SAND2020-2044C

A hybrid machine learning and reservoir simulation approach to estimating global gas hydrate occurrence using open-source software

PRESENTED BY

Michael Nole

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

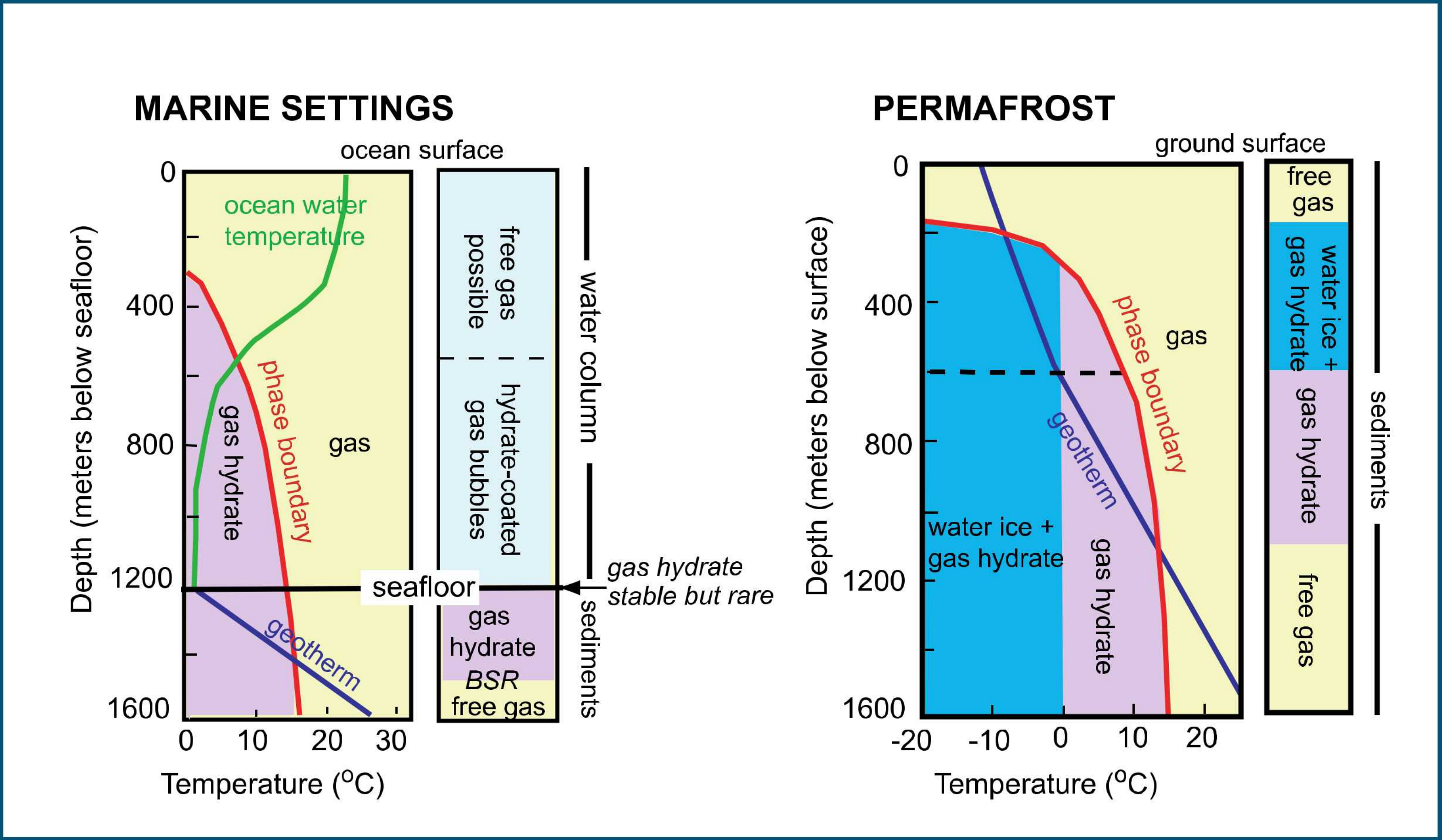
Acknowledgements

- Billy Eymold, The Ohio State University/Sandia National Labs
- Taylor Lee, Naval Research Laboratory
- Ben Phrampus, Naval Research Laboratory
- Warren Wood, Naval Research Laboratory
- Jenn Frederick, Sandia National Labs

Key Points

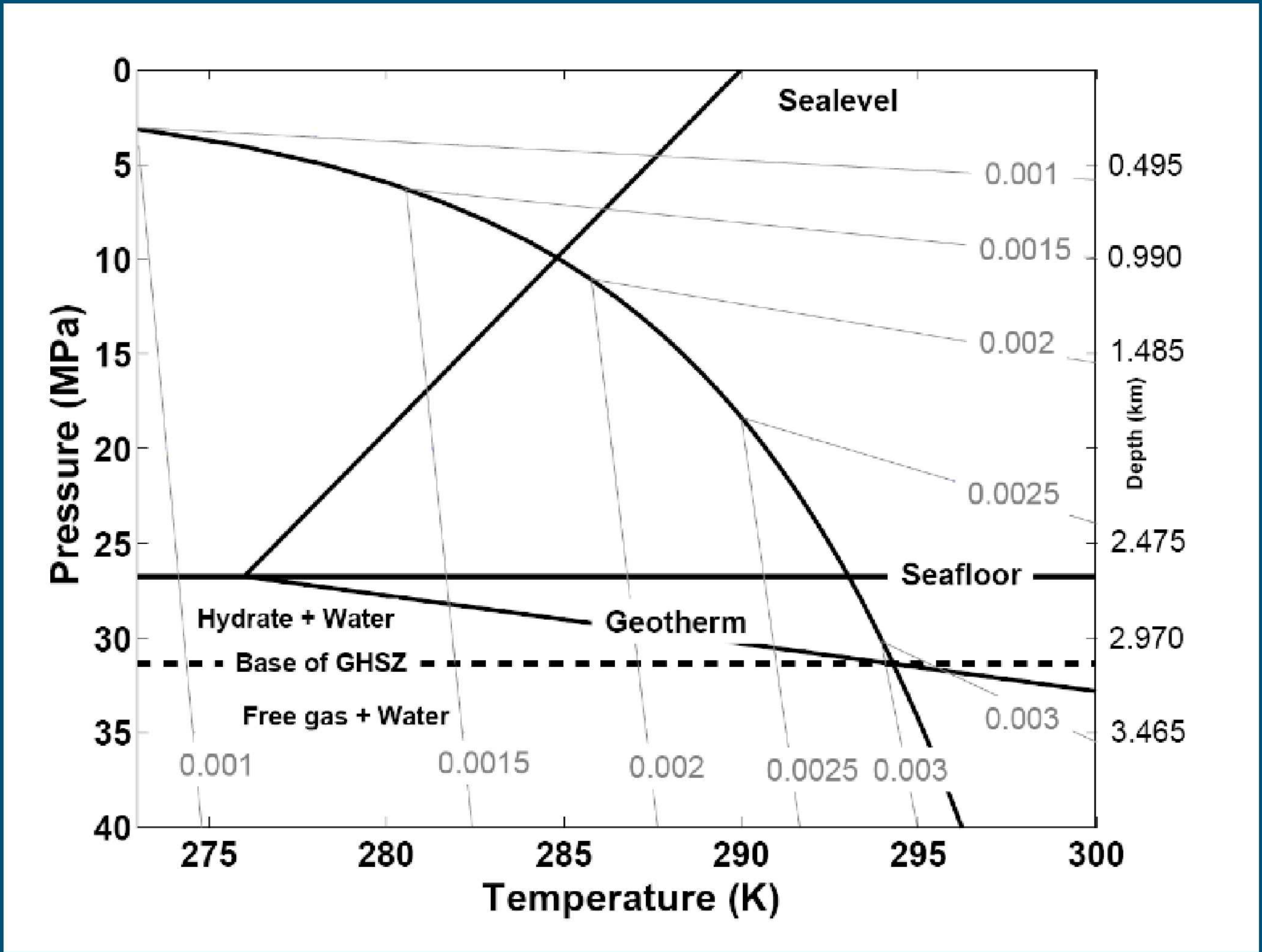
- The expression of gas hydrate in nature is controlled by complex interactions between gas sources, migration mechanisms, hydrate reservoirs, and (thermodynamic) seals
- Forward modeling these systems often requires:
  - Multi-phase, multi-component simulation
  - 3D capability to honor lateral heterogeneity and quantify competing influences of different migration mechanisms
- Predicting continuous distributions of inputs to a simulator is challenging when operating data-limited
  - How do we overcome this challenge, and can we quantify associated uncertainties?
- We can use machine learning to estimate the inputs to a simulator based off of proximity in geologic predictor space instead of simply spatial proximity

