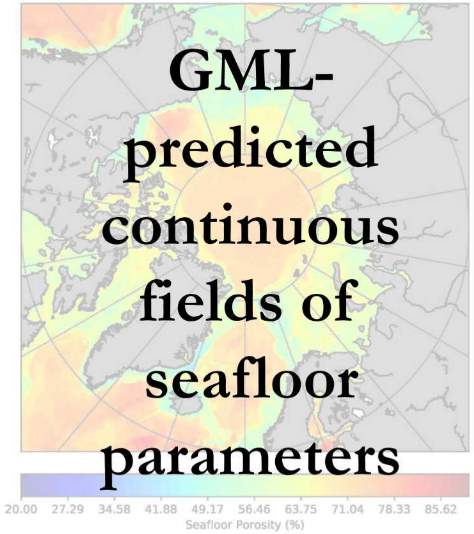
- Warren Wood (machine learning, code development)
- Ben Phrampus (machine learning, code development)

UT Austin

- Hugh Daigle (petrophysics, modeling)

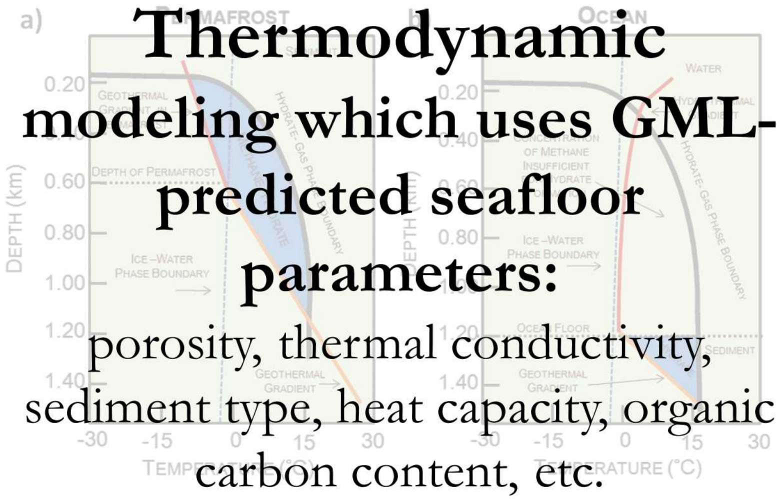


Project Overview



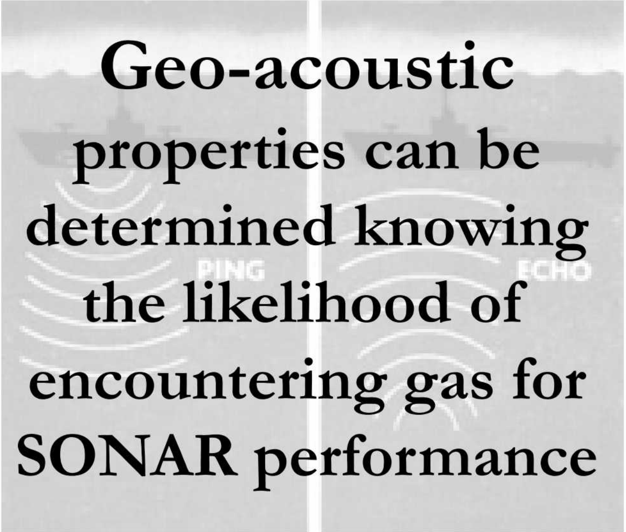
GML-predicted continuous fields of seafloor parameters

+

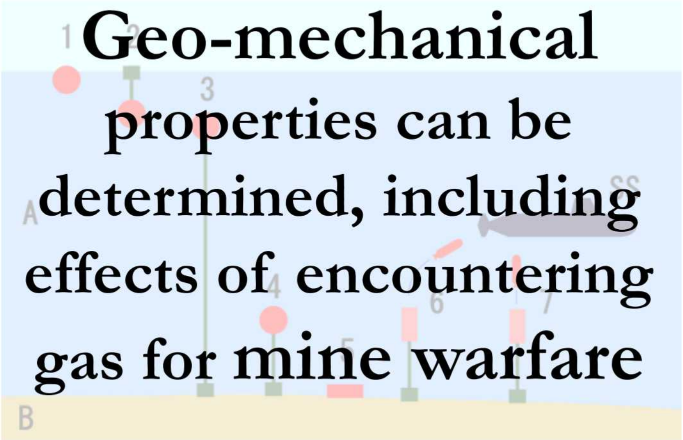


Thermodynamic modeling which uses GML-predicted seafloor parameters:

porosity, thermal conductivity, sediment type, heat capacity, organic carbon content, etc.

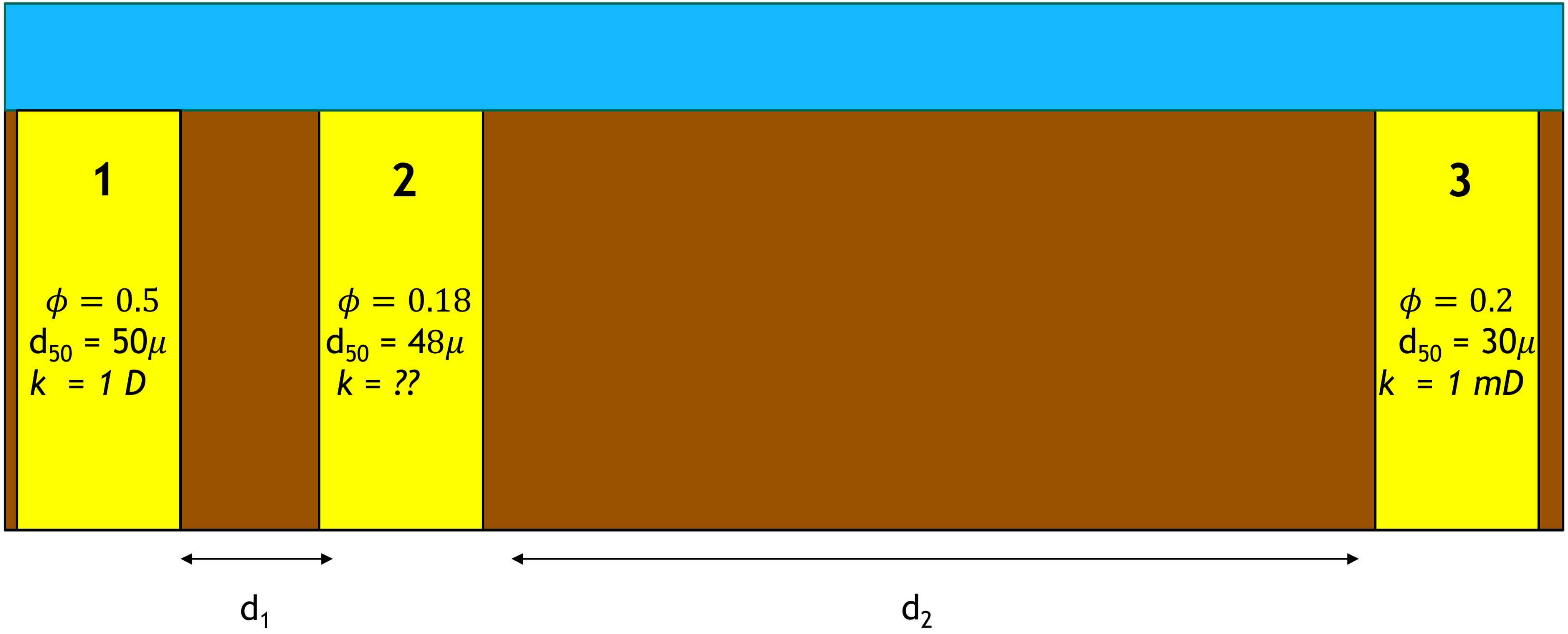


Geo-acoustic properties can be determined knowing the likelihood of encountering gas for SONAR performance



Geo-mechanical properties can be determined, including effects of encountering gas for mine warfare

Why Machine Learning?



GPSM

Global Predictive Seafloor Model

- Developed at NRL by Warren Wood and Ben Phrampus

k-Nearest Neighbors Machine Learning

- Uses proximity in parameter space (predictor space) as a proxy for similarity
- Non-parametric (does not make assumptions about underlying probability distribution of observed data)
- Only predicts values from within the range of observed data (linear interpolation)
- Interpretive bias comes in selection of k

GPSM

Observed Value
- e.g. permeability

Predicted value (predictand)
- e.g. permeability

Ex.

