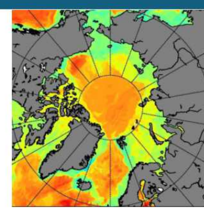
SAND2019-10401PE

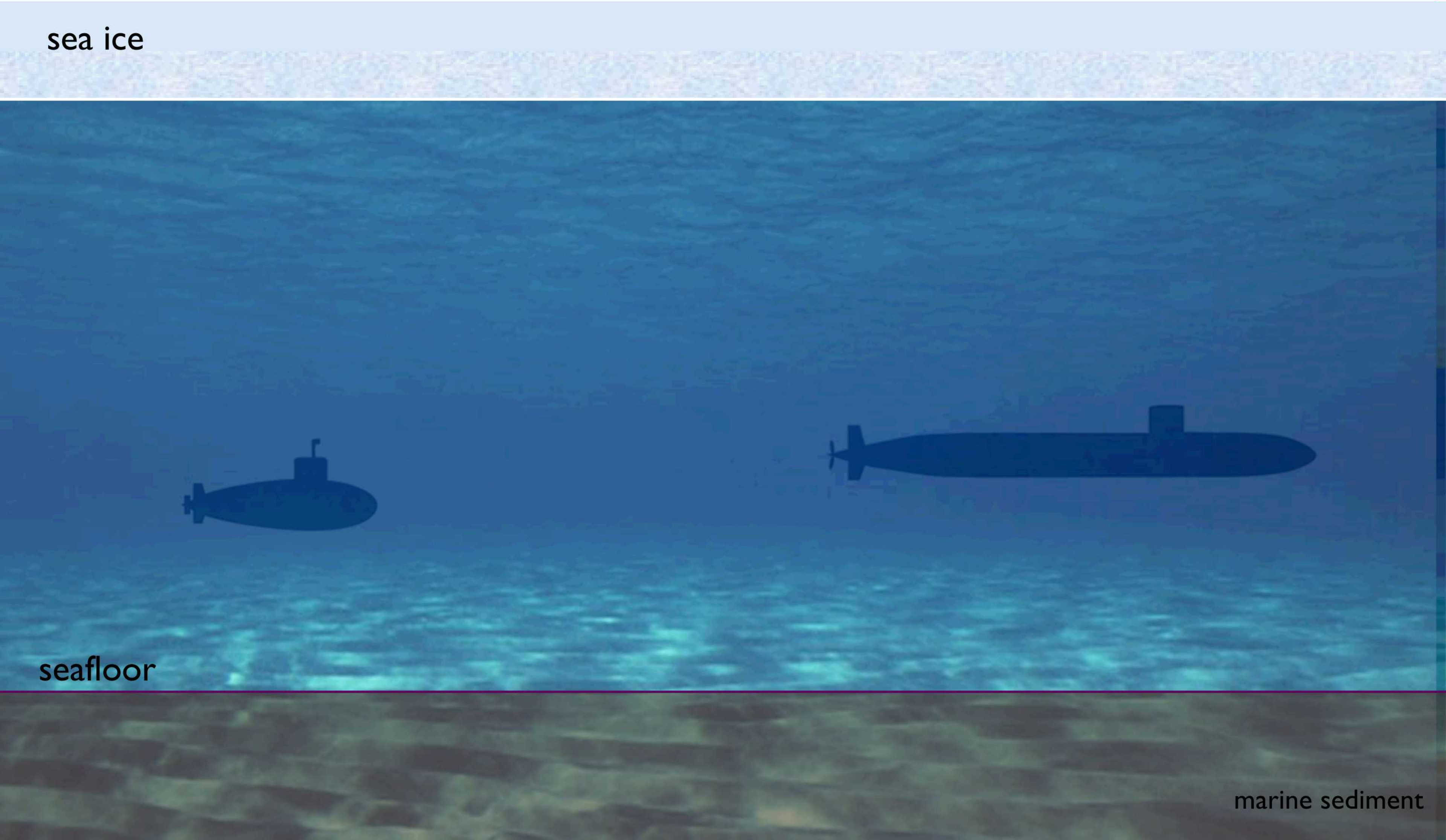
An open-source , probabilistic gas hydrate reservoir modeling framework using geospatial machine learning



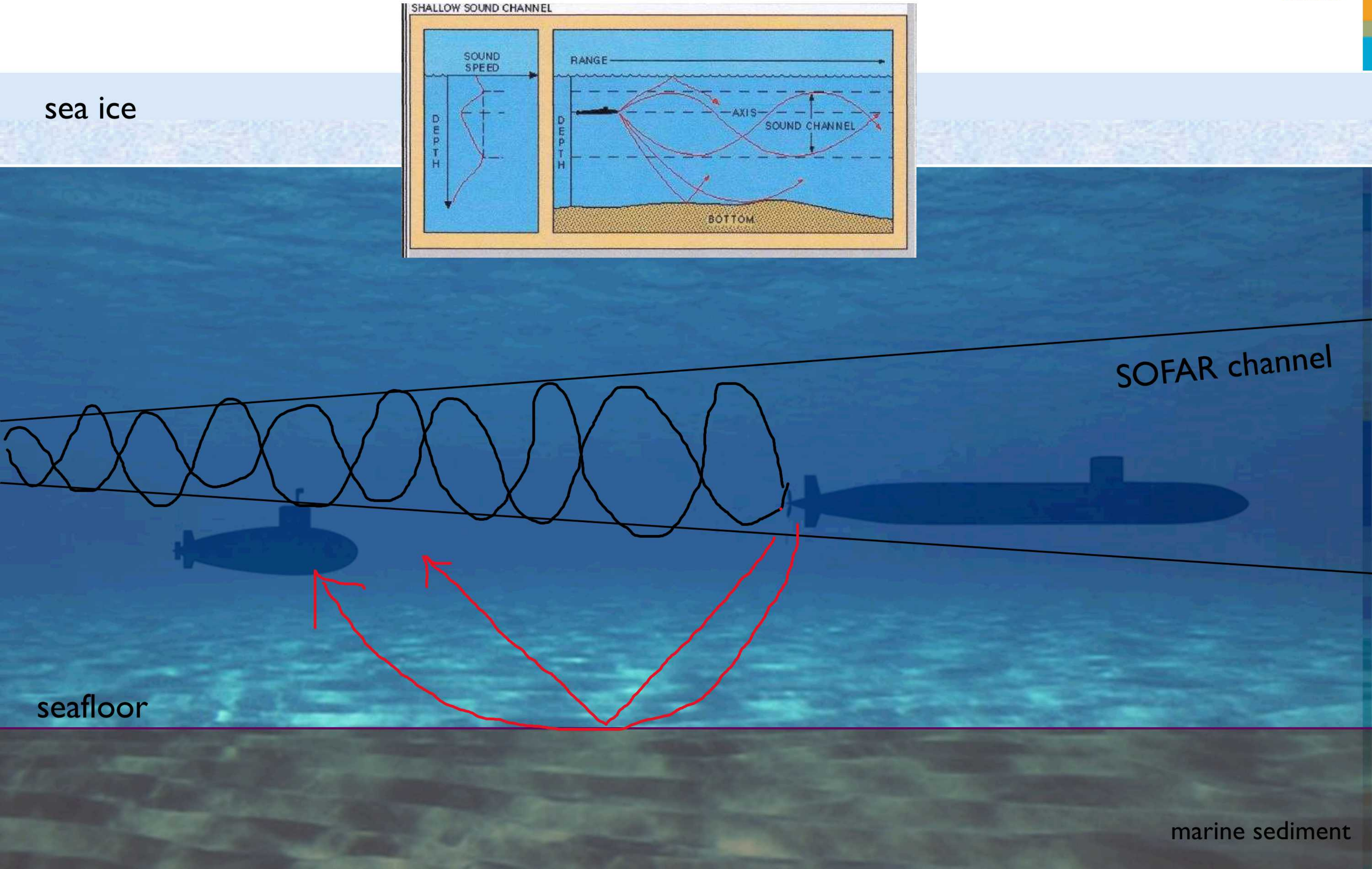
PRESENTED BY

Michael Nole, Sandia National Laboratories

What does the submarine Arctic environment look like? (simplified)



What does the submarine Arctic environment look like? (simplified)



How much do we know about these?

(blue – database)

2-D maps of:

(Green - algorithms)

Known physics

seafloor

Geologic Parameter
(in order of importance)

Gas Fraction
Porosity
Grainsize
Grain Type:
Fraction Clay
Terrigenous-Biogenous
Granitic-Basaltic
Calcareous-Siliceous
Temperature
Pressure
Salinity

Low Frequency
(< 1kHz) "Effective Medium" theory (Dvorkin-Nur, 1999)

Grain and Fluid properties as function of P,T (Mavko 2008)

High Frequency
(> 1kHz) "Squirt" theory (Biot-Stoll, 1989)

Bottom Loss & Backscatter (function of angle & frequency)

Simulated Acoustic Propagation

Geoacoustic Parameter
Soundspeed, Density, Attenuation, Backscatter

How much do we know about these?

(blue – database)
2-D maps of:

(Green - algorithms)
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?

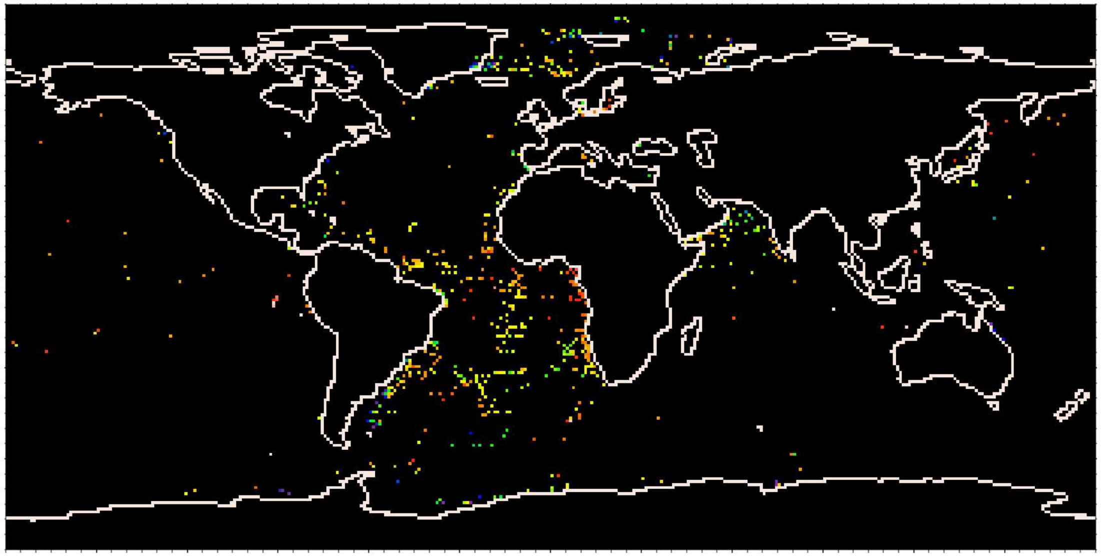
We have some geological maps, created by hand-drawing contours based on sparse observations.