Thermodynamics



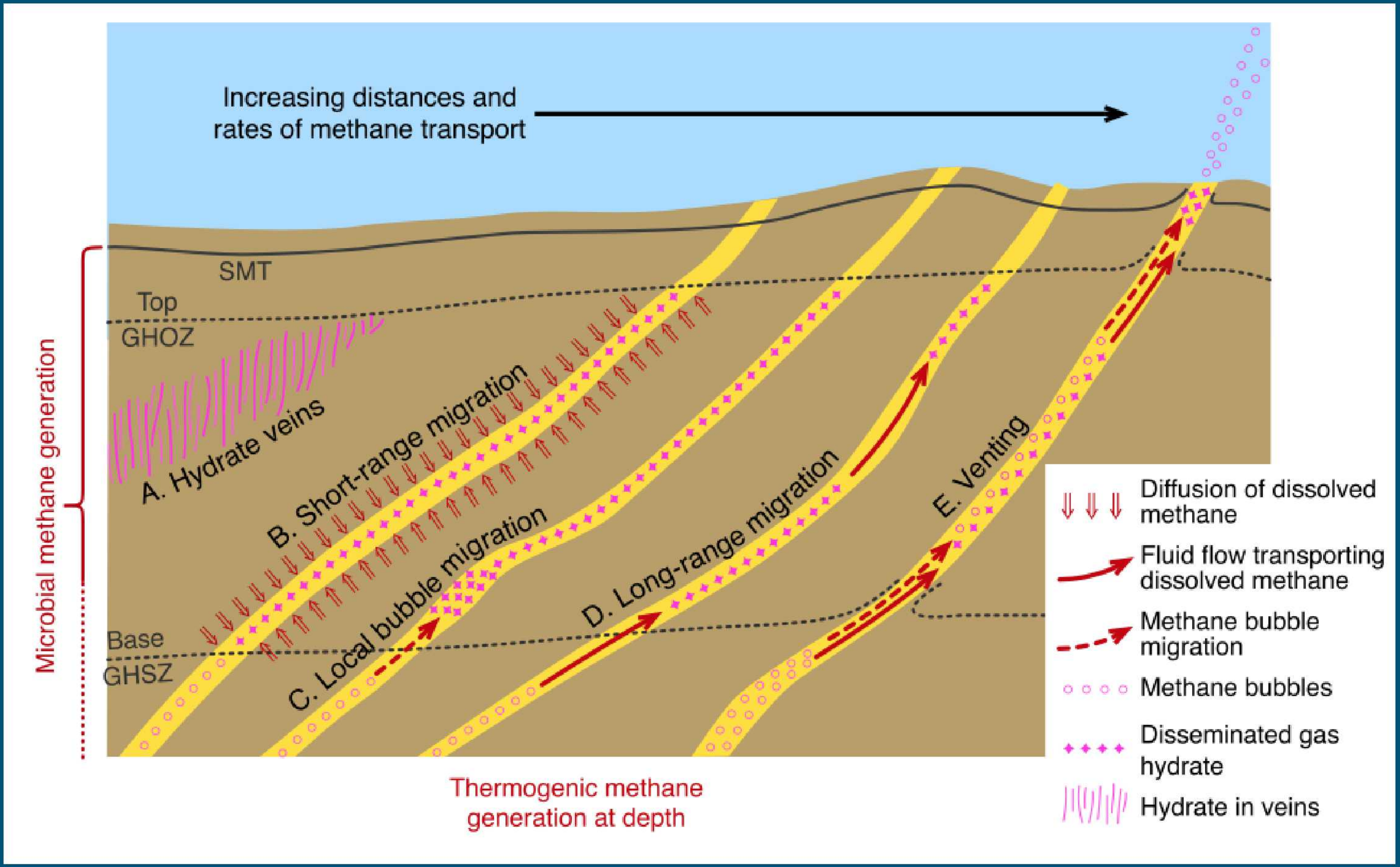
Ruppel, 2007

Methane Availability



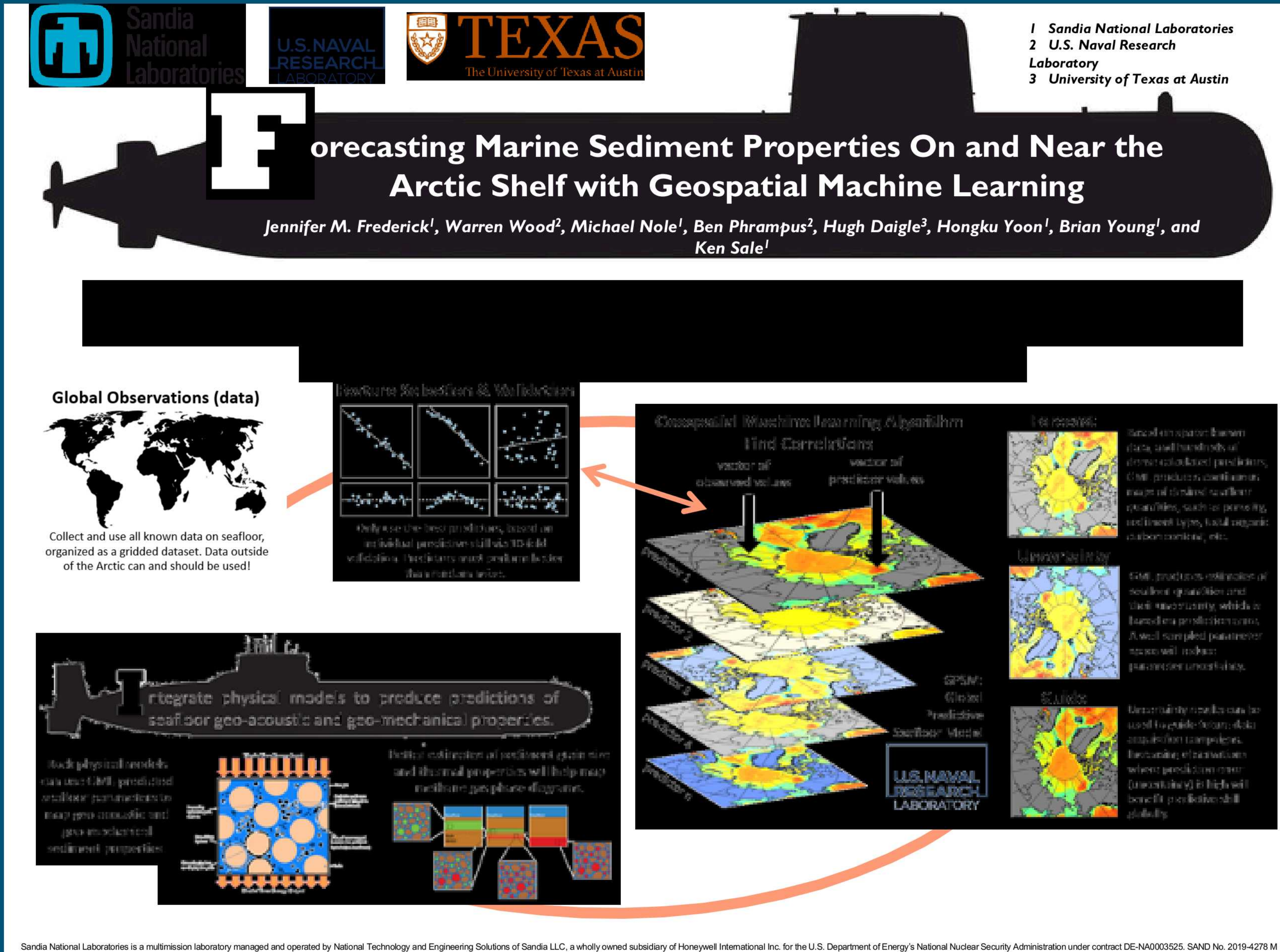
Bhatnagar et al., 2007

Transport

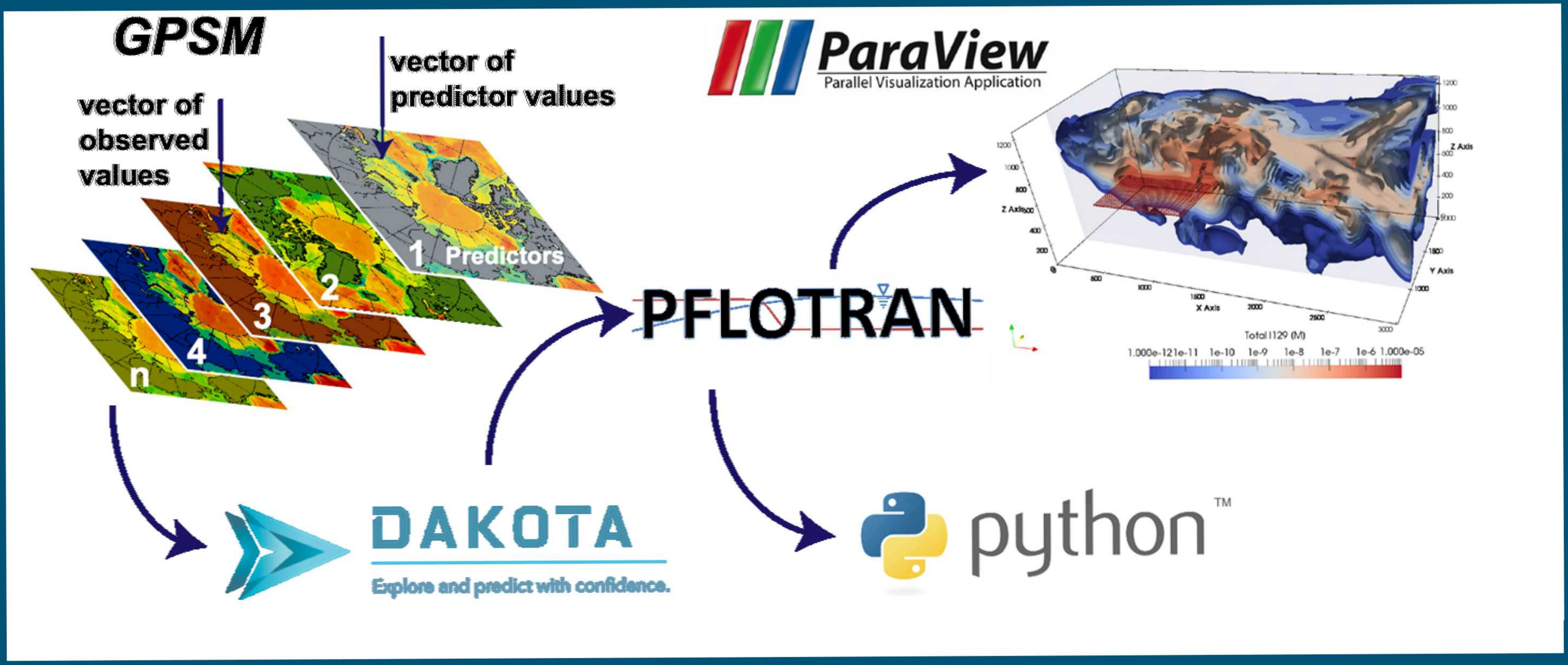


Malinverno and Goldberg, 2015

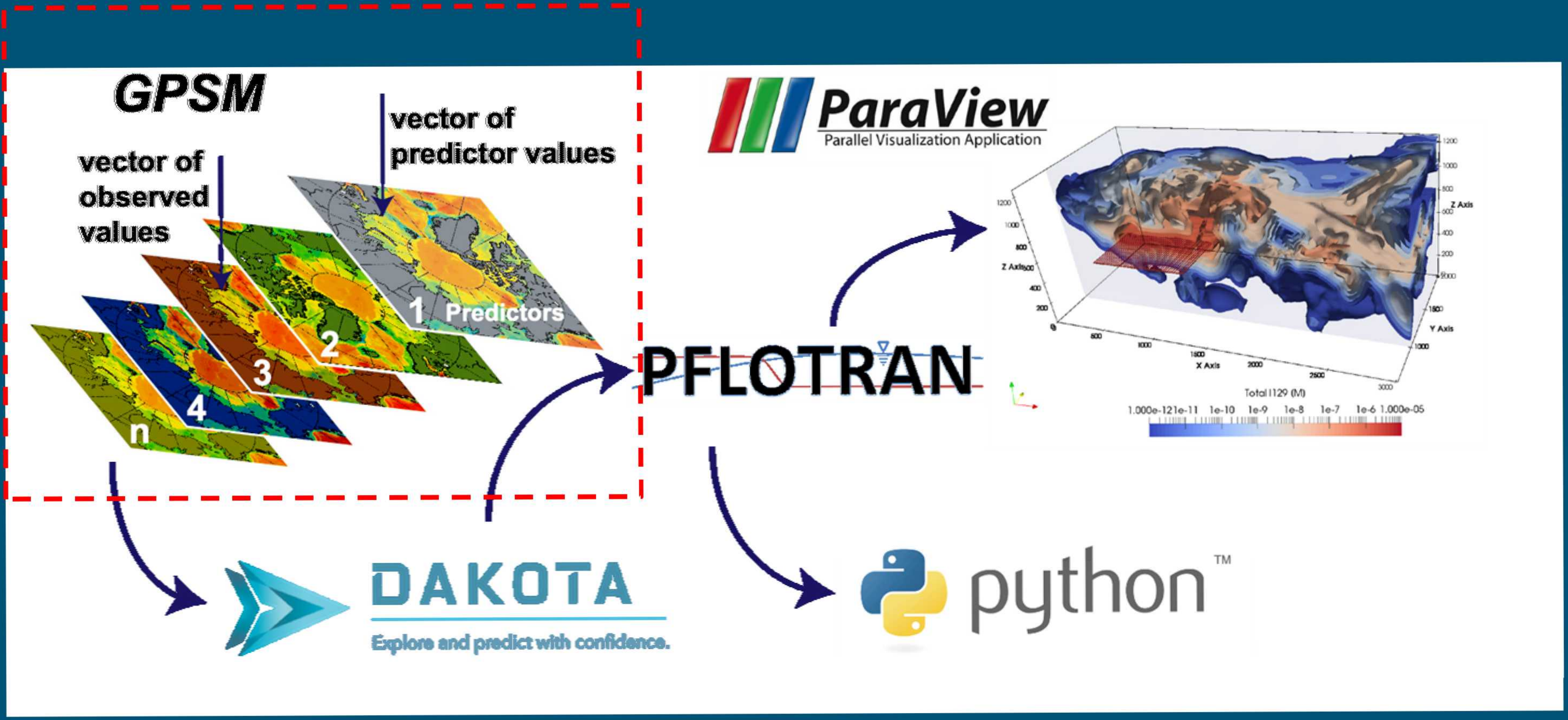
Motivation


1 Sandia National Laboratories
2 U.S. Naval Research Laboratory
3 University of Texas at Austin
TEXAS
The University of Texas at Austin
Forecasting Marine Sediment Properties On and Near the Arctic Shelf with Geospatial Machine Learning
Jennifer M. Frederick[1], Warren Wood[2], Michael Nole[1], Ben Phrampus[2], Hugh Daigle[3], Hongku Yoon[1], Brian Young[1], and Ken Sale[1]
[redacted]
Global Observations (data)
Collect and use all known data on seafloor, organized as a gridded dataset. Data outside of the Arctic can and should be used!
Integrate physical models to produce predictions of seafloor geo-acoustic and geo-mechanical properties.
U.S. NAVAL RESEARCH LABORATORY
Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. SAND No. 2019-4278 M