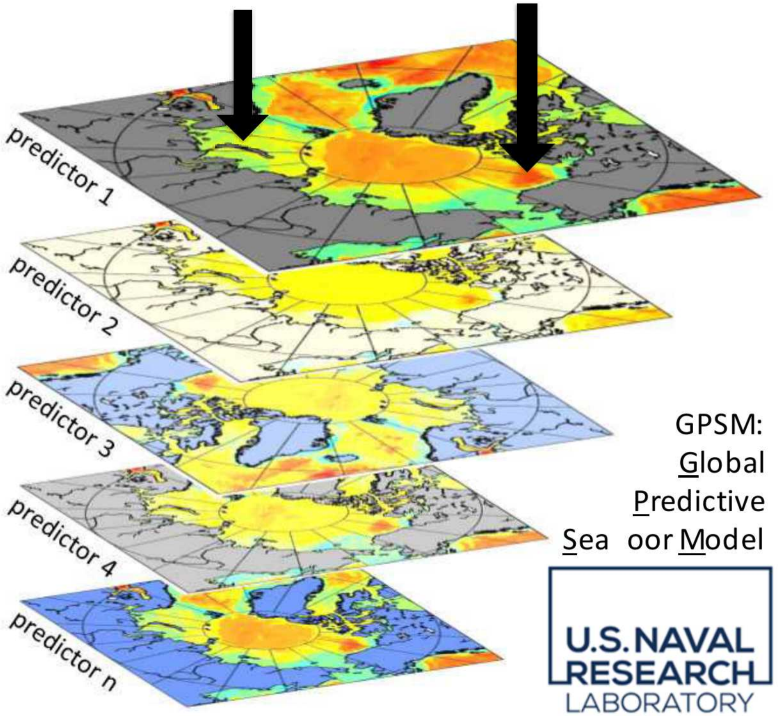
1. ϕ
2. α
3. v_{sed}
4. dist.
5. etc.

Geospatial Machine Learning Algorithm

Find Correlations

vector of observed values

vector of predictor values



GPSM:
Global
Predictive
Sea oor Model

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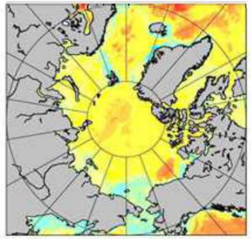
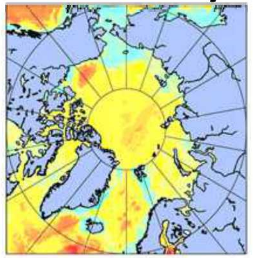
Forecast



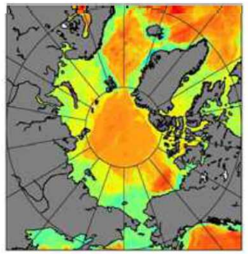
Based on sparse known data, and hundreds of dense calculated predictors, GML produces continuous maps of desired sea oor quantities, such as porosity, sediment type, total organic carbon content, etc.

Uncertainty



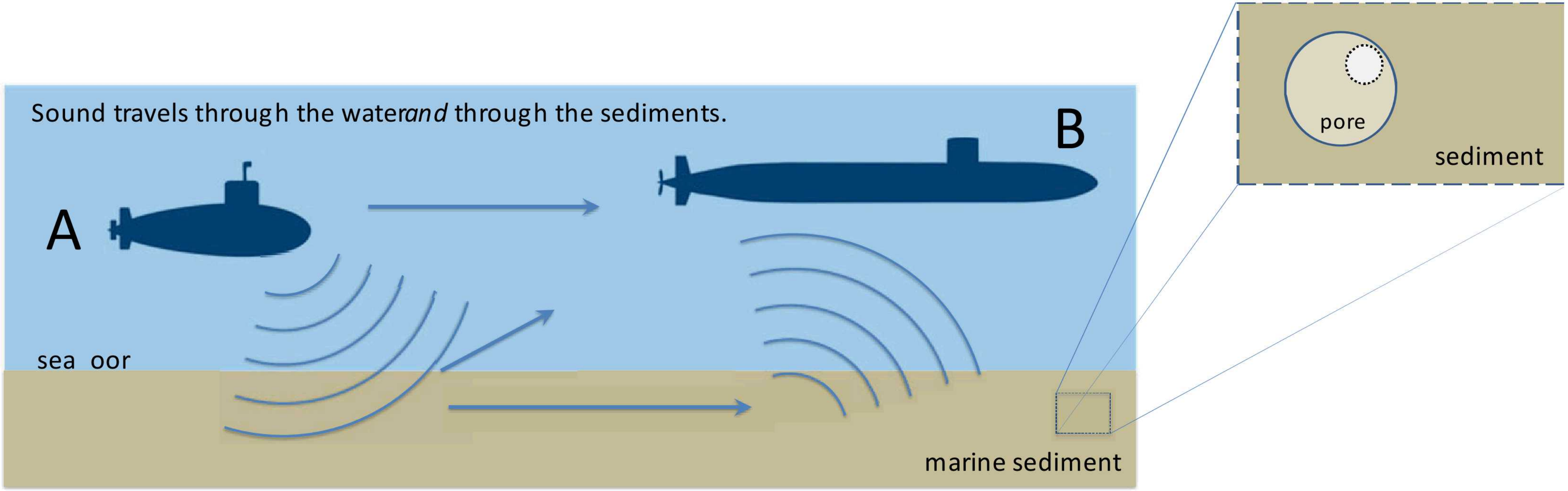
GML produces estimates of sea oor quantities and their uncertainty, which is based on prediction error. A well sampled parameter space will reduce parameter uncertainty.

Guide



Uncertainty results can be used to guide future data acquisition campaigns. Increasing observations where prediction error (uncertainty) is high will bene t predictive skill globally.

What geophysical properties would we want to predict?

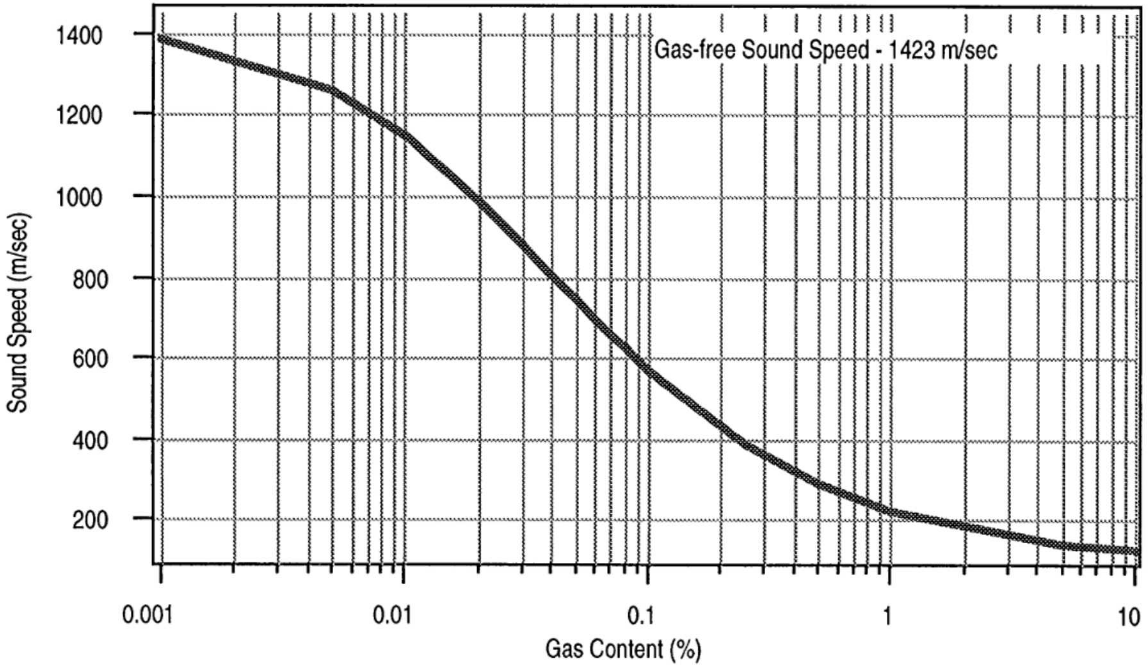


- Gas has a huge effect on the speed of sound in a composite medium

Elastic Mechanics Models

$$V_p = \sqrt{\frac{K + \frac{4}{3}G}{\rho}}$$

$$K_{composite} = f(K_{solid}, K_{fluid}, \phi)$$
$$G_{composite} = f(G_{solid}, \phi)$$