We have a good idea for T, P, S on the seafloor from oceanographic models. . . . But function of depth would require heat flux measurements.

Order of importance

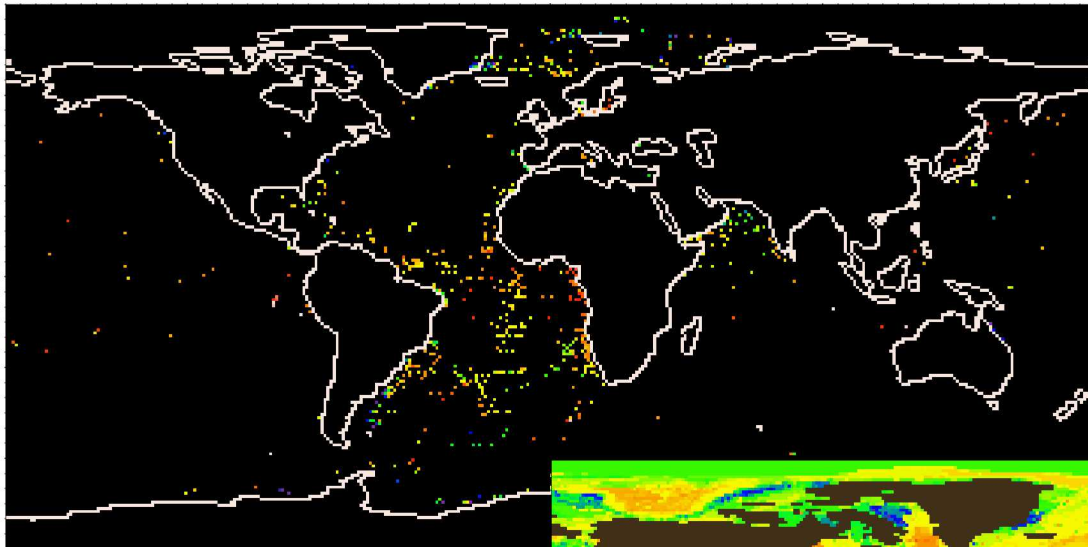
We have geospatially sparse data. . . . .

What we have: **geospatially sparse**

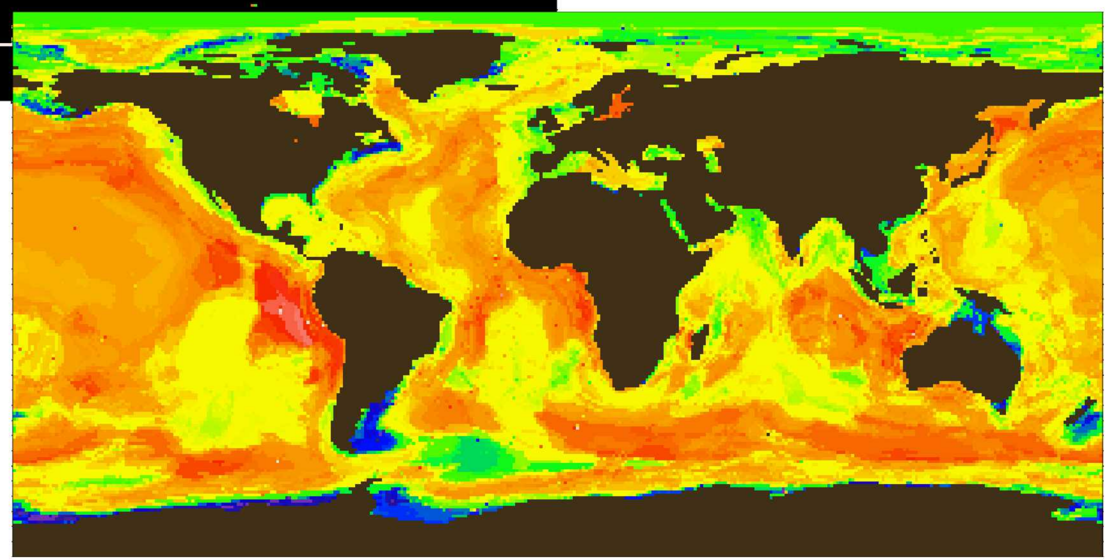


We have geospatially sparse data. . . . .

What we have: **geospatially sparse**



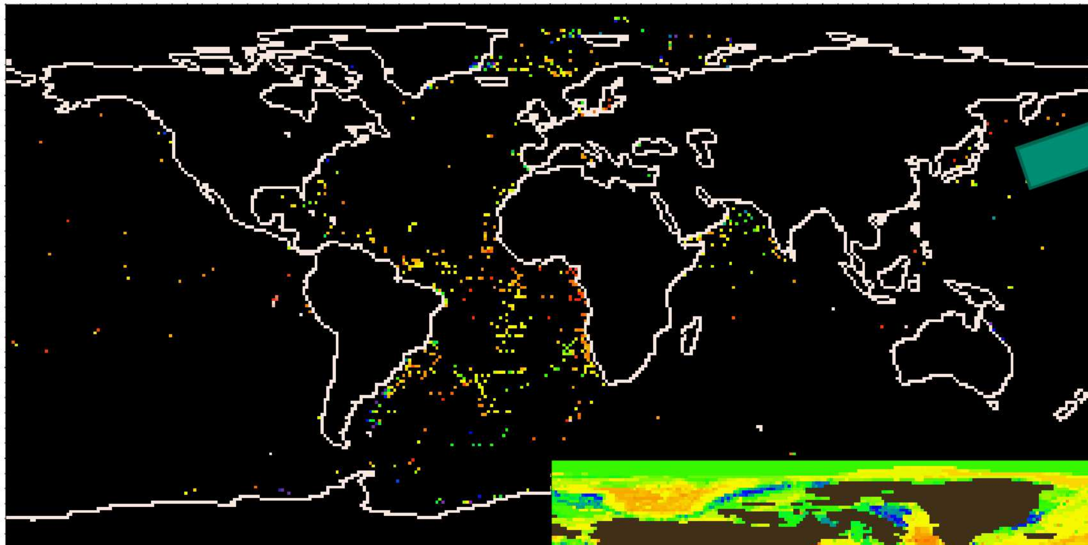
What we want:



geospatially extensive prediction

BASIC MACHINE LEARNING

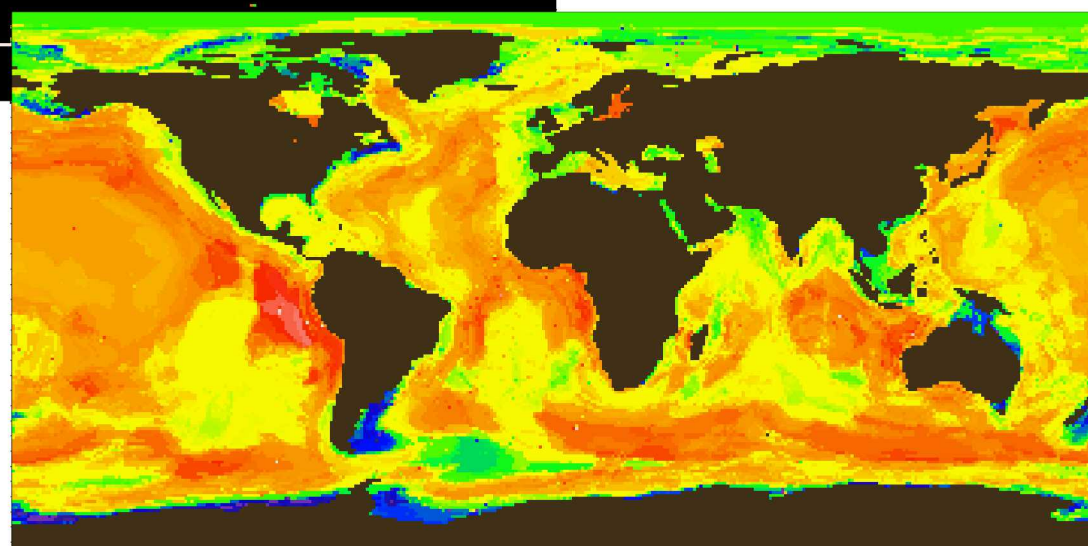
What we have: **geospatially sparse**



In a "geologic predictor space", this data may not actually be sparse at all!

Basic ML algorithms

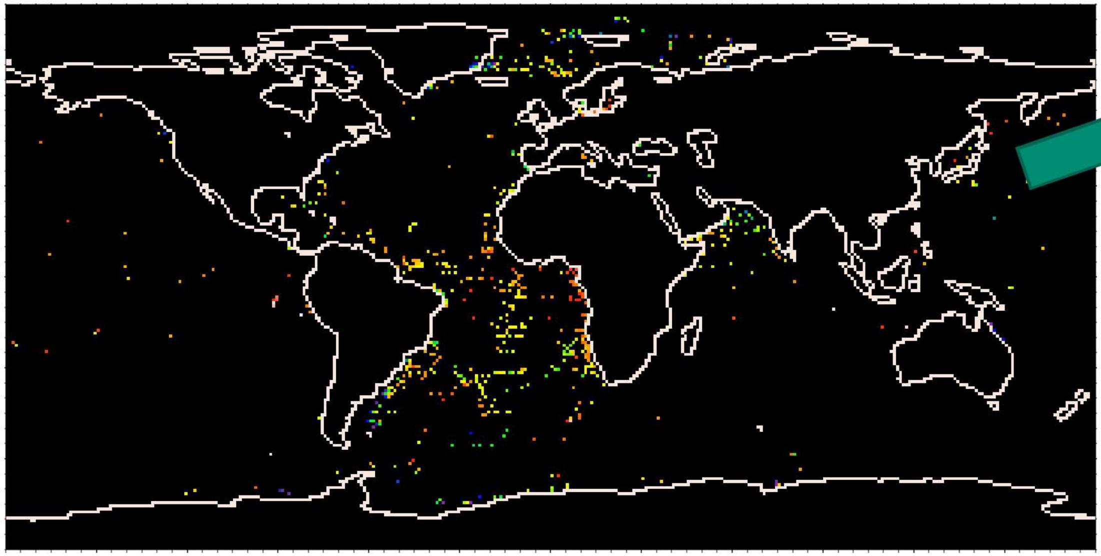
What we want:



geospatially extensive prediction

BASIC MACHINE LEARNING - KNN

What we have: **geospatially sparse**

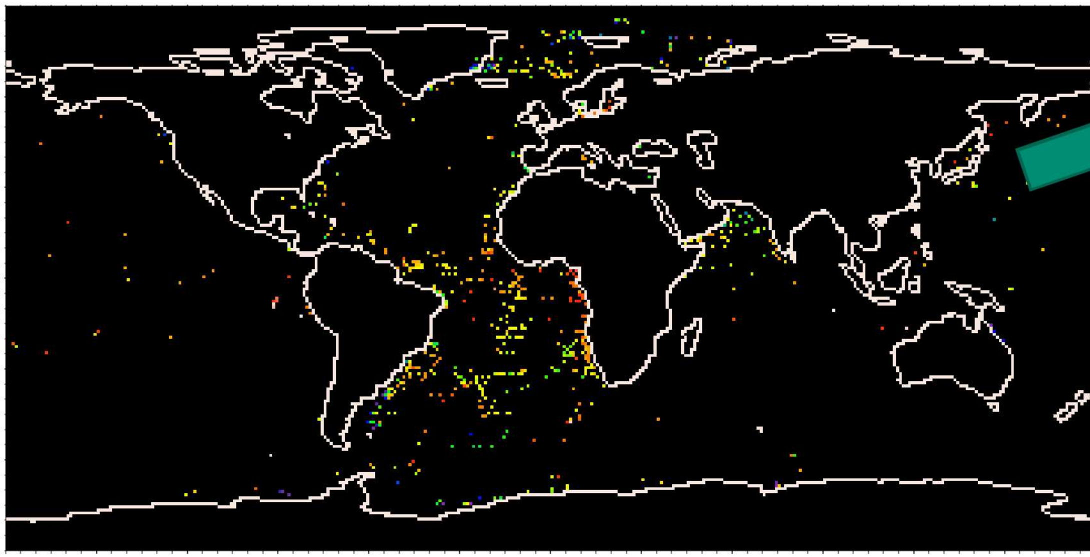


In a "geographic predictor space", this data may not actually be sparse at all!