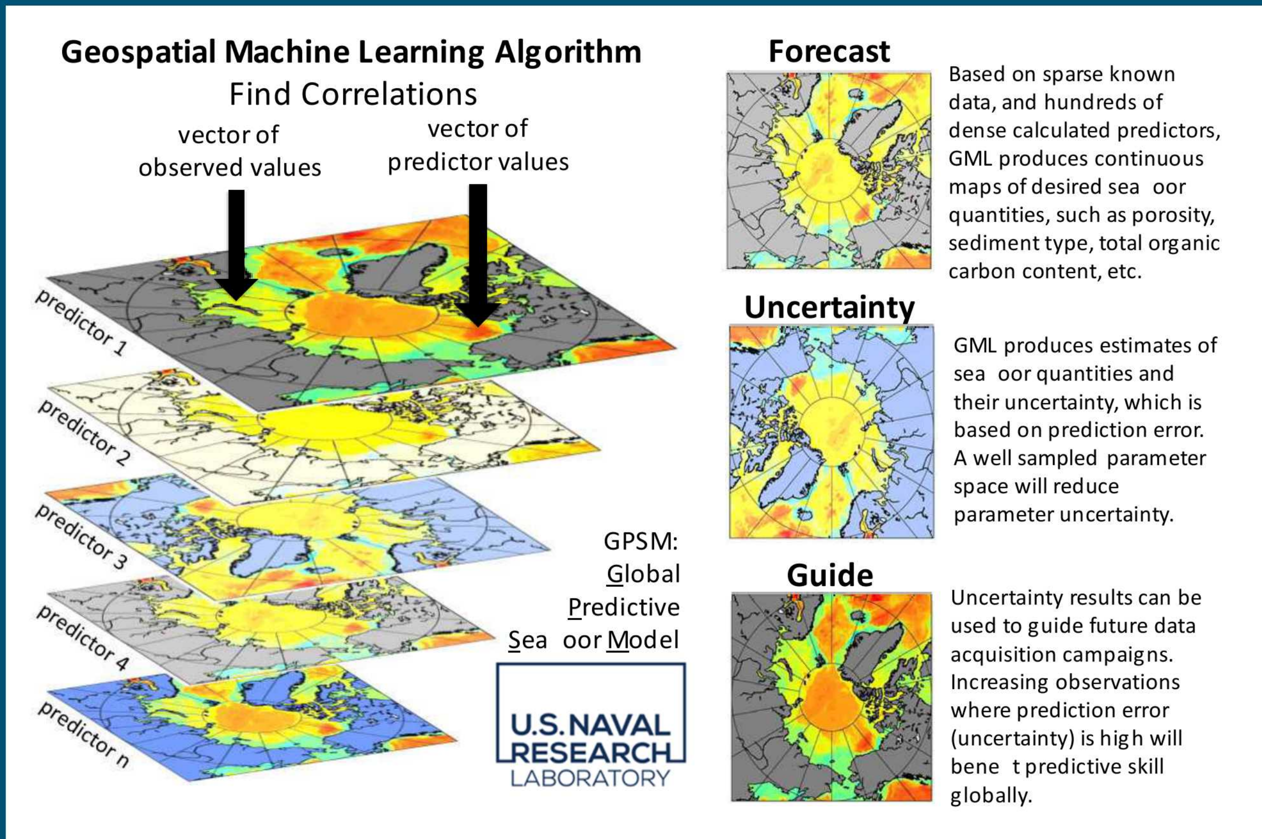
Framework


GPSM
vector of predictor values
vector of observed values
1 Predictors
2
3
4
n
ParaView
Parallel Visualization Application
PFLOTRAN
Total I129 (M)
DAKOTA
Explore and predict with confidence.
python

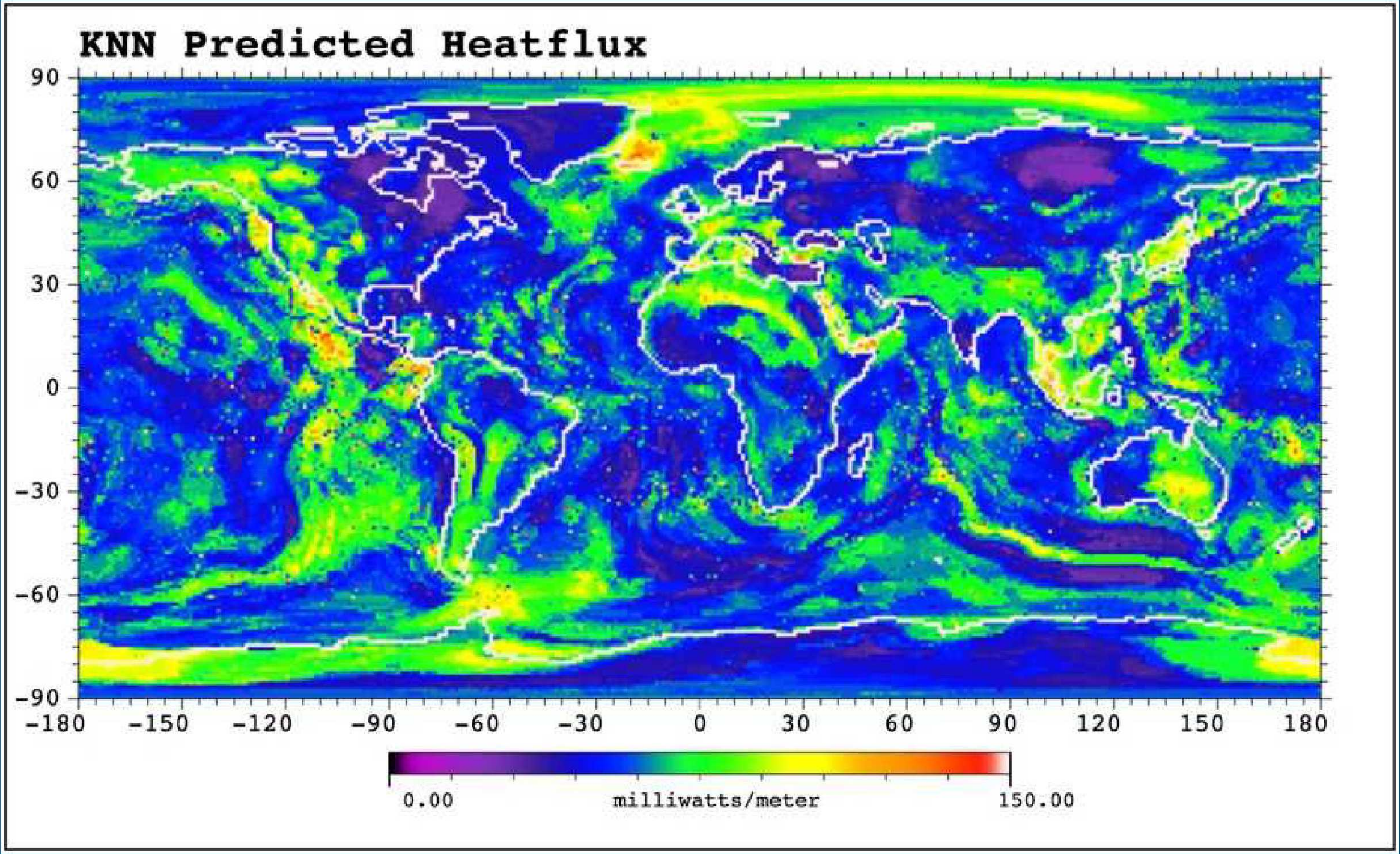
Framework


GPSM
vector of observed values
vector of predictor values
1 Predictors
2
3
4
n
PFLOTRAN
ParaView
Parallel Visualization Application
DAKOTA
Explore and predict with confidence.
python™

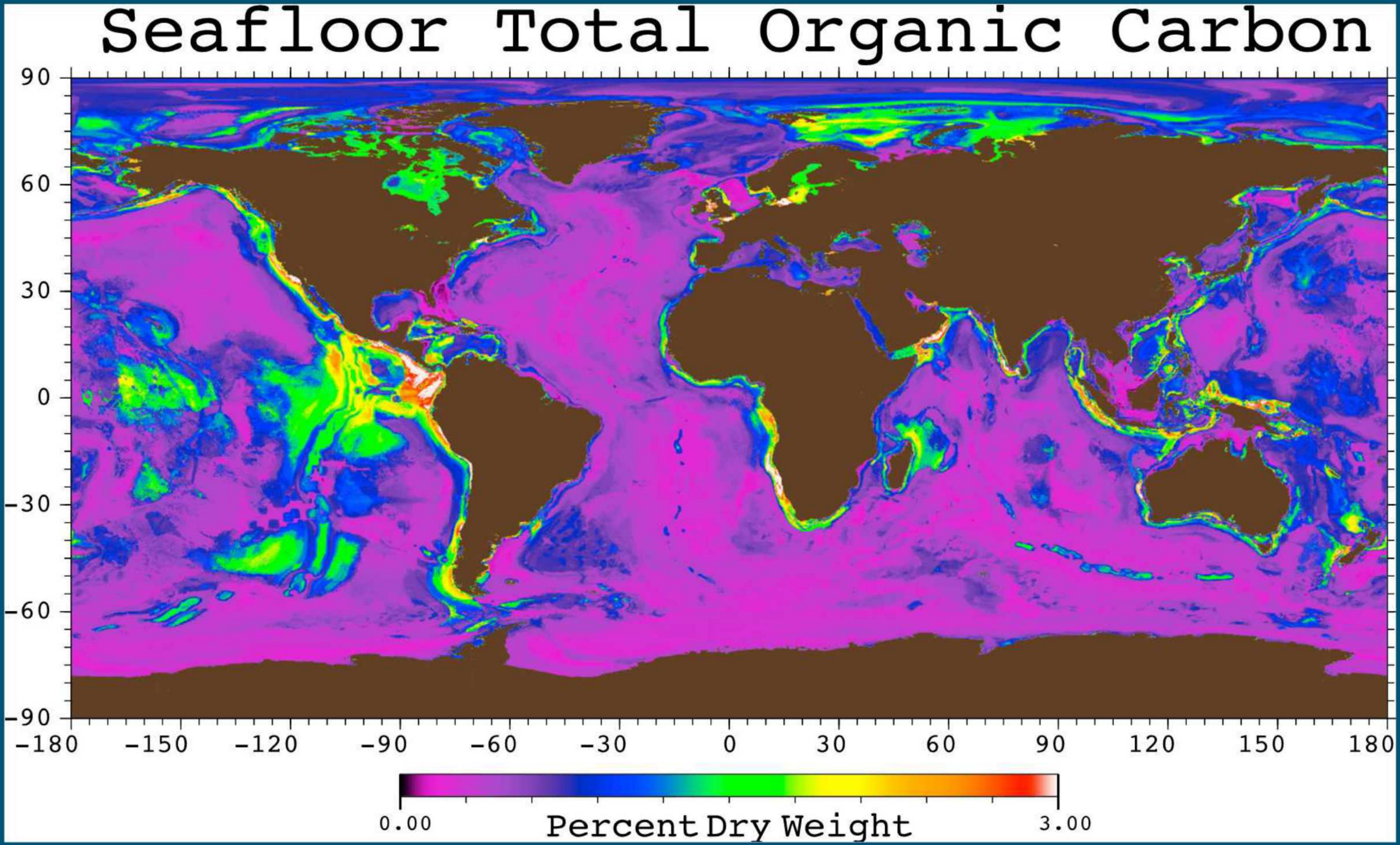
GPSM


Geospatial Machine Learning Algorithm
Find Correlations
vector of observed values
vector of predictor values
predictor 1
predictor 2
predictor 3
predictor 4
predictor n
GPSM:
Global
Predictive
Sea oor Model
U.S. NAVAL RESEARCH LABORATORY
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.