Wilkins and Richardson, 1998

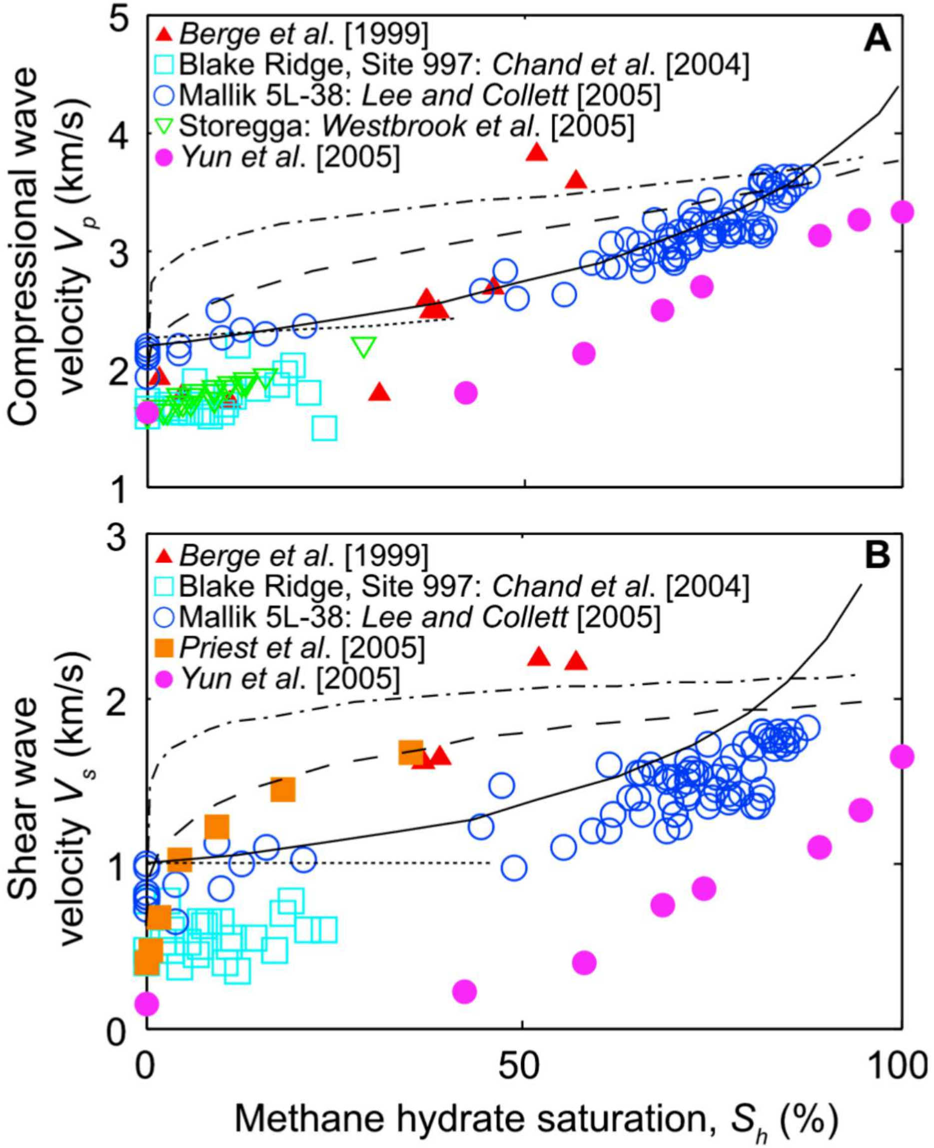
- V_p is a strong function of S_g
- S_g is f(ϕ, ρ_g, k, k_{rg}, T, P, organic carbon content, and on and on and on…)

Elastic Mechanics Models

$$V_p = \sqrt{\frac{K + \frac{4}{3}G}{\rho}}$$

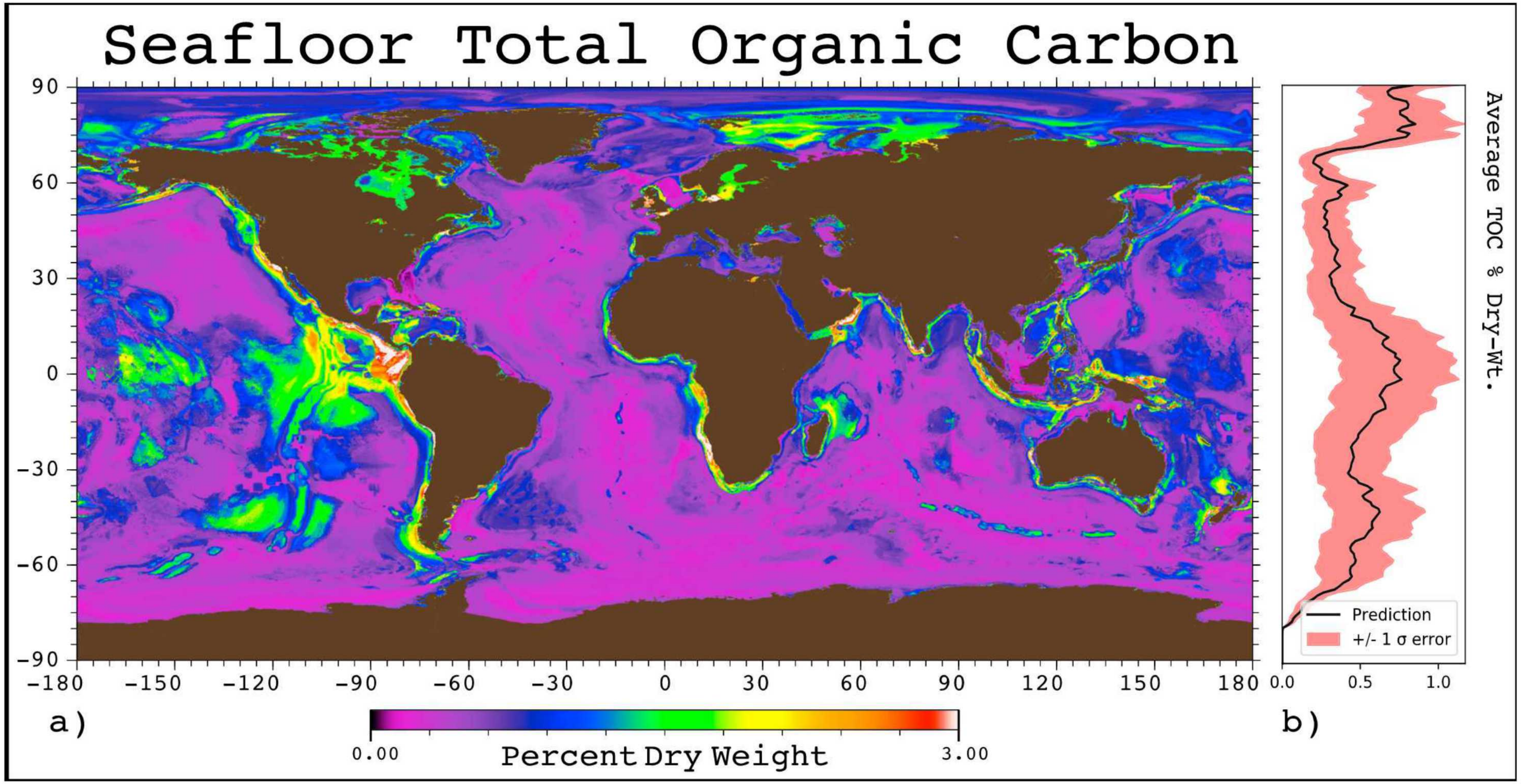
$$V_s = \sqrt{\frac{G}{\rho}}$$

$$K_{composite} = f(K_{solid}, K_{fluid}, \phi)$$
$$G_{composite} = f(G_{solid}, \phi)$$