Nearest neighbor: Finds the sample already measured that came from the most **geologically similar** environment – Not the **geographically** closest!

BASIC MACHINE LEARNING - KNN

What we have: **geospatially sparse**



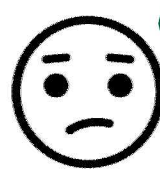
In a "geographic predictor space", this data may not actually be sparse at all!

"dense" predictors:
water depth, bottom current, dist. from river mount

Pros: No binning, no fitting of models, virtually no adjustments, statistically rigorous – **Black Box**

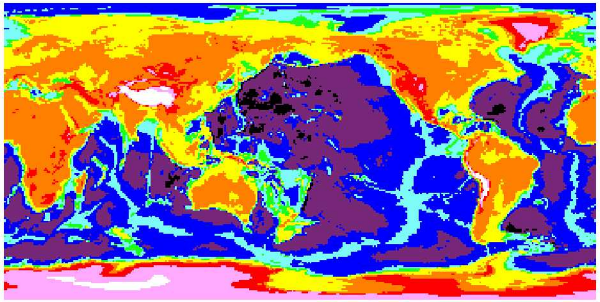
Cons: The model space must be well sampled. The system can only predict what it has seen before.

"The last time I saw a sediment: at this water depth, with this bottom current, this far from a river mouth, (etc.) the bearing strength was _x_."

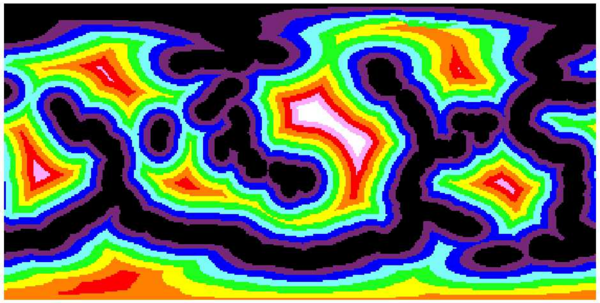


To get Predictands, we need Predictors. . .

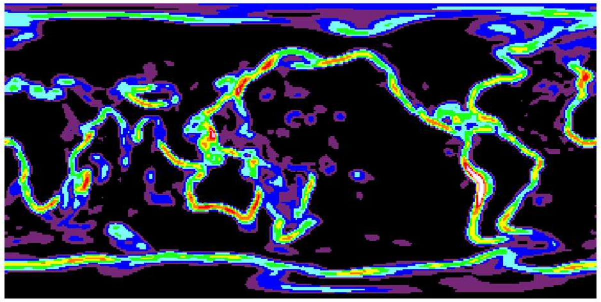
Published grids
(Elevation, Crustal Models, remote sensing, previous predictions, etc.)


ELEVATION (water depth)

Distance to; coastline, ridge, trench, transform, river mouth, etc.

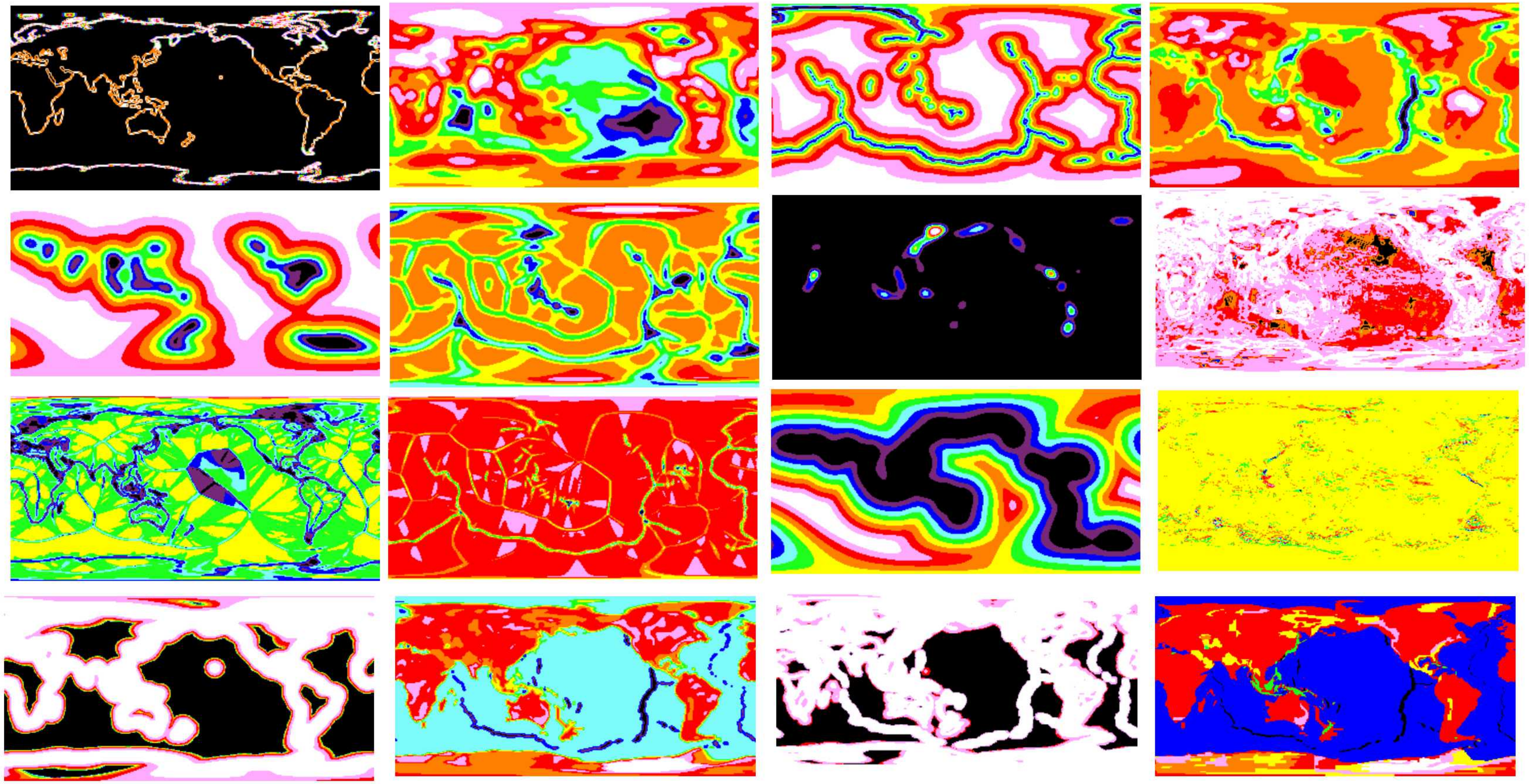

DISTANCE TO SPREADING RIDGE

Also statistics; Mean, and absolute deviation over various radii.


SEAFLOOR SLOPE

To get Predictands, we need Predictors. . .

Here are 16 out of about 4000, NRL has generated at 1x1 arc degree pitch

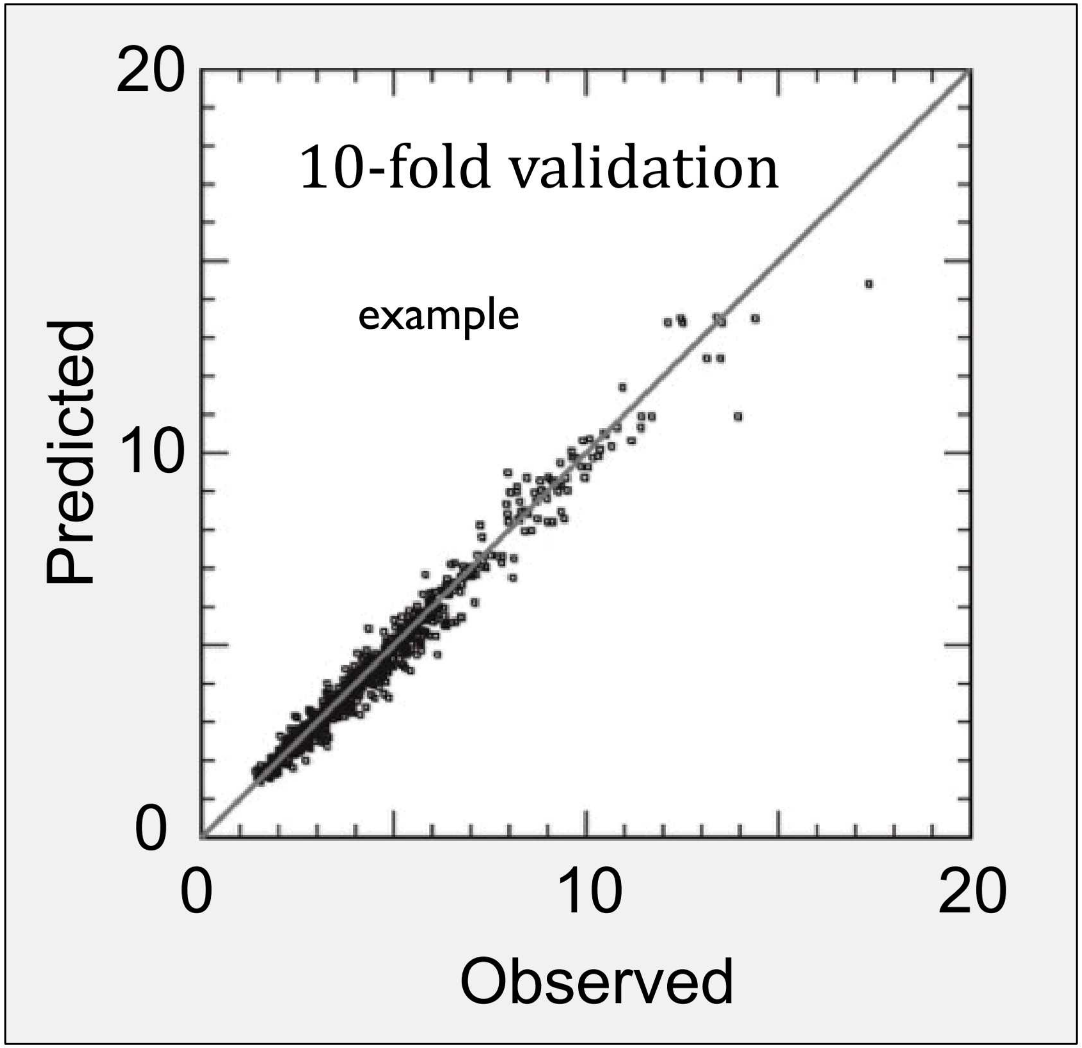


Validation & Estimating Uncertainty

How well can we predict some withheld observations?