GPSM machine-learned maps



GPSM machine-learned maps



Lee et al., 2019

Machine learning ←→ Mechanistic Simulation

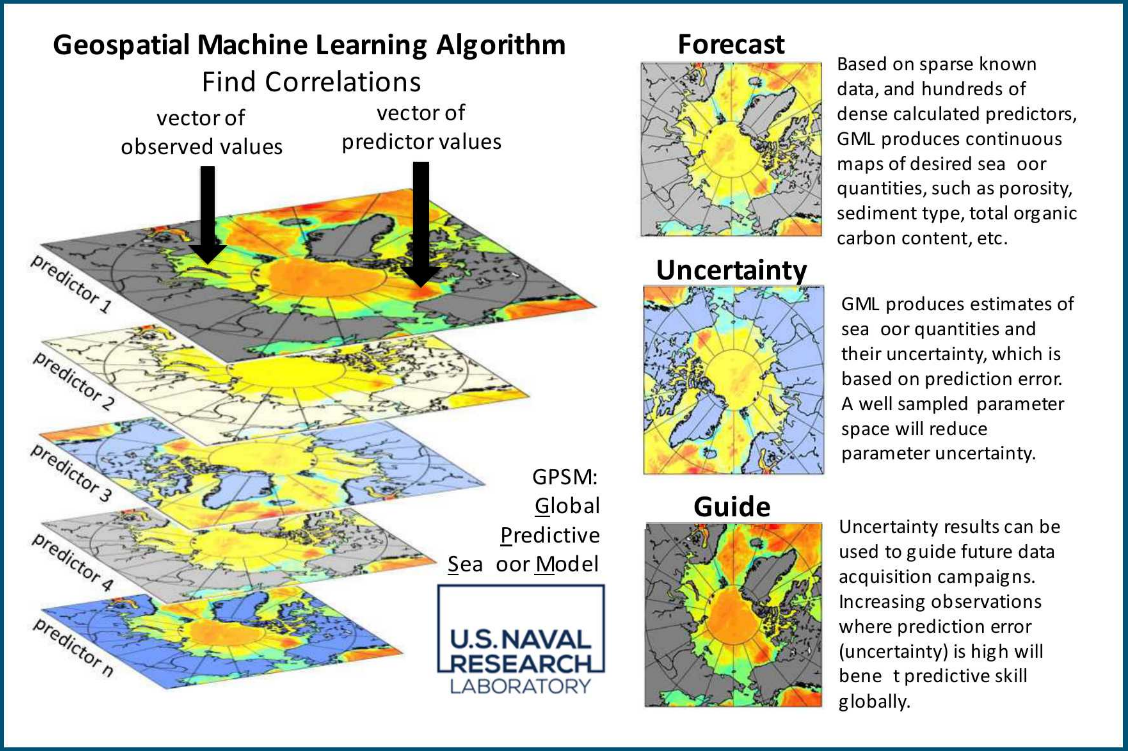
Observed Value
- e.g. permeability

Predicted value (predictand)
- e.g. permeability

- Probabilistic maps quantify uncertainties in the seafloor parameters we are interested in
- How do these uncertainties propagate downward?
- What can confidence intervals on e.g. seafloor temperature, seafloor depth, seafloor organic carbon content, or heat flux tell us about the **likelihood of shallow gas or gas hydrate**?

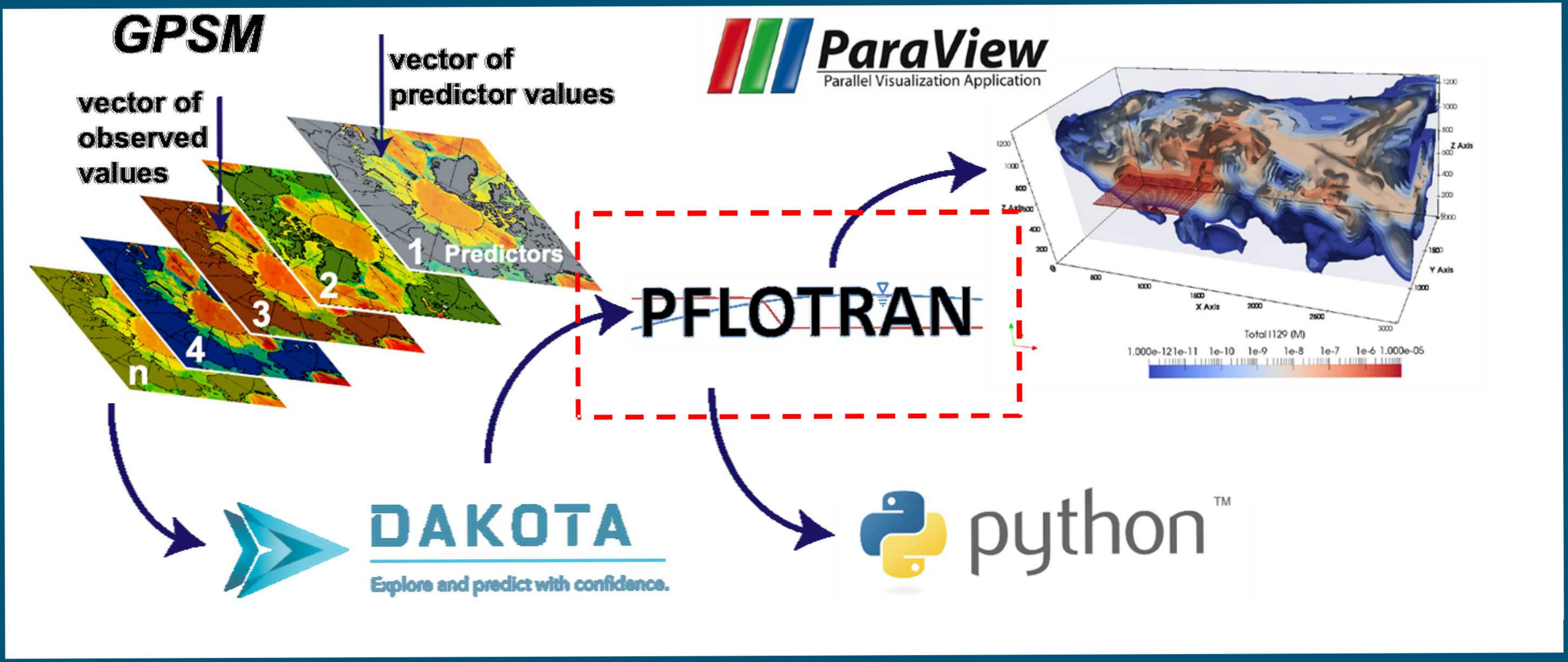
Ex.

1. ϕ
2. α
3. v_{sed}
4. dist.
5. etc.