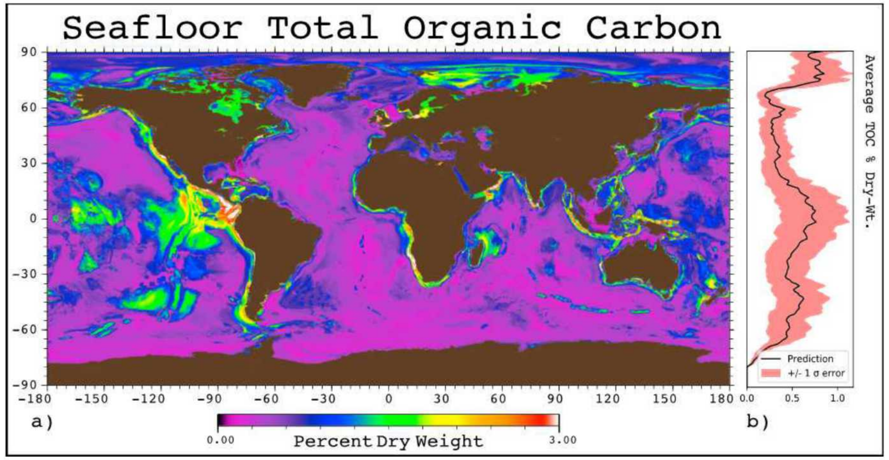
Waite et al., 2009

Machine Learning in Geosciences



Lee et al., 2019

Coupled Machine Learning – Physics Model Approach

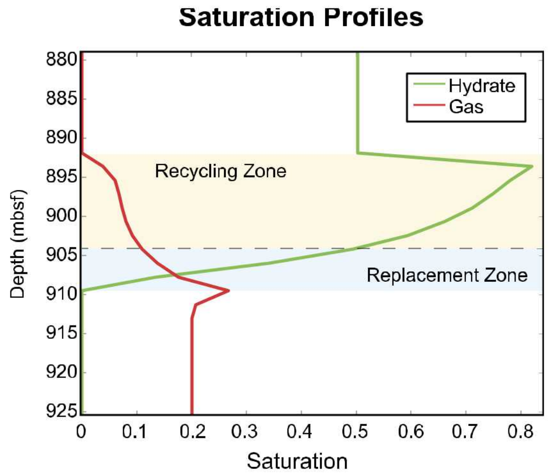


- Use maps of predictors (including probabilistic maps) as inputs to petrophysical models

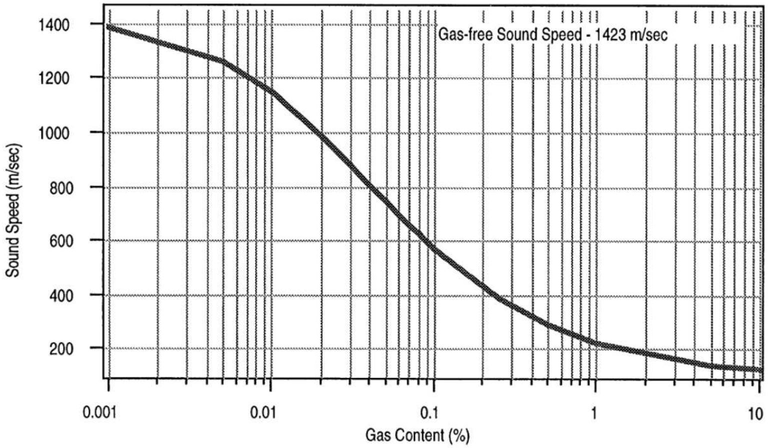
$$P_c \approx P_{ce} f(S_w)$$
$$\boldsymbol{k_r} = f(S_w, S_g)$$
$$\boldsymbol{q}^m(z) = k_\alpha \lambda \alpha$$

- Use machine learning to generate probabilistic maps constrained by physical principles

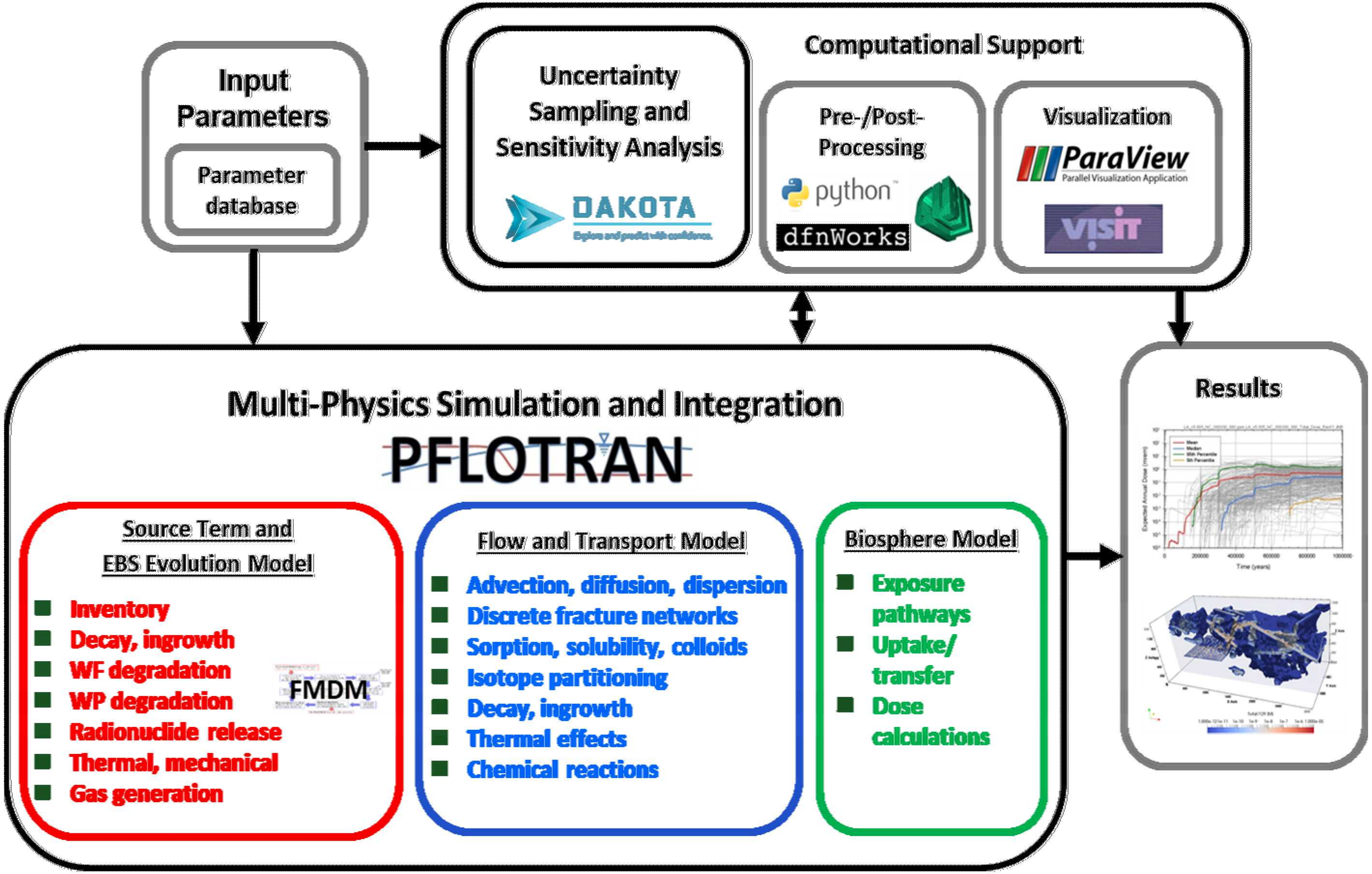
- Use petrophysical models to deterministically simulate for unknowns (i.e. S_g, S_h)



- Use maps of unknowns to update geophysical models (i.e. V_p)



Open-source Software Development



PFLOTRAN

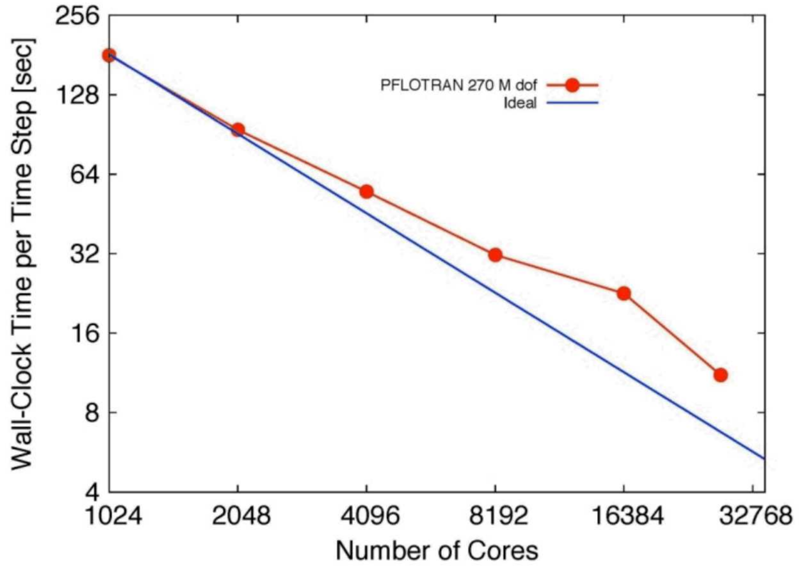
Petascale reactive multiphase flow and transport code