Predicted values were obtained for each withheld point using the set of remaining points as potential nearest neighbors.

Error (predictive skill) can give you an estimate of uncertainty.



What determines seabed acoustic properties?

(blue – database)

2-D maps of:

seafloor

Geologic Parameter

(in order of importance)

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Porosity

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Grain Type:

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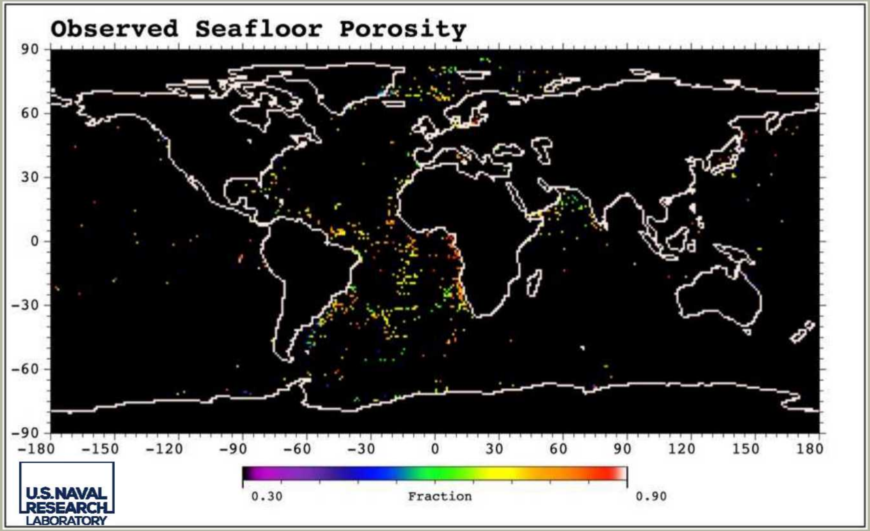
Temperature

Pressure

Salinity



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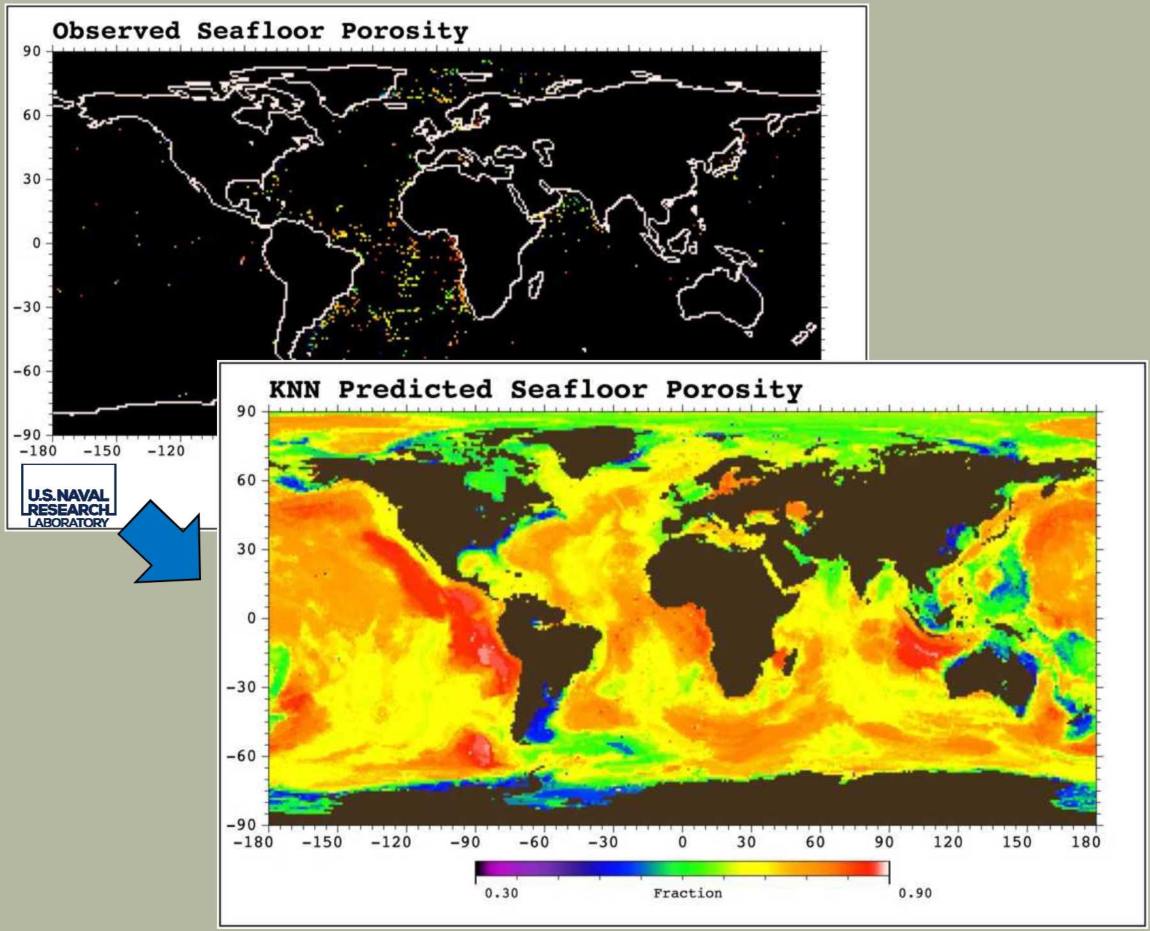

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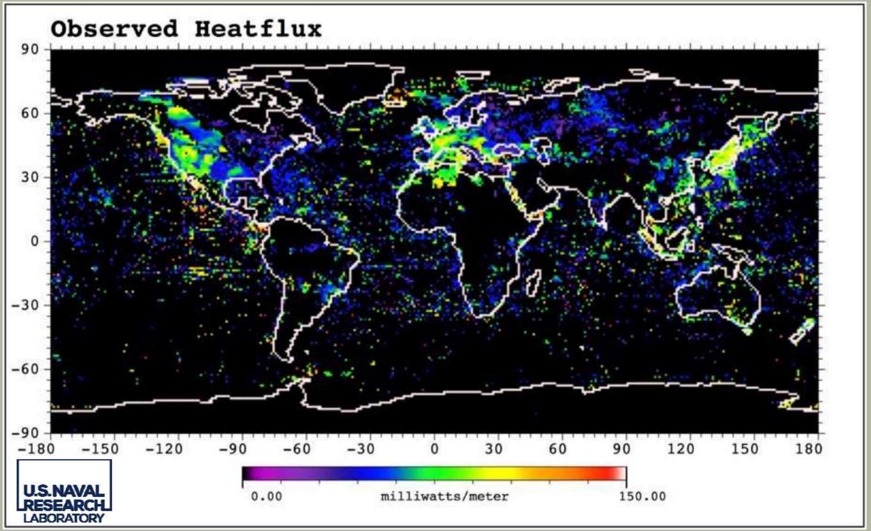

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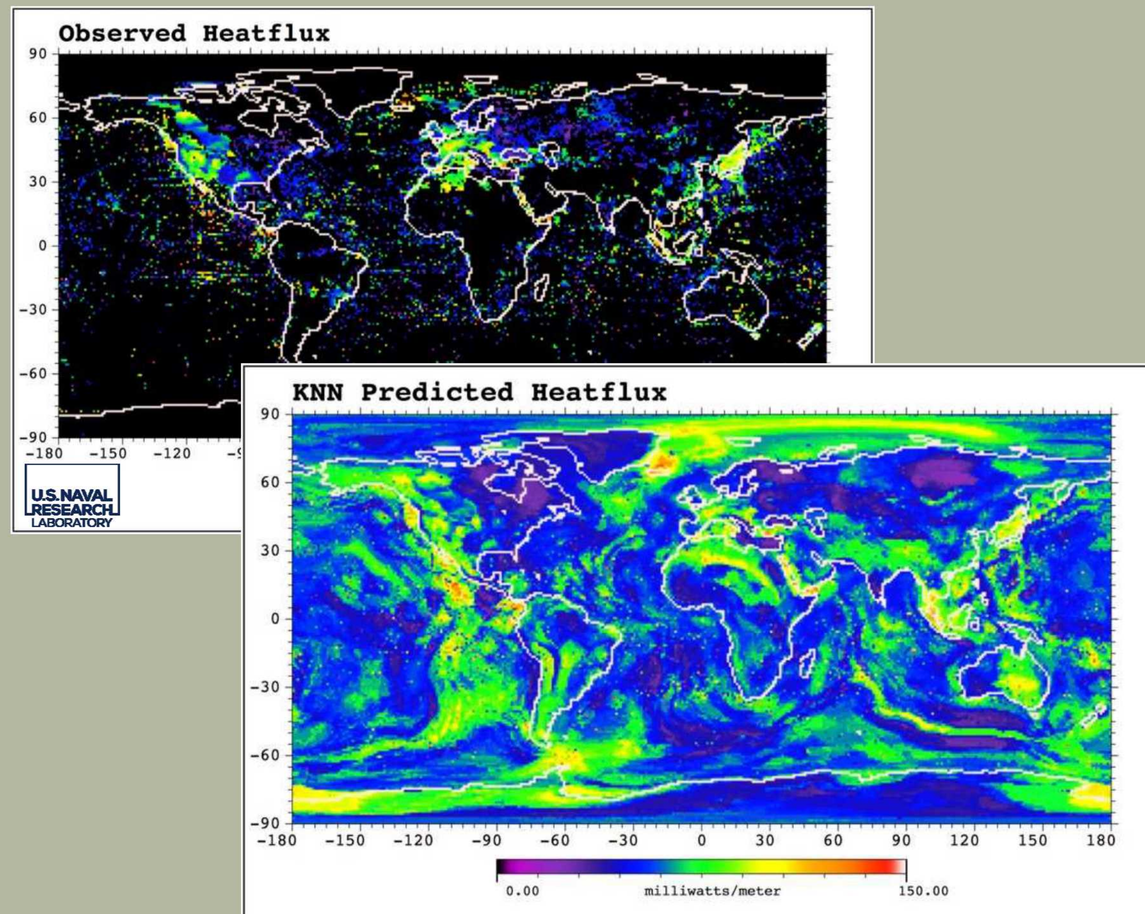

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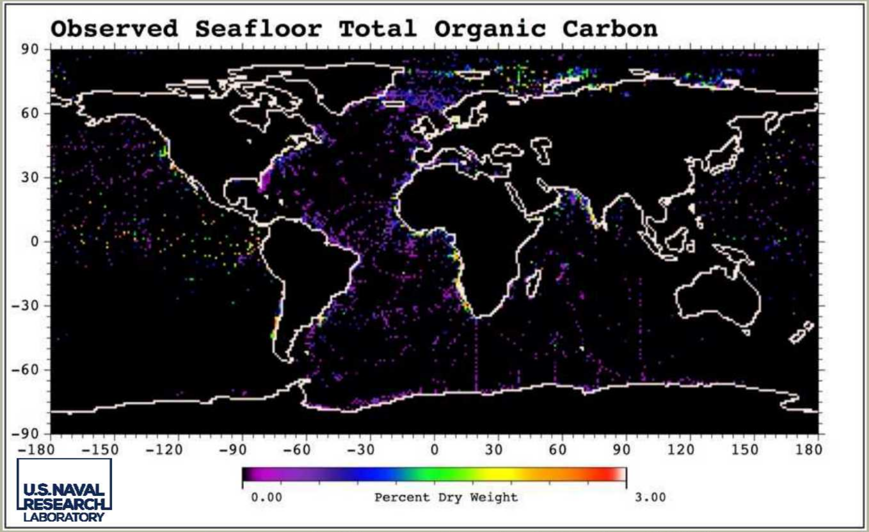

Lee, et al., Biogeochemical Cycles, 2019

We started by using total organic carbon as a proxy to predicting likelihood of free gas.