We need thermodynamic models

Framework


GPSM
vector of observed values
vector of predictor values
1 Predictors
2
3
4
n
ParaView
Parallel Visualization Application
PFLOTRAN
DAKOTA
Explore and predict with confidence.
python

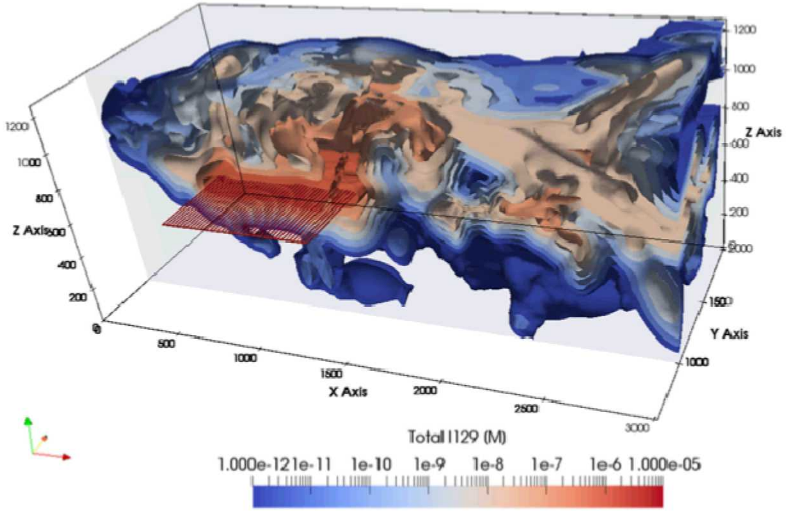
Forward modeling: open-source software development

PFLOTRAN

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

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

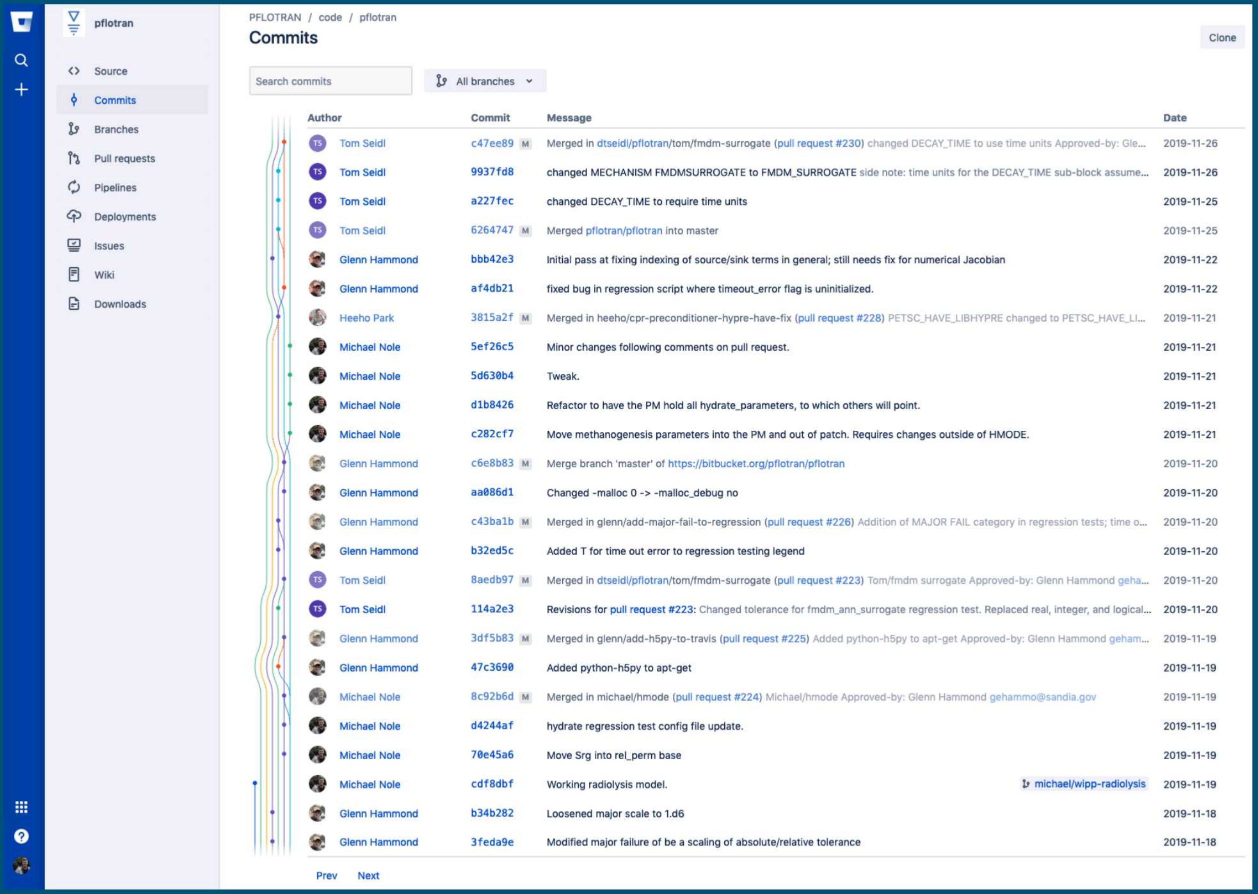
$$\frac{\partial e}{\partial t} = -\nabla \cdot \left(\rho_l H_l \boldsymbol{q}_l + \rho_g H_g \boldsymbol{q}_g - \kappa_{\mathrm{eff}} \nabla T\right) + q_e^G,$$



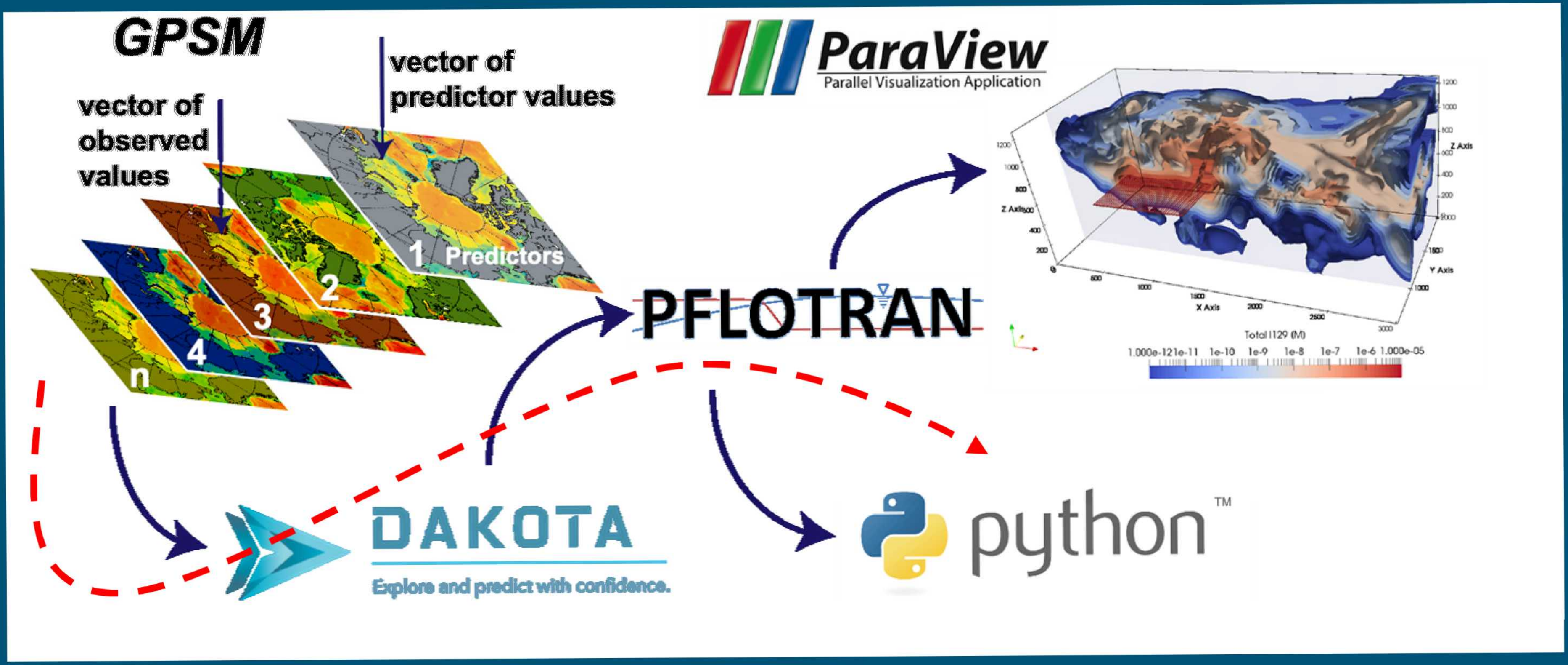
Open-source software development

PFLOTRAN

- Version control (git)
- Regression testing
- Online documentation/user's manual
- Continuous integration