Open source license (GNU LGPL 2.0)

Object-oriented Fortran 2003/2008
- Pointers to procedures
- Classes (extendable derived types with member procedures)

Founded upon well-known (supported) open source libraries
- MPI, PETSc, HDF5, METIS/ParMETIS/CMAKE

Demonstrated performance
- Maximum # processes: 262,144 (Jaguar supercomputer)
- Maximum problem size: 3.34 billion degrees of freedom
- Scales well to over 10K cores

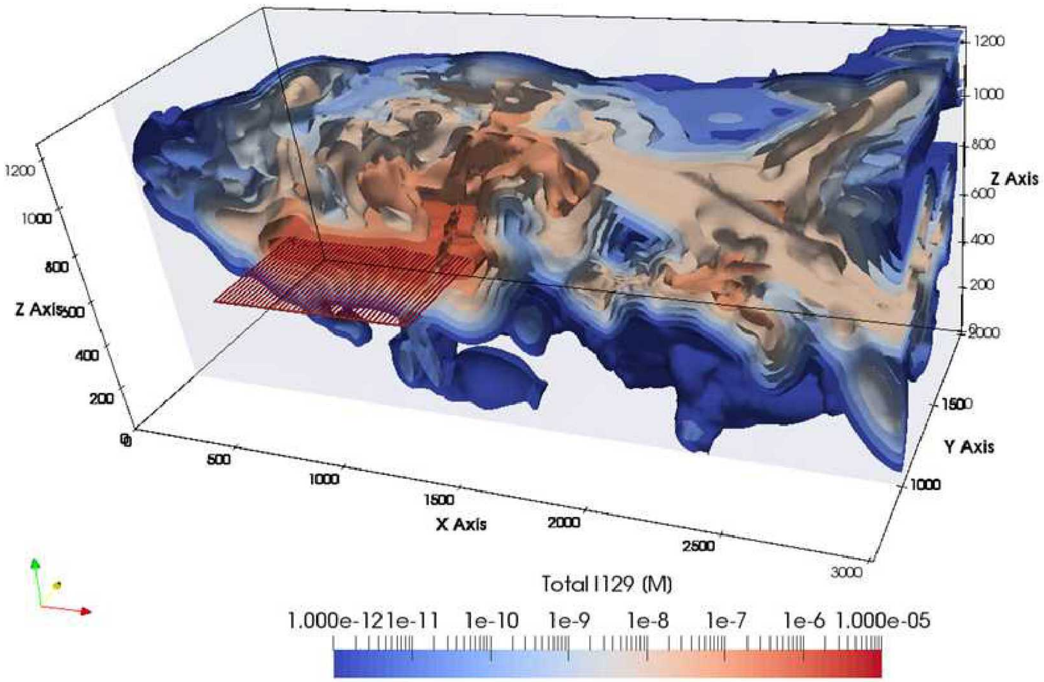


Gas Hydrate Simulation Capability in PFLOTRAN

$$\frac{\partial m_a}{\partial t} = -\nabla \cdot \left(\rho_l X_a^l \boldsymbol{q}_l + \rho_g X_a^g \boldsymbol{q}_g + \boldsymbol{J}_a^l + \boldsymbol{J}_a^g\right) + q_a^G,$$

$$\frac{\partial m_w}{\partial t} = -\nabla \cdot \left(\rho_l X_w^l \boldsymbol{q}_l + \rho_g X_w^g \boldsymbol{q}_g + \boldsymbol{J}_w^l + \boldsymbol{J}_w^g\right) + q_w^G,$$

$$\frac{\partial e}{\partial t} = -\nabla \cdot \left(\rho_l H_l \boldsymbol{q}_l + \rho_g H_g \boldsymbol{q}_g - \kappa_{\text{eff}} \nabla T\right) + q_e^G,$$



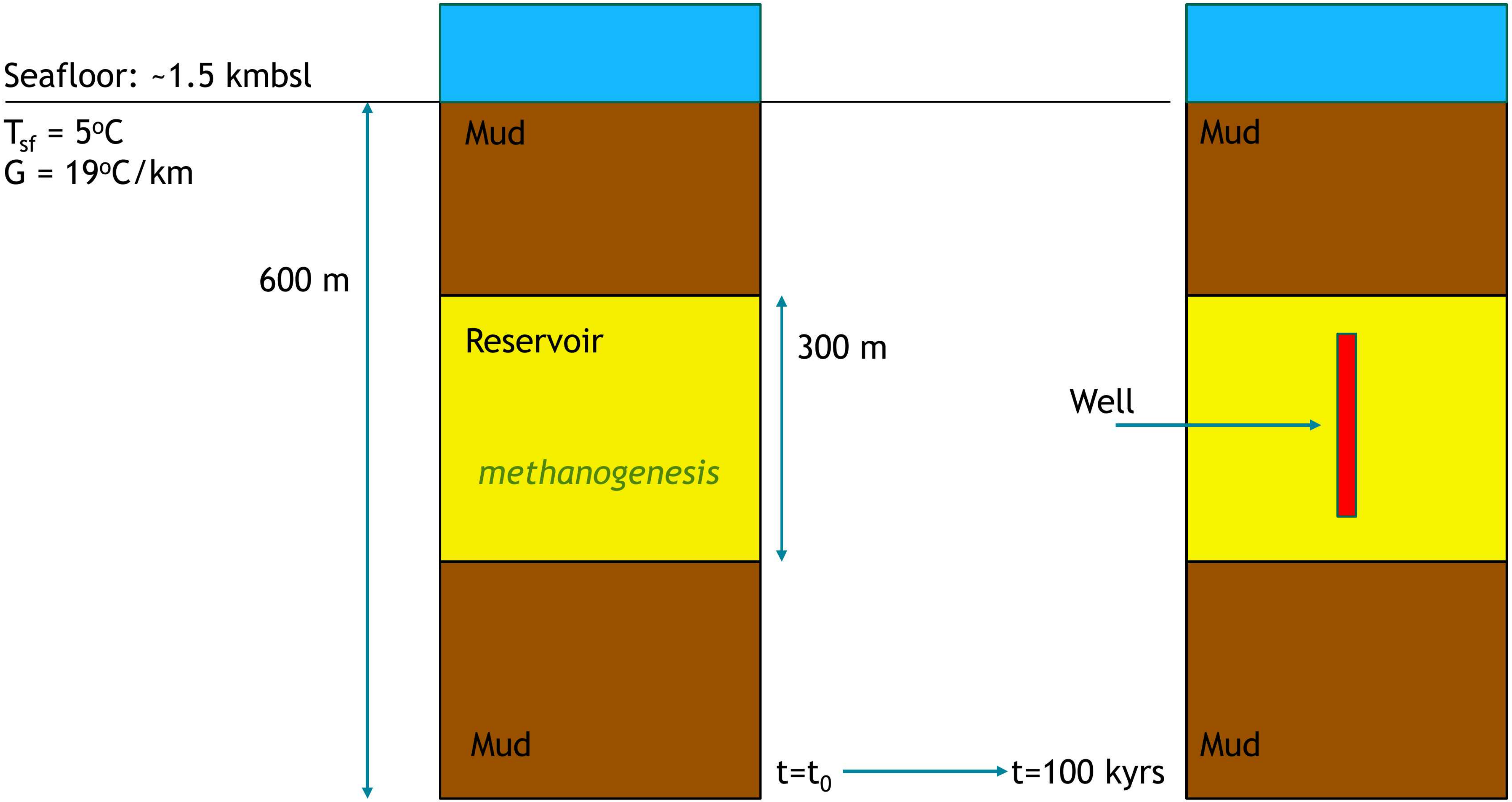
Gas Hydrate Simulation Capability in PFLOTRAN