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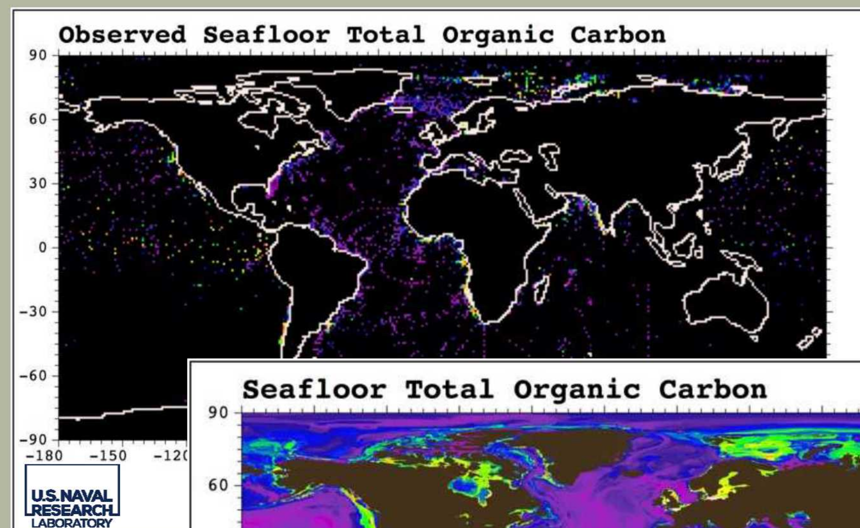

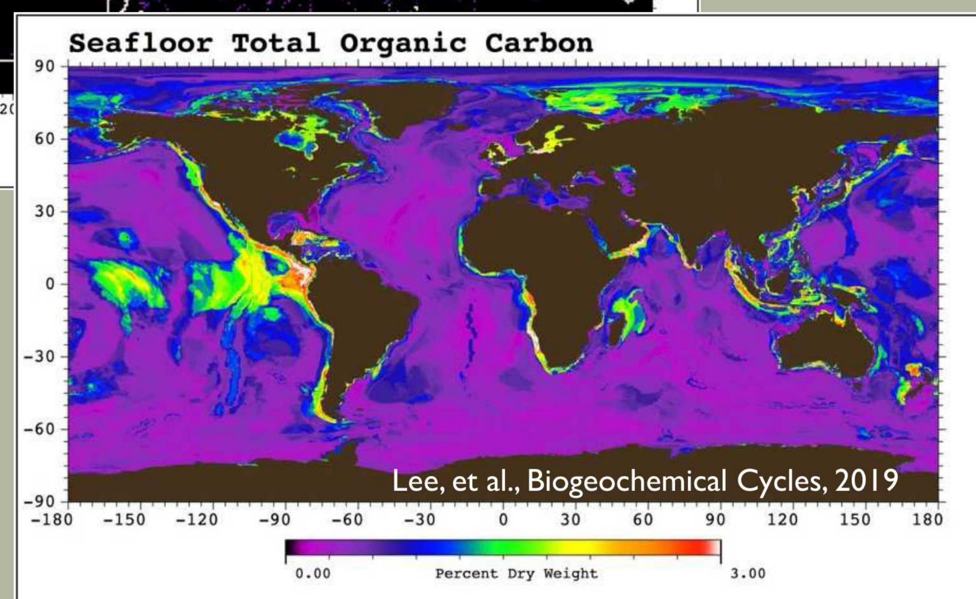

You may look at the validation, and think, "That Doesn't Look So Good…"

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2-D maps of:

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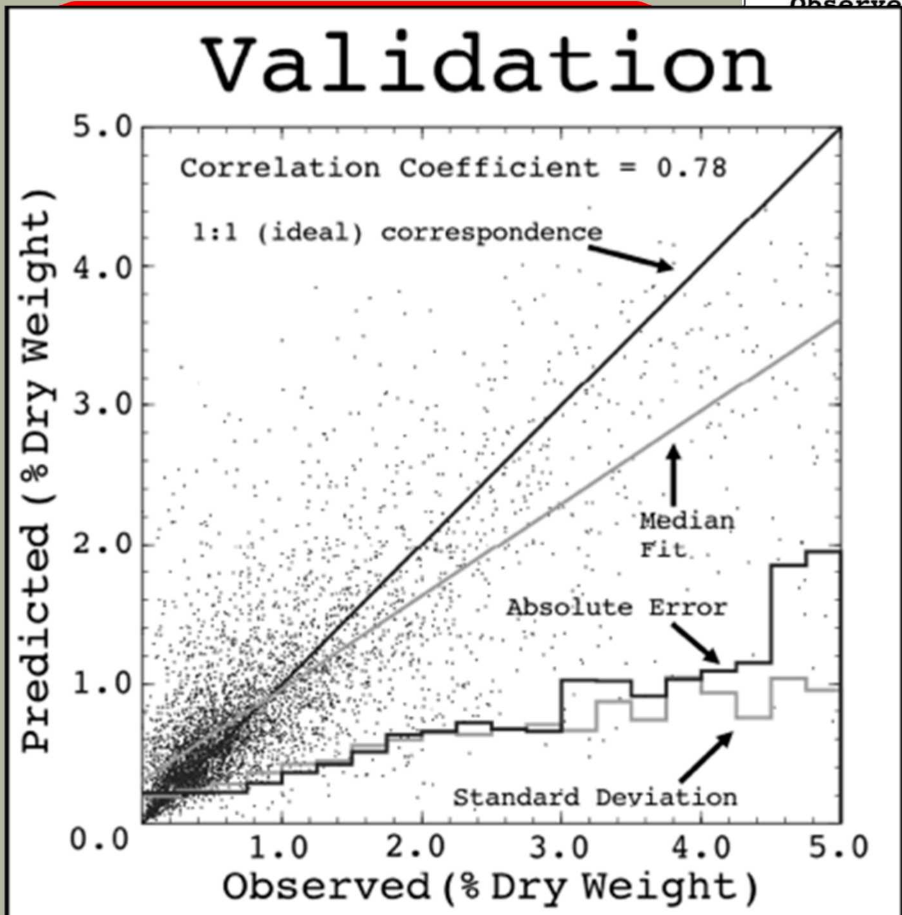