Framework

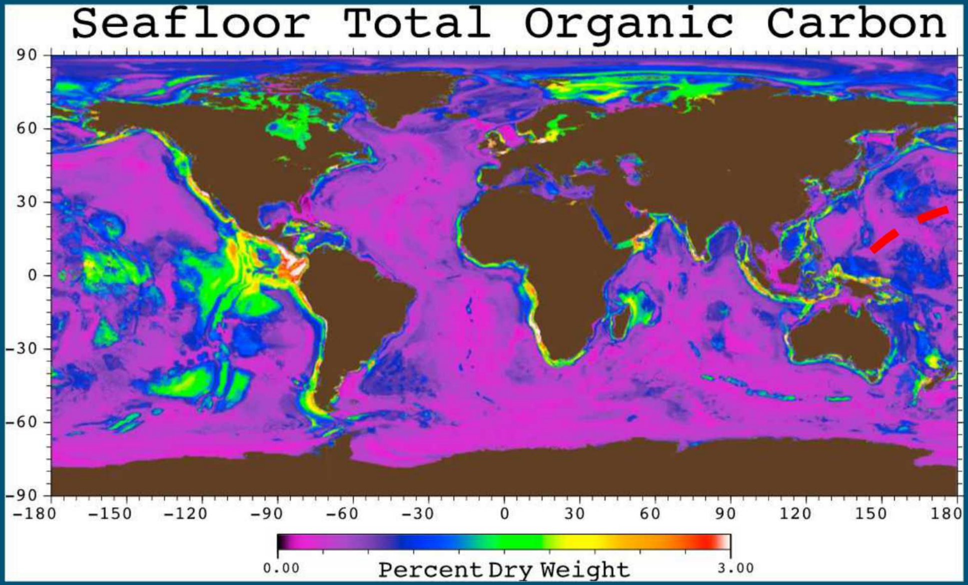

GPSM
vector of observed values
vector of predictor values
1 Predictors
2
3
4
n
ParaView
Parallel Visualization Application
PFLOTRAN
DAKOTA
Explore and predict with confidence.
python™
X Axis
Y Axis
Z Axis
Total I129 (M)

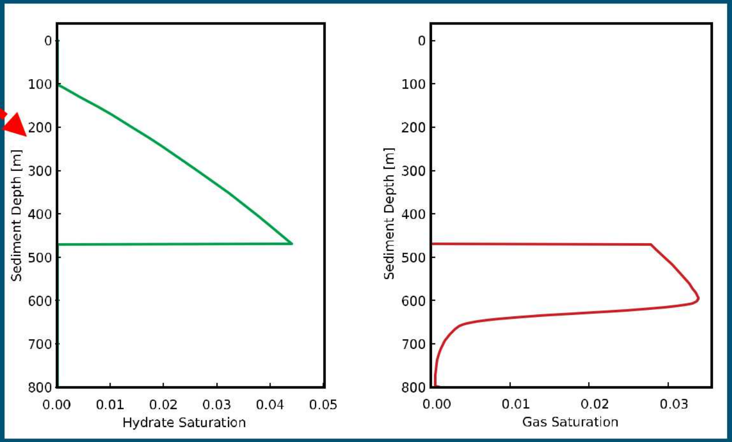
Applying the Framework

Using GPSM maps for:

- TOC
- Sedimentation rate
- Heat flux
- Bathymetry
- Seafloor temperature

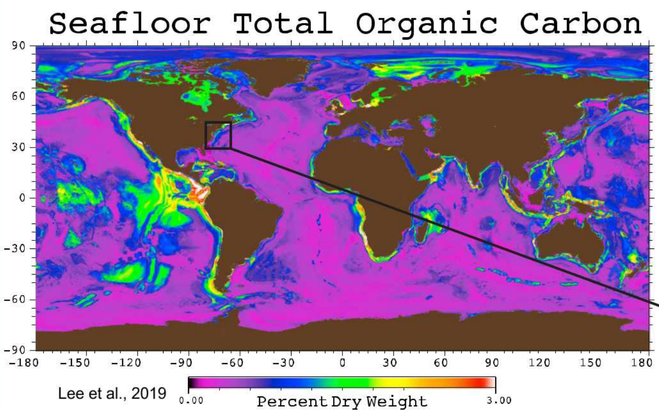
We can use mechanistic simulations to project downward into sediments





Applying the Framework

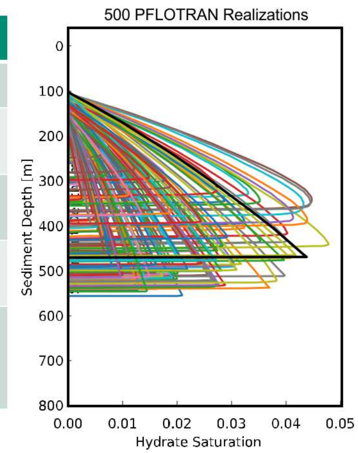
GPSM

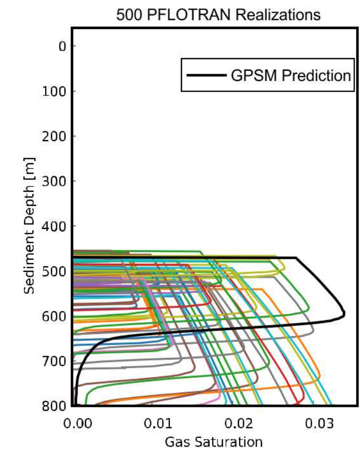


DAKOTA
Explore and predict with confidence

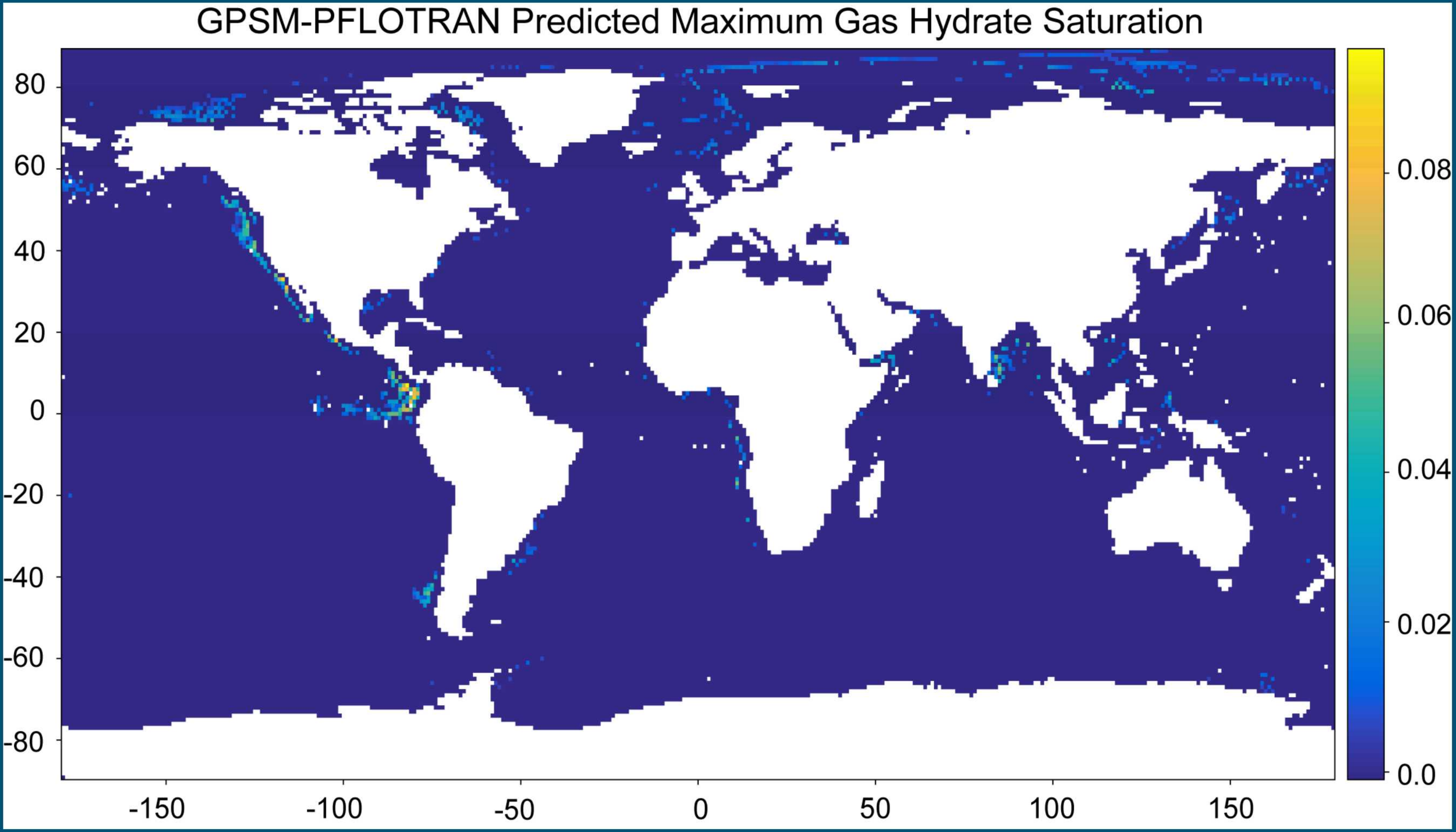
Parameter	Distribution	Min	Max	Current (GPSM)
Seafloor Depth (m)	Uniform	2760	2800	2780
Seafloor Temperature (C)	Uniform	3	5	4
Heat Flux (W/m^2)	Uniform	0.03	0.08	0.06
Sedimentation Rate (m/yr)	Log-uniform	$1x10^{-4}$	$1x10^{-3}$	$2x10^{-4}$
Seafloor Organic Carbon Fraction	Log-Uniform	$1x10^{-3}$	$2x10^{-2}$	$1x10^{-2}$