Model Domains

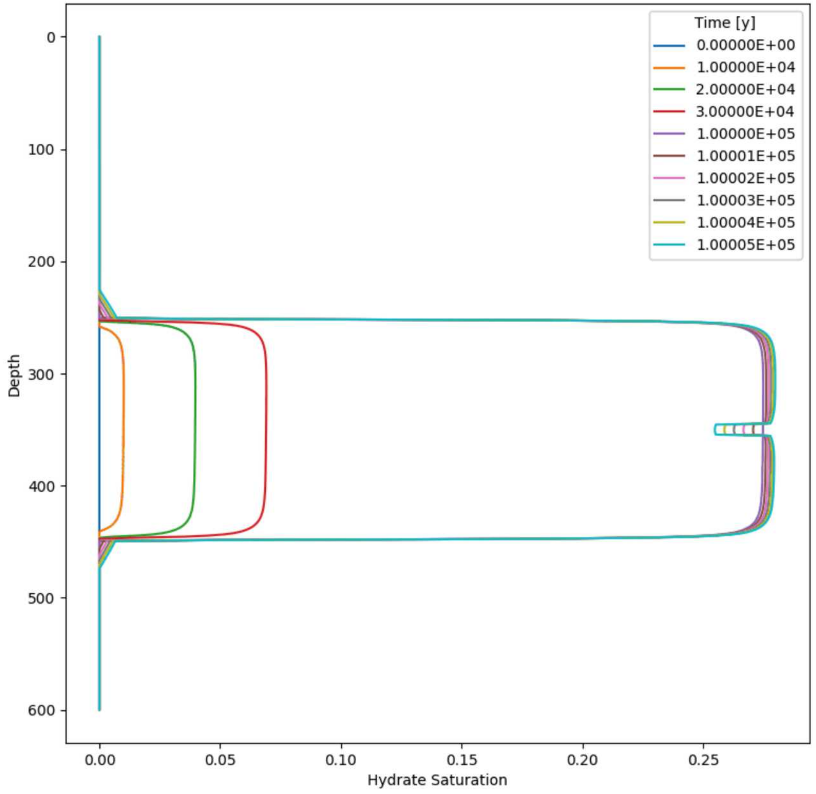
- Hydrate reservoir
  - $\phi = 0.4$
  - k = 10 mD; 1×10^{-14} m^2
  - Thickness: 200 m
- Bounding muds
  - $\phi = 0.3$
  - k = 0.010 mD; 1×10^{-17} m^2
  - Thickness: 250 m on top and bottom
- Simulation:
  - Generate methane in situ to form hydrate for 100 kyrs
  - Dissolve + dissociate hydrate for 50 years
    - 1D: Pumping (mass sink)
    - 3D: Heating (heat source)

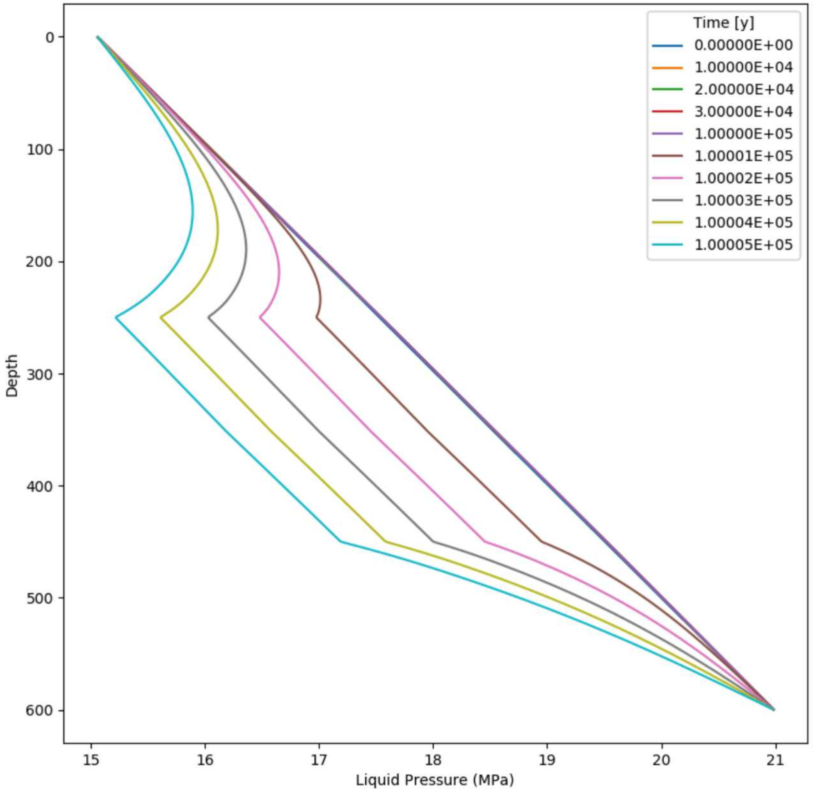
- 1D
  - Grid: 600 @ 1 m
  - Well
    - 10 m long
    - Pumping 8.7×10^{-4} g/s water, 1.3×10^{-4} g/s methane
  - **Runtime**: 6 sec
- 3D
  - Grid: 10 x 10 x 302
    - **X**: 10 @ 10m
    - **Y**: 10 @ 10m
    - **Z**: 2 @ 150 m on top and bottom; 300 @ 1 m in reservoir
  - Heat Source
    - 150 m long
    - 12 kW; 0.8 W/m^3
  - **Runtime**:
    - 4 cores
    - ~1 hr (mainly taken up in 3-phase state with buoyant flow)