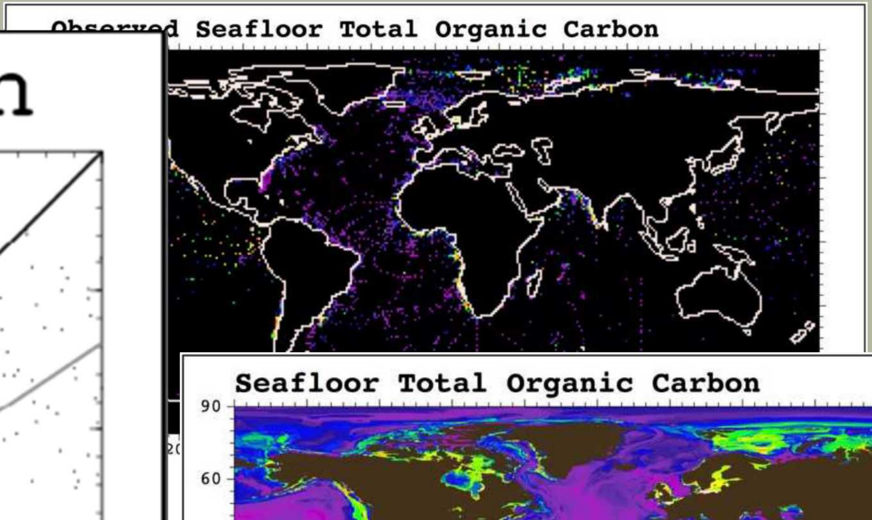

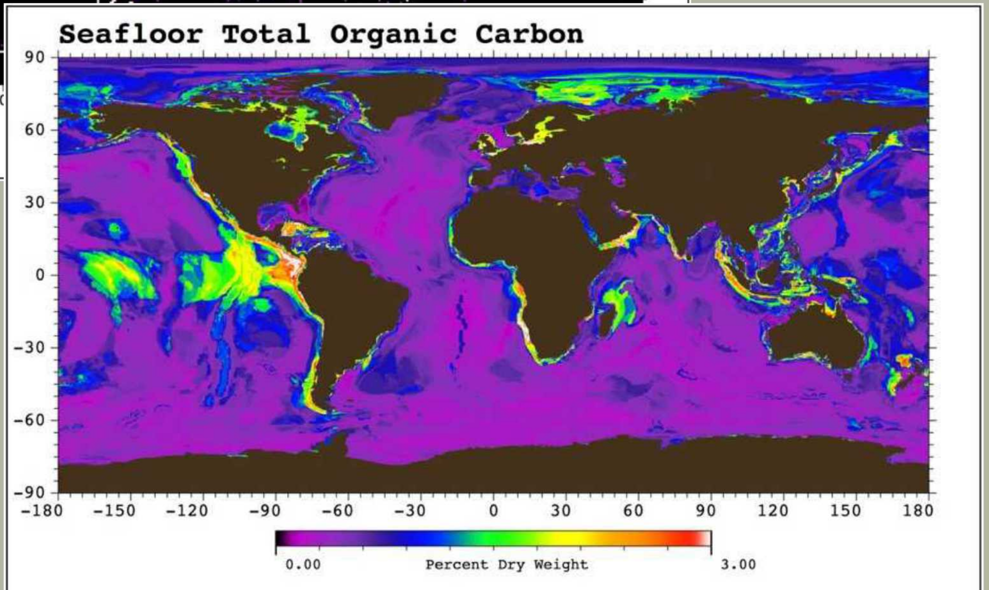

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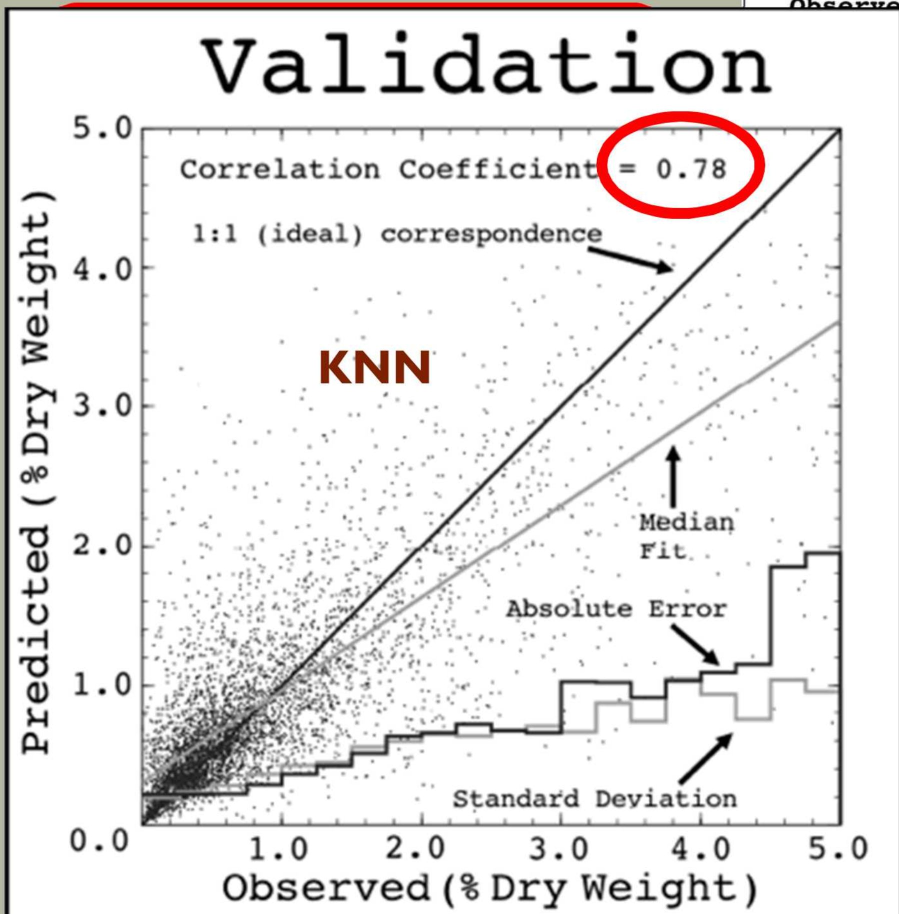
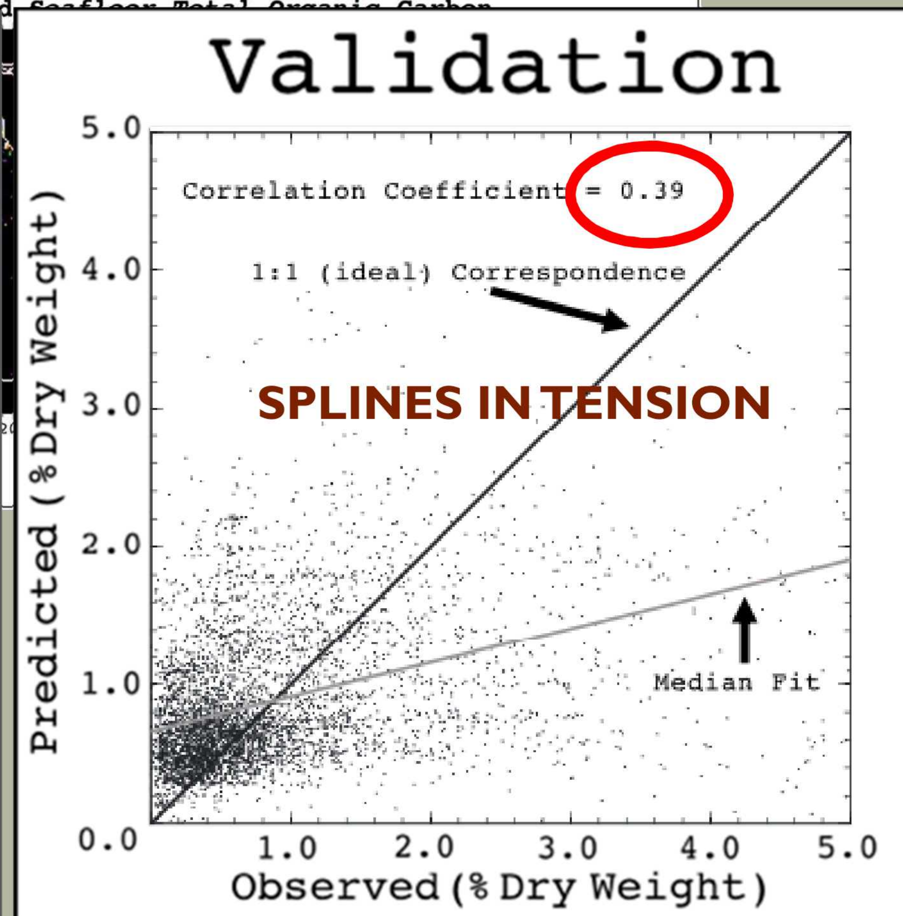
Relative to what?

(blue – database)

2-D maps of:

seafloor Lee, et al., Biogeochemical Cycles, 2019





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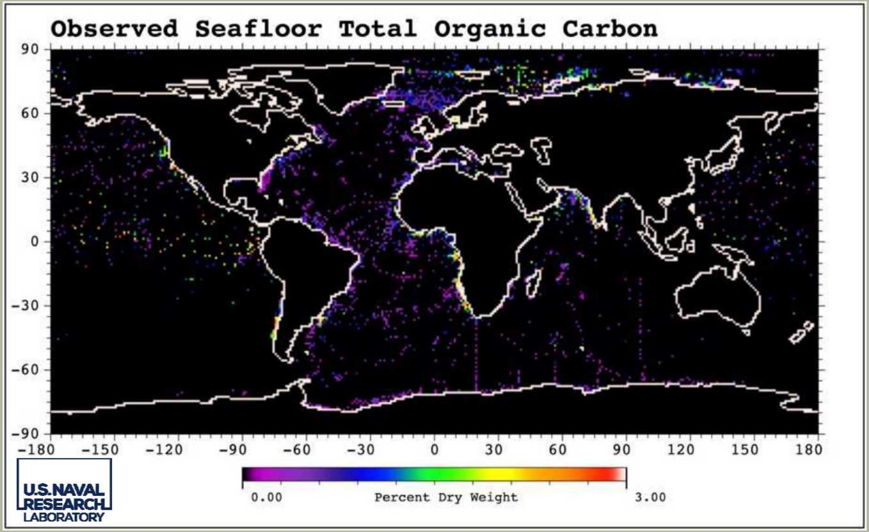

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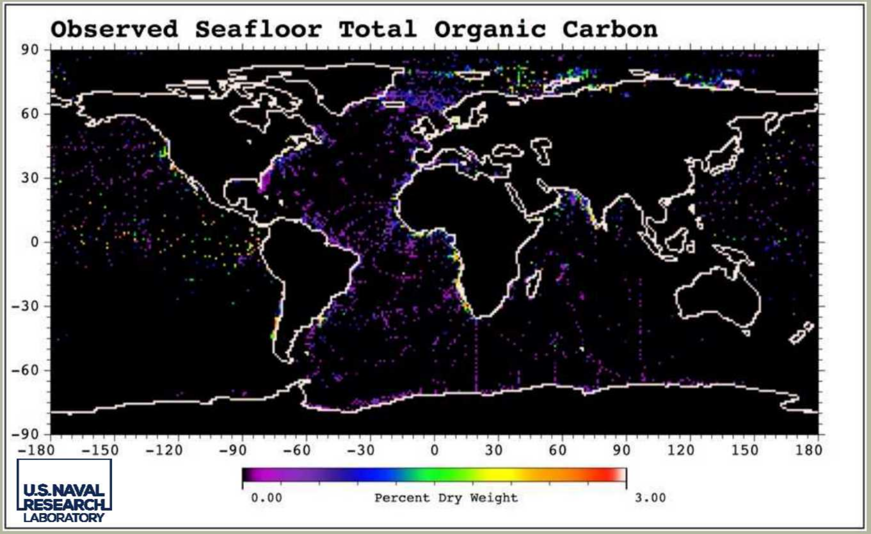

~~We started by using total organic carbon as a proxy to predicting likelihood of free gas.~~

Let's try to actually model it, using a hybrid GML + physical modeling technique!

What determines seabed acoustic properties?

(blue – database)

2-D maps of:

seafloor

Geologic Parameter

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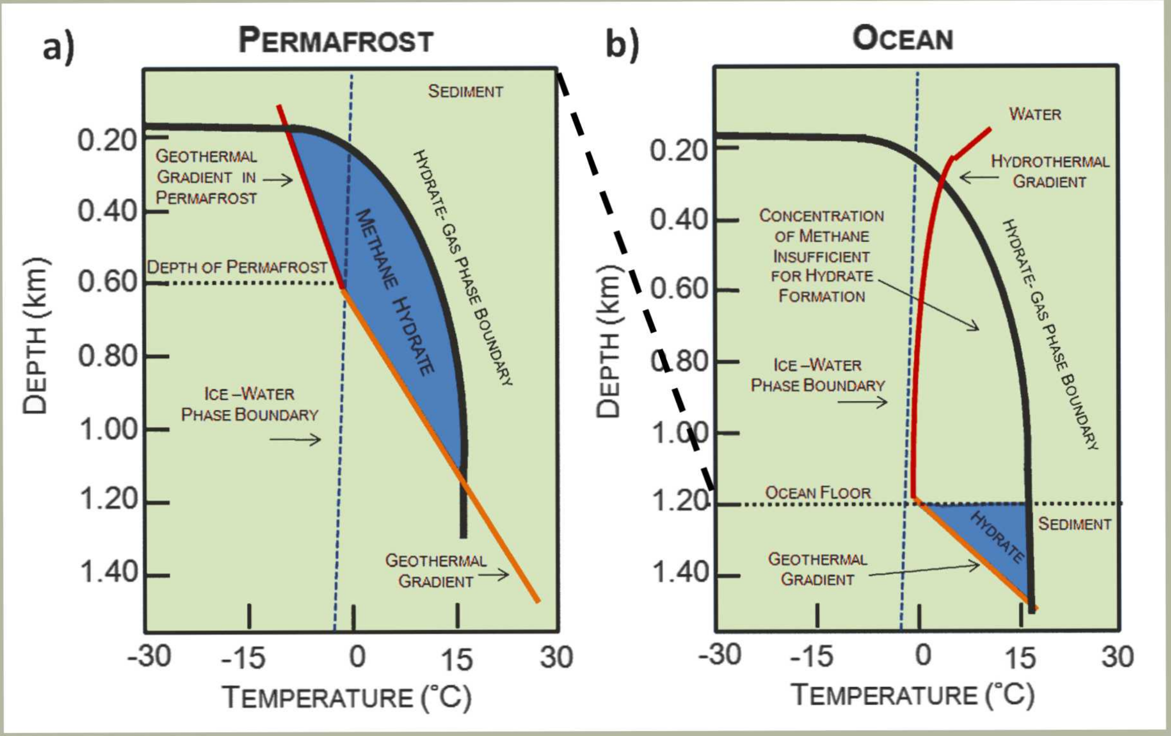
Methane and gas hydrate stability:



Need a thermodynamic numerical model for this…

1 Sandia National Laboratories
2 U.S. Naval Research Laboratory
3 University of Texas at Austin

Forecasting Marine Sediment Properties On and Near the Arctic Shelf with Geospatial Machine Learning

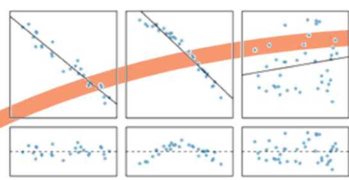
Jennifer M. Frederick[1], Warren Wood[2], Michael Nole[1], Ben Phrampus[2], Hugh Daigle[3], Hongku Yoon[1], Brian Young[1], and Ken Sale[1]

Forecast seafloor conditions via a novel integration of geospatial machine learning and physical models:

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!