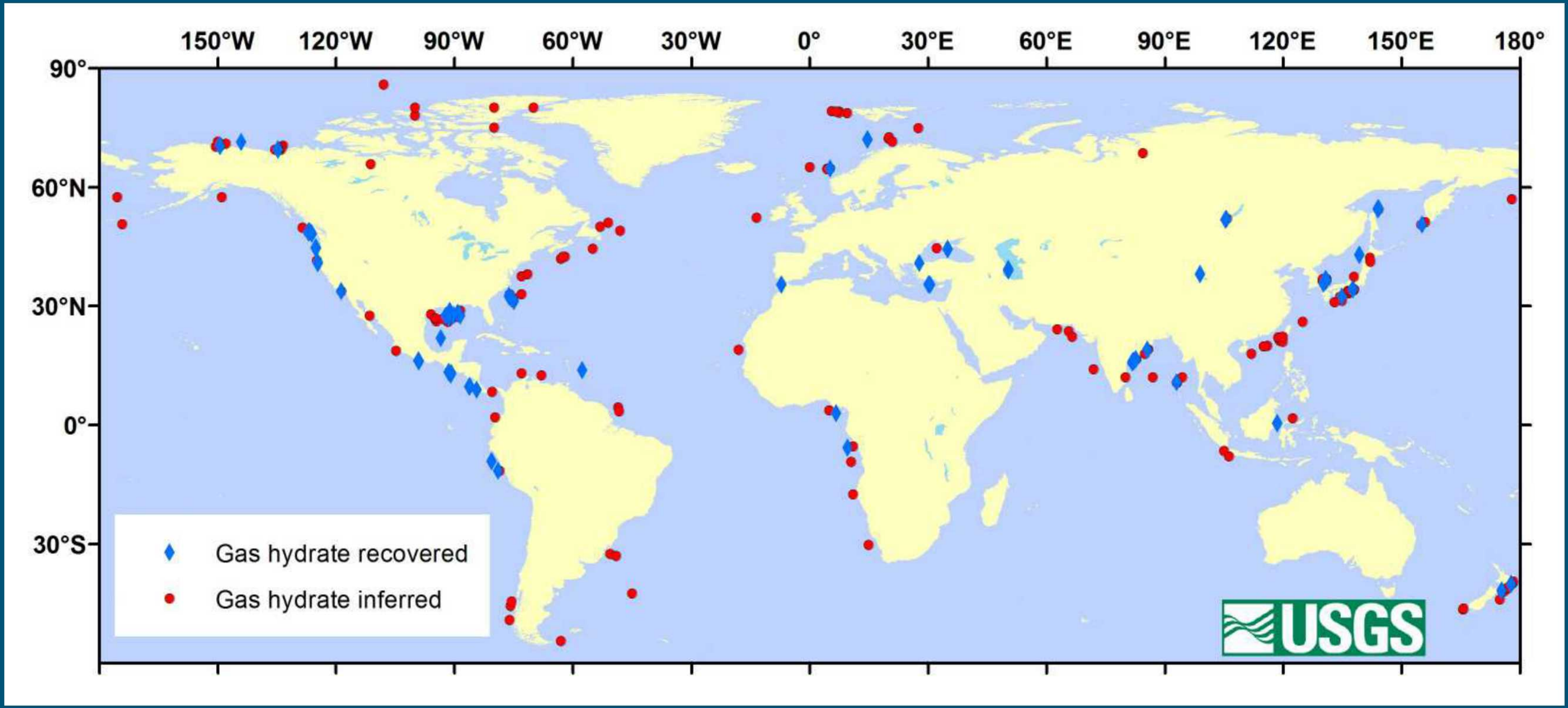
PFLOTRAN

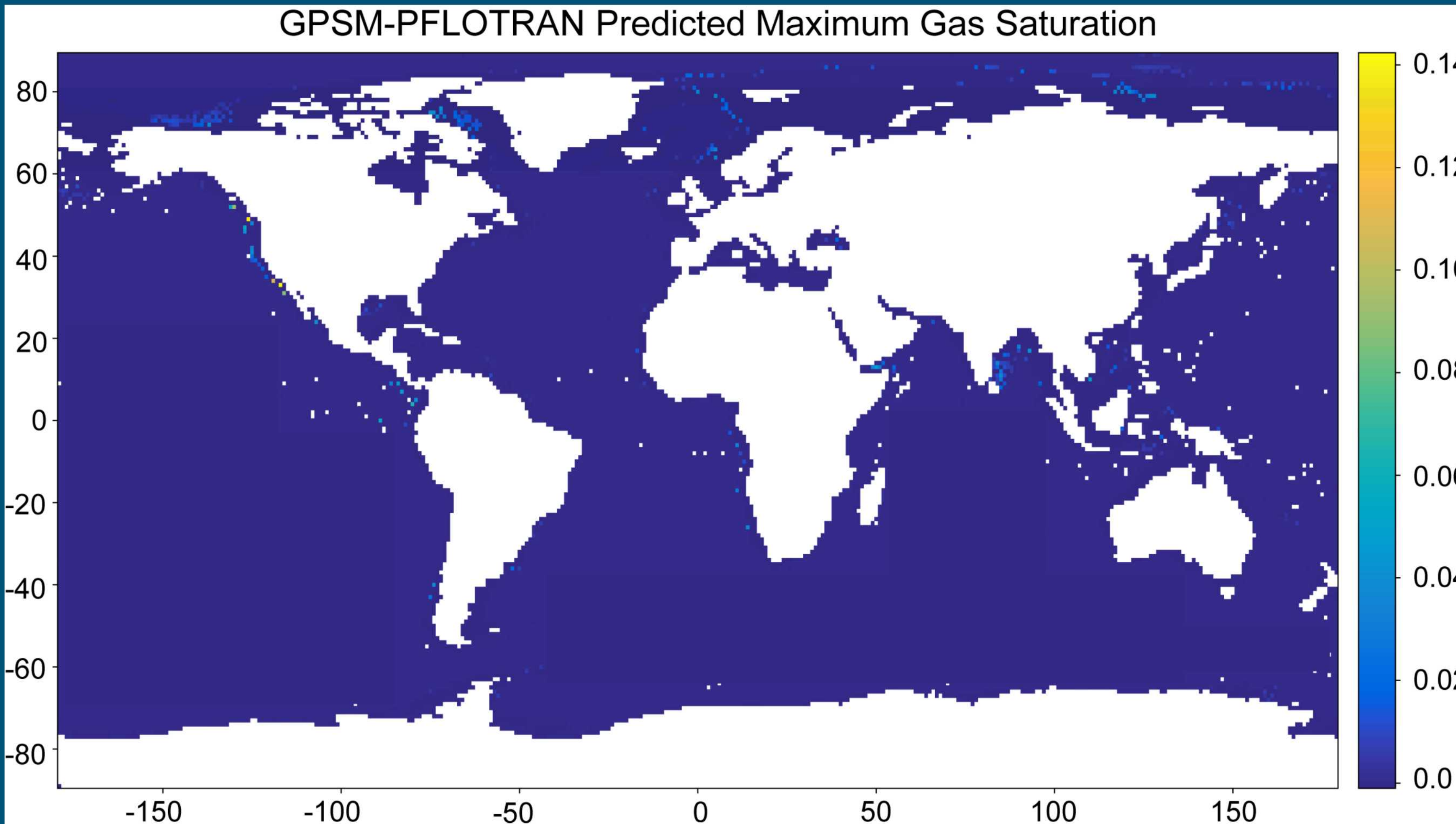




*See Frederick et al. poster at the GRC!


GPSM-PFLOTRAN Predicted Maximum Gas Hydrate Saturation
80
60
40
20
0
-20
-40
-60
-80
-150
-100
-50
0
50
100
150
0.08
0.06
0.04
0.02
0.0


150°W
120°W
90°W
60°W
30°W
0°
30°E
60°E
90°E
120°E
150°E
180°
90°
60°N
30°N
0°
30°S
Gas hydrate recovered
Gas hydrate inferred
USGS


GPSM-PFLOTRAN Predicted Maximum Gas Saturation
80
60
40
20
0
-20
-40
-60
-80
-150
-100
-50
0
50
100
150
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.0

Future Work

- Higher-resolution maps, zoomed in sub-sampling
- Quantify uncertainty
- Sub-sample, do 3D
- Mixed migration mechanisms
- Expanded capabilities (mixed hydrates [with UT Austin], geomechanics/slope stability with CSM, etc)

Affiliated posters you should check out

- Jenn Frederick
- David Fukuyama