Gas Hydrate Simulation Capability in PFLOTRAN

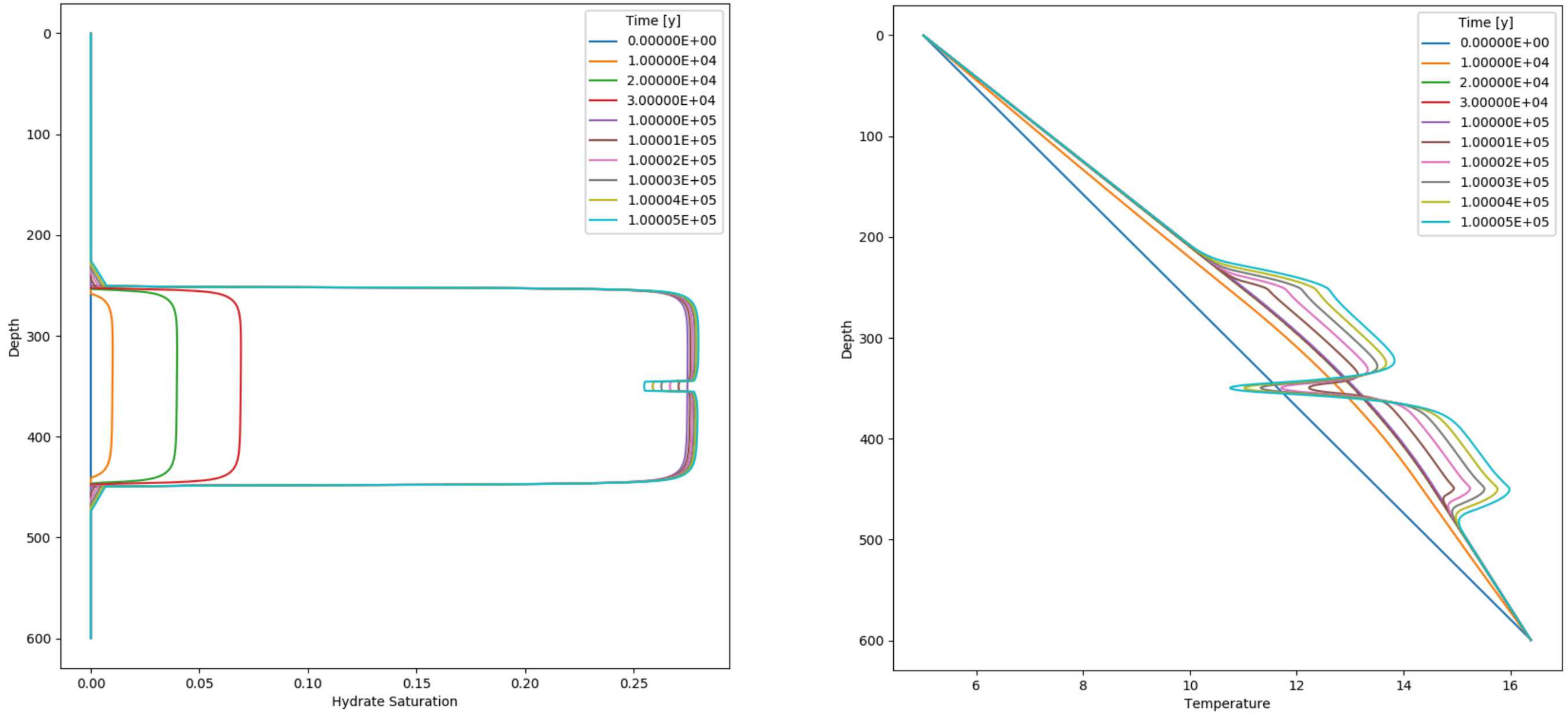


Gas Hydrate Simulation Capability in PFLOTRAN



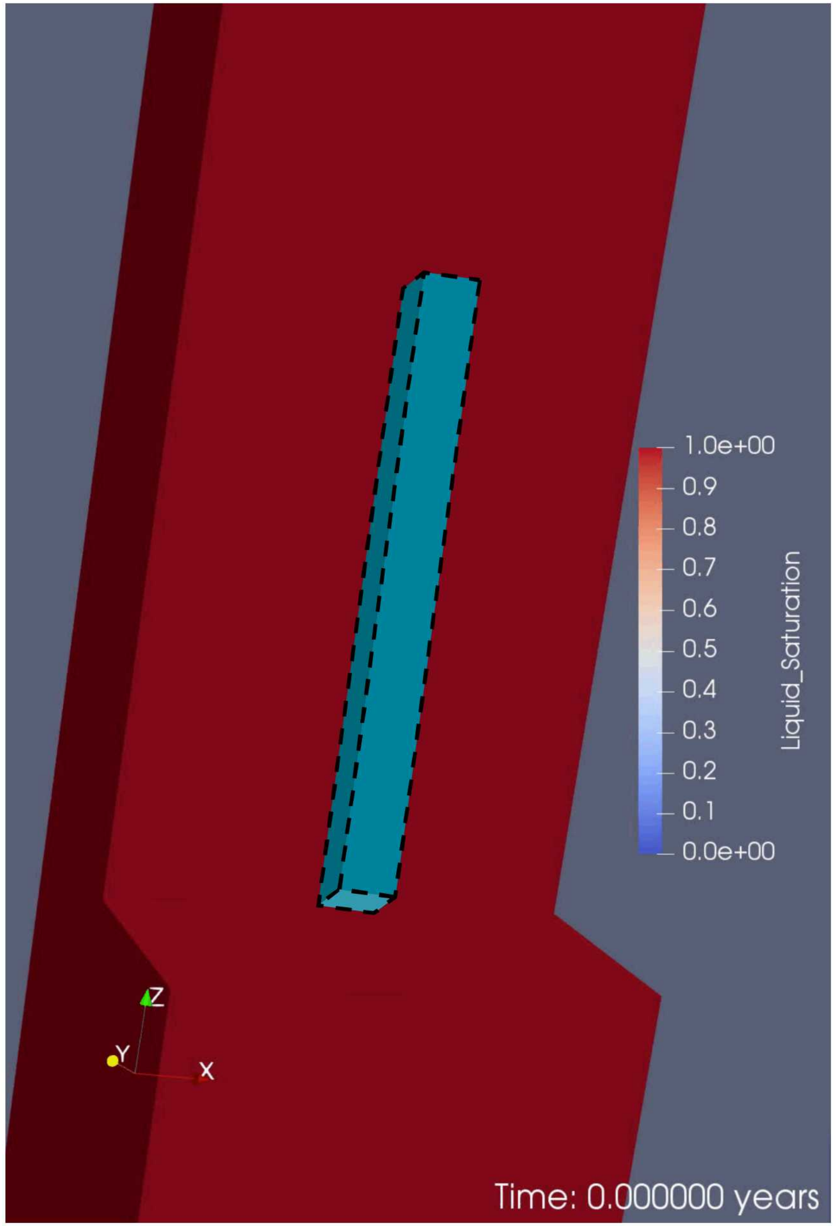


Gas Hydrate Simulation Capability in PFLOTRAN

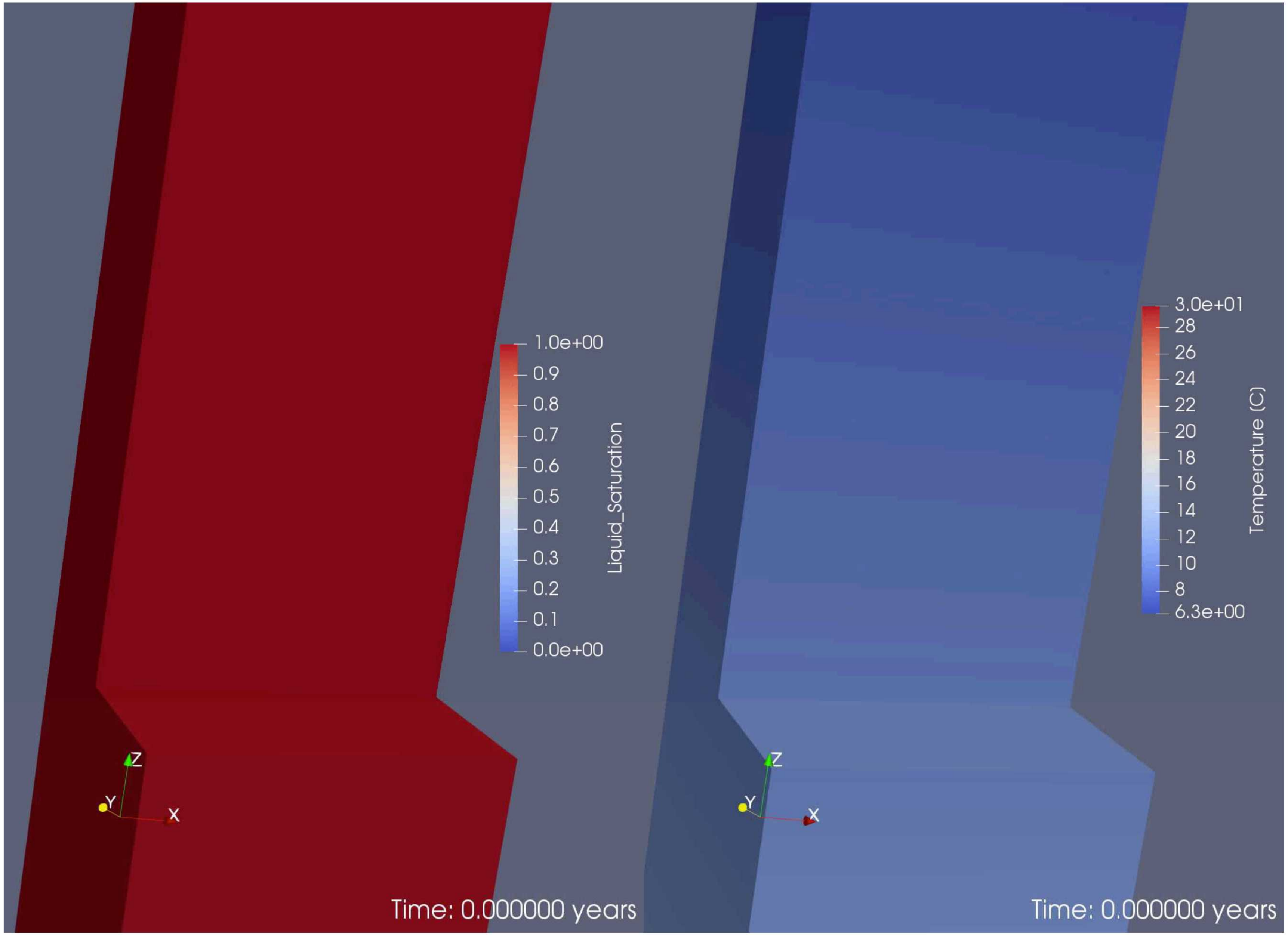


Gas Hydrate Simulation Capability in PFLOTRAN

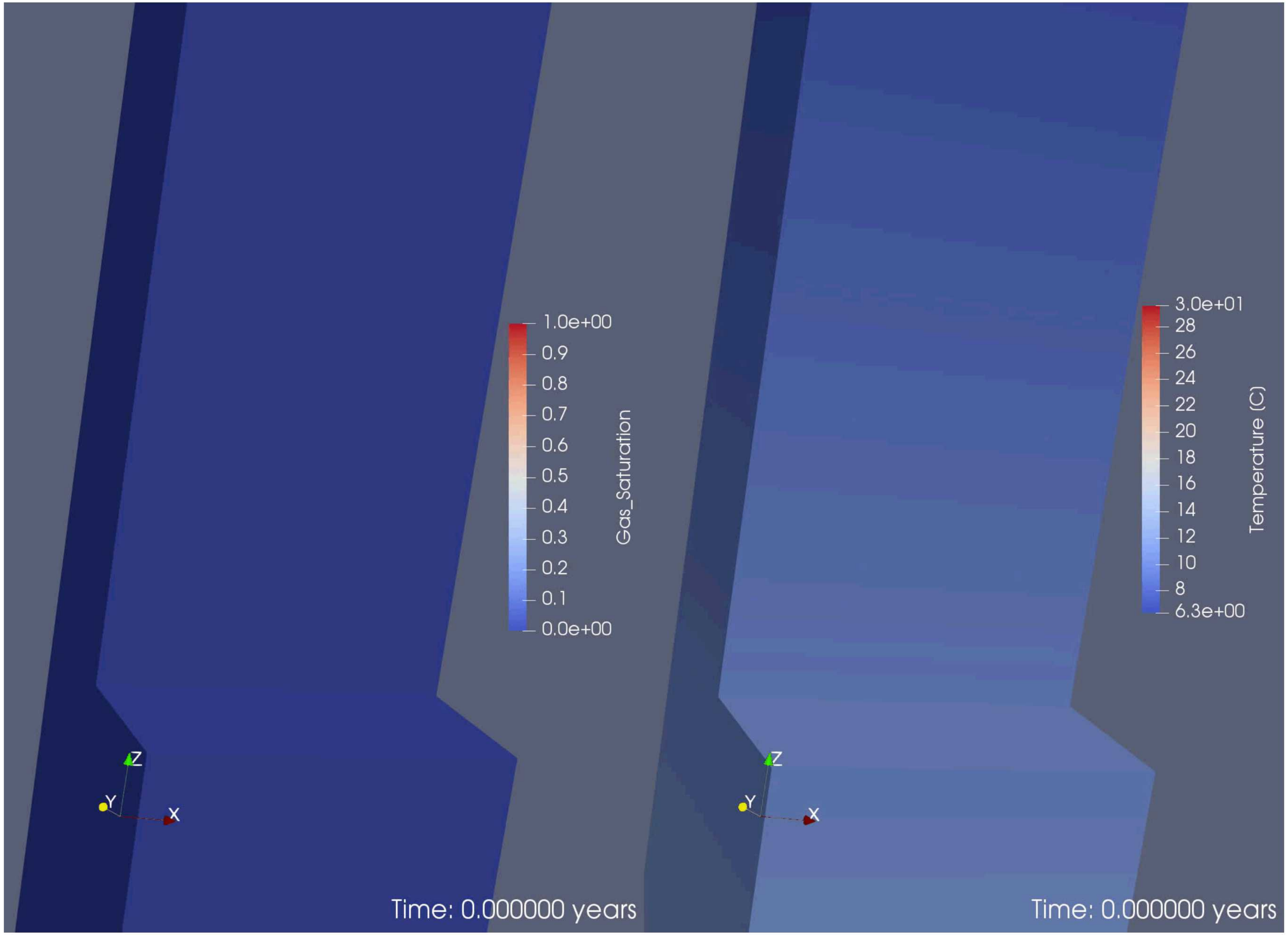
- Cross section of 3D model domain cut to show insertion of the heat source in the center of the reservoir (outlined)
- $S_h = 1 - S_l - S_g$
- Gas hydrate is generated from an in situ source for 100 kyrs
- Heat source is turned on at 100 kyrs for 50 yrs



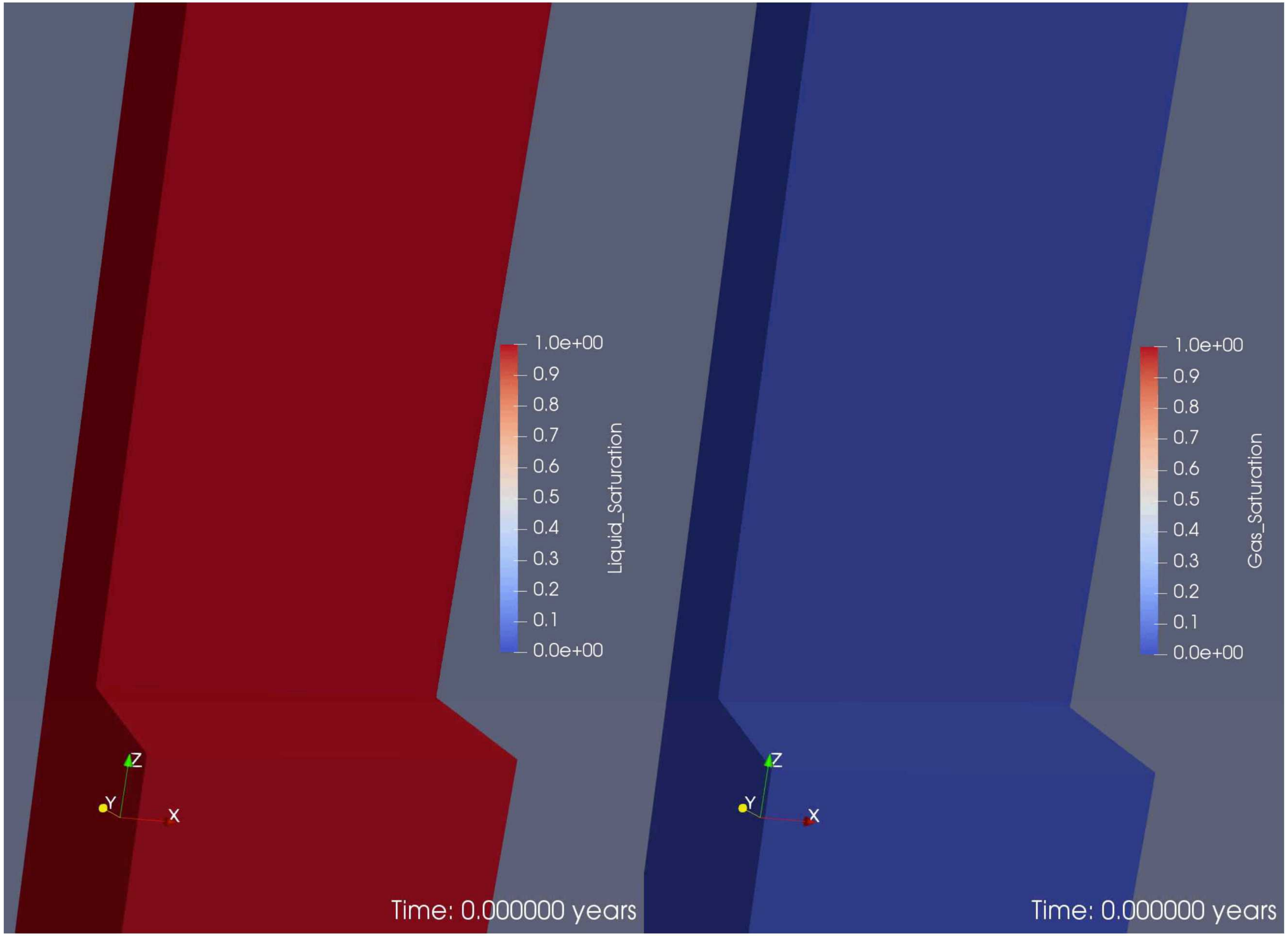
Gas Hydrate Simulation Capability in PFLOTRAN



Gas Hydrate Simulation Capability in PFLOTRAN



Gas Hydrate Simulation Capability in PFLOTRAN



Modeling Gas Hydrate Systems with PFLOTRAN

Opportunities

- An open source gas hydrate systems simulator
- Can take advantage of HPC resources (basin-scale, probabilistic runs)

Areas for Improvement

- Arctic focus will require ice implementation as well
- Salinity effects should be fully coupled in (right now this can be achieved through sequential coupling)
- Heterogeneity parameterization
- Better description of capillary phenomena
- Integration with petrophysical models
- Coupling with geomechanics

Thank You