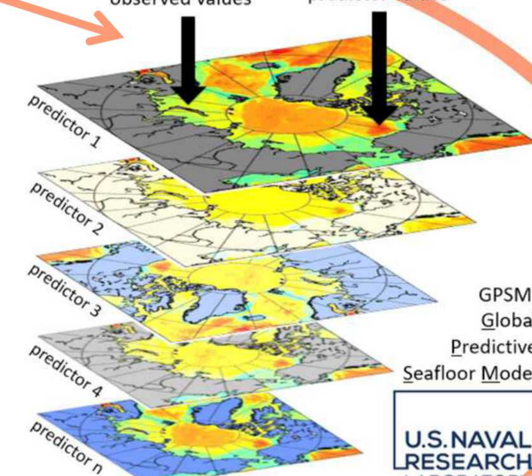
Feature Selection & Validation



Only use the best predictors, based on individual predictive skill via 10-fold validation. Predictors must perform better than random noise.

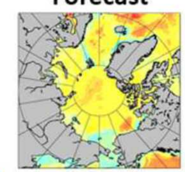
Geospatial Machine Learning Algorithm

Find Correlations



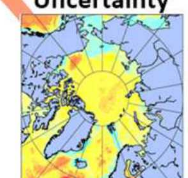
GPSM: Global Predictive Seafloor Model

Forecast



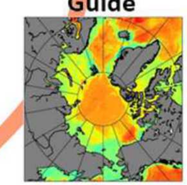
Based on sparse known data, and hundreds of dense calculated predictors, GML produces continuous maps of desired seafloor quantities, such as porosity, sediment type, total organic carbon content, etc.

Uncertainty



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

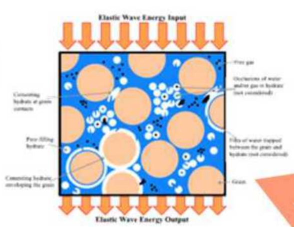
Guide



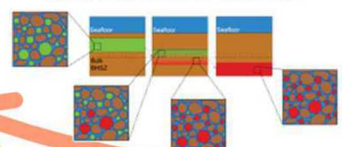
Uncertainty results can be used to guide future data acquisition campaigns. Increasing observations where prediction error (uncertainty) is high will benefit predictive skill globally.

Integrate physical models to produce predictions of seafloor geo-acoustic and geo-mechanical properties.

Rock physical models can use GML-predicted seafloor parameters to map geo-acoustic and geo-mechanical sediment properties.



Better estimates of sediment grain size and thermal properties will help map methane gas phase diagrams.



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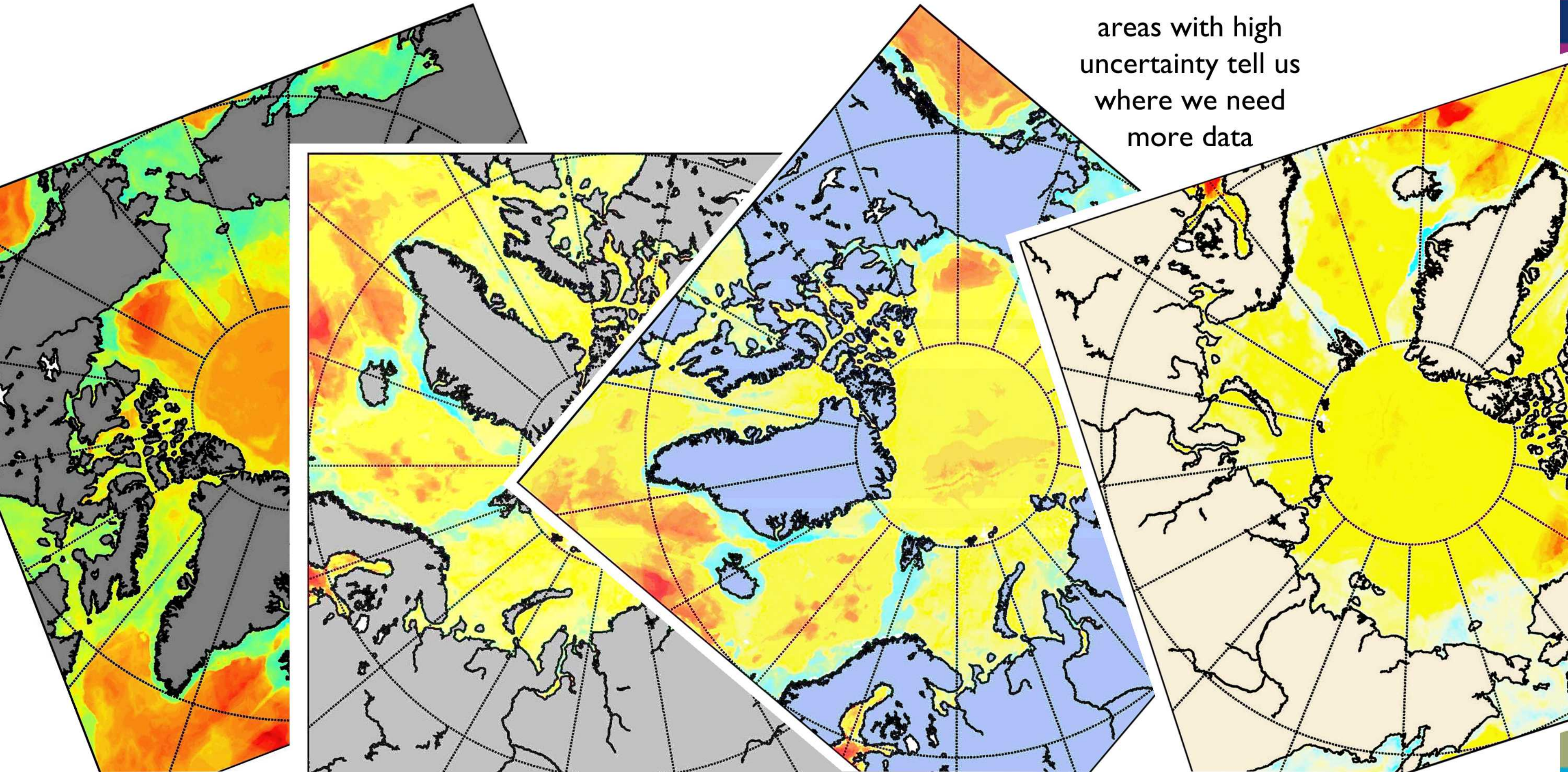
Resulting in Probabilistic Maps

U.S.NAVAL RESEARCH LABORATORY

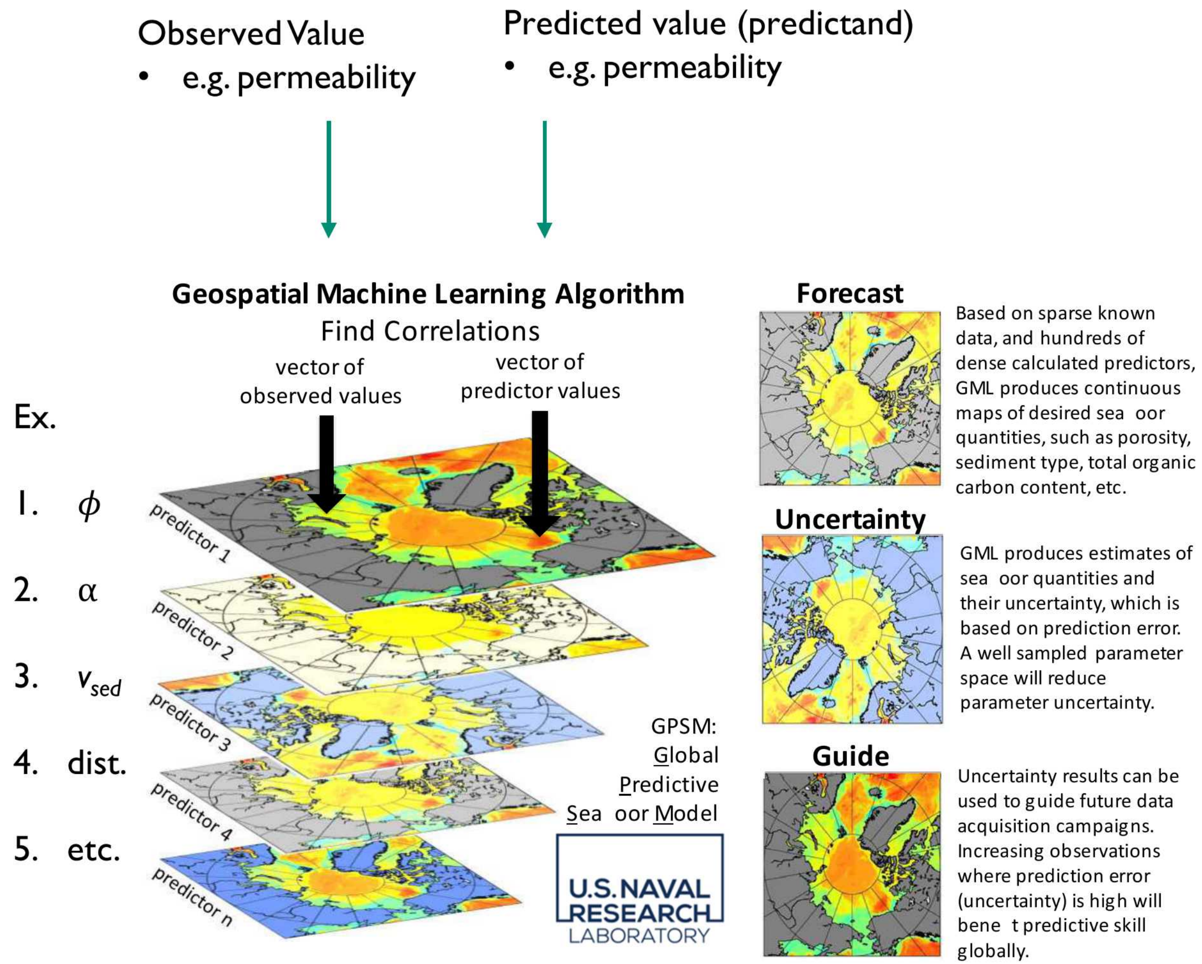
These maps will provide the best calculated estimates of continuous seafloor properties to date.

areas with high uncertainty tell us where we need more data



Applying the Framework

- 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**?

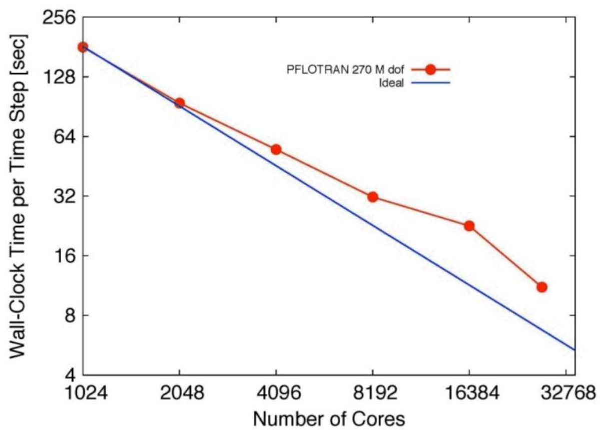


We need thermodynamic models

Applying the Framework

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 libra
  - 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



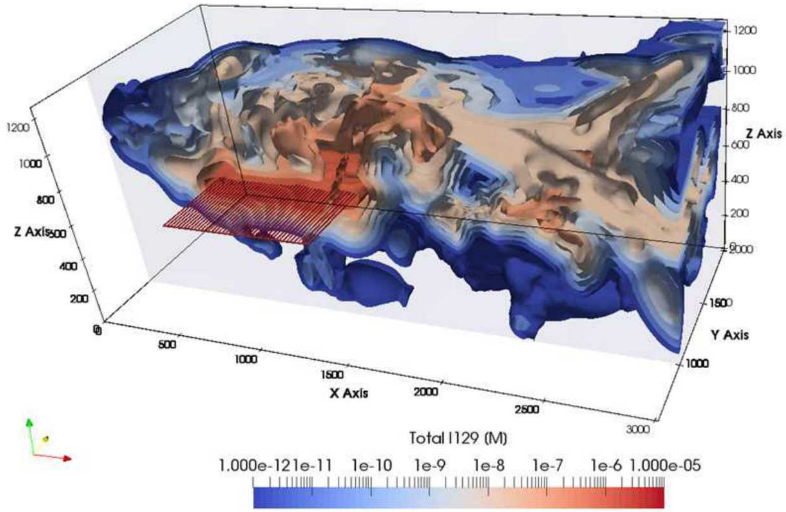
Applying the Framework

PFLOTRAN

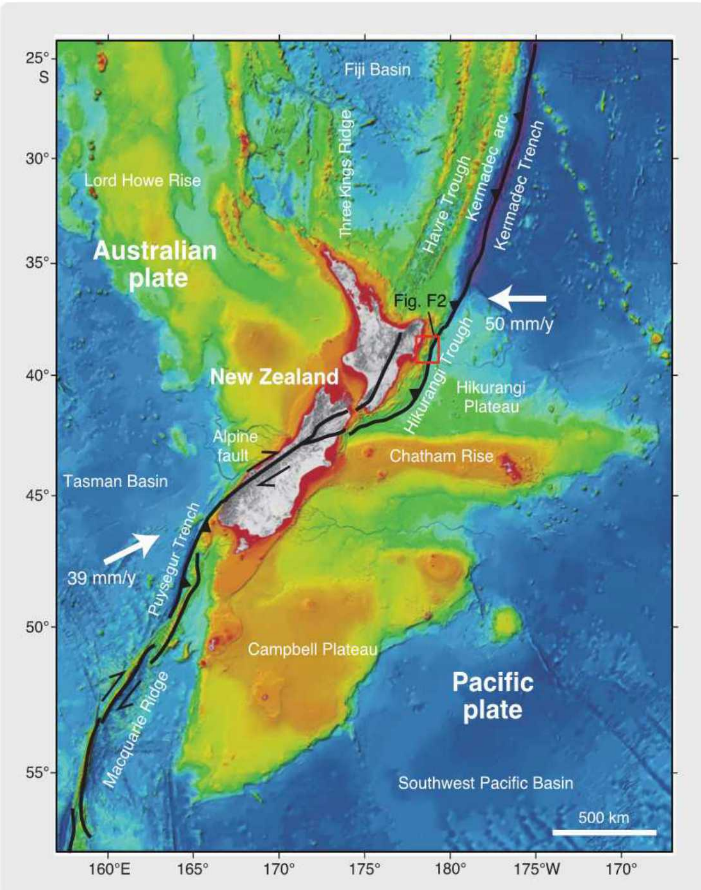
$$\frac{\partial m_a}{\partial t} = -\nabla \cdot \left(\rho_l X_a^l \boldsymbol{q}_l + \rho_g X_a^g \boldsymbol{q}_g + \boldsymbol{J}_a^l + \boldsymbol{J}_a^g\right) + q_a^G,$$

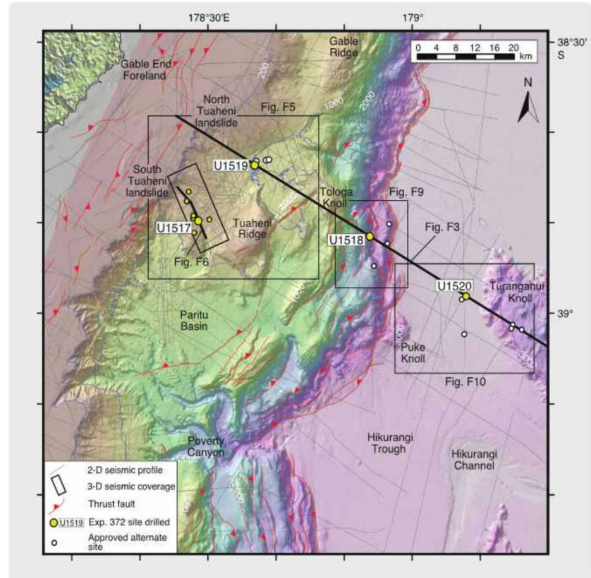
$$\frac{\partial m_w}{\partial t} = -\nabla \cdot \left(\rho_l X_w^l \boldsymbol{q}_l + \rho_g X_w^g \boldsymbol{q}_g + \boldsymbol{J}_w^l + \boldsymbol{J}_w^g\right) + q_w^G,$$

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

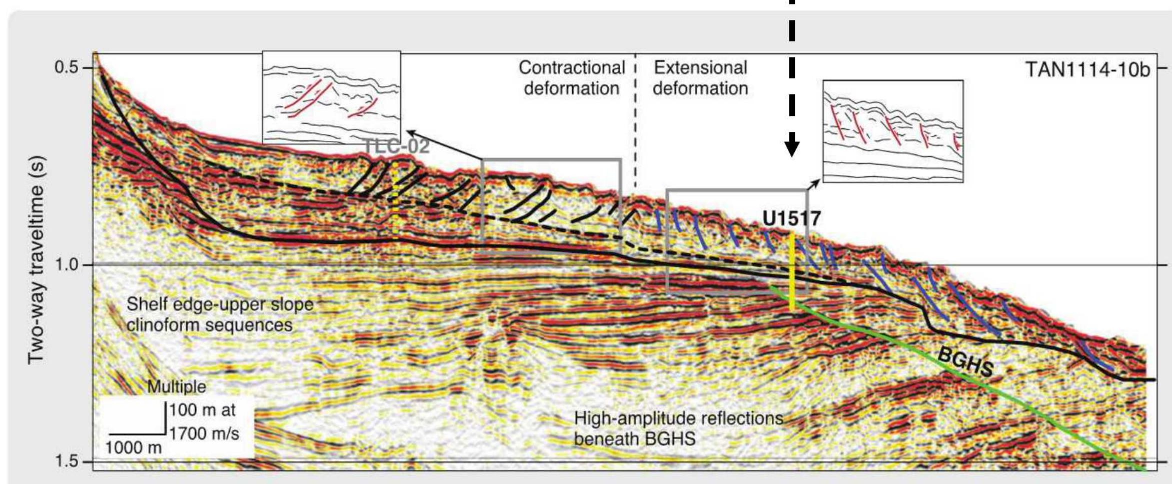


Applying the Framework: IODP 372





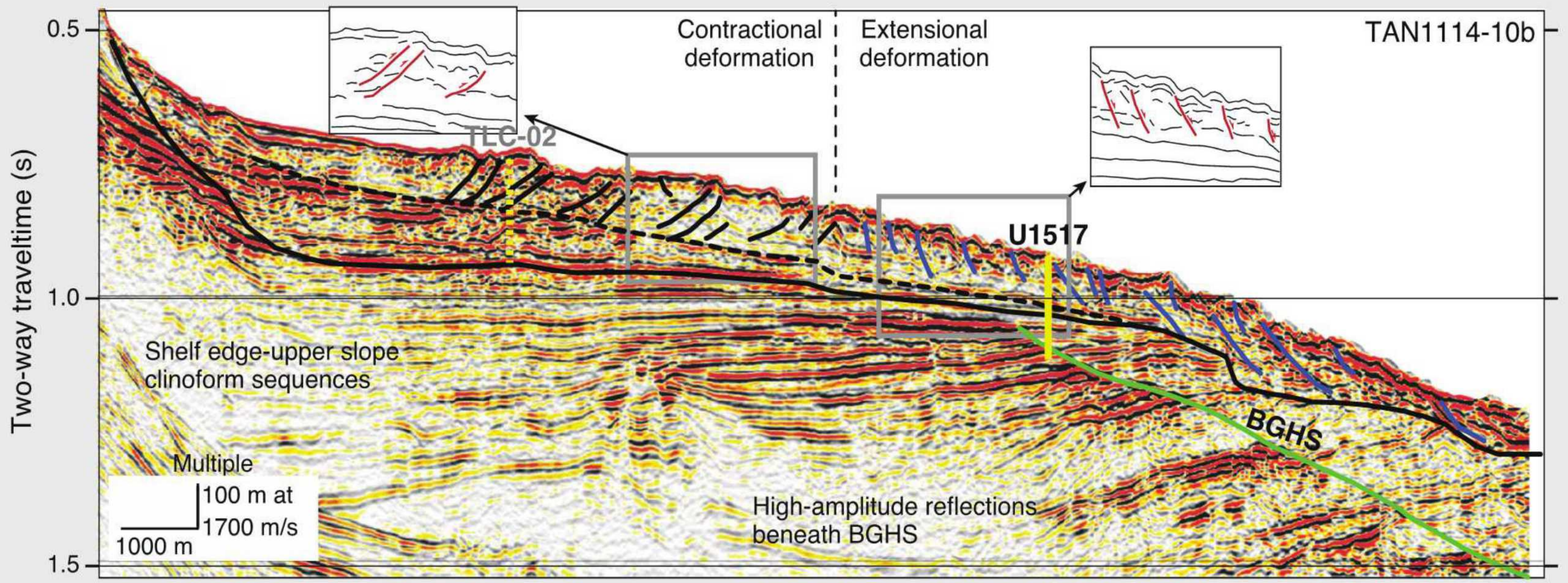
Hydrate observed at 150 mbsf at U1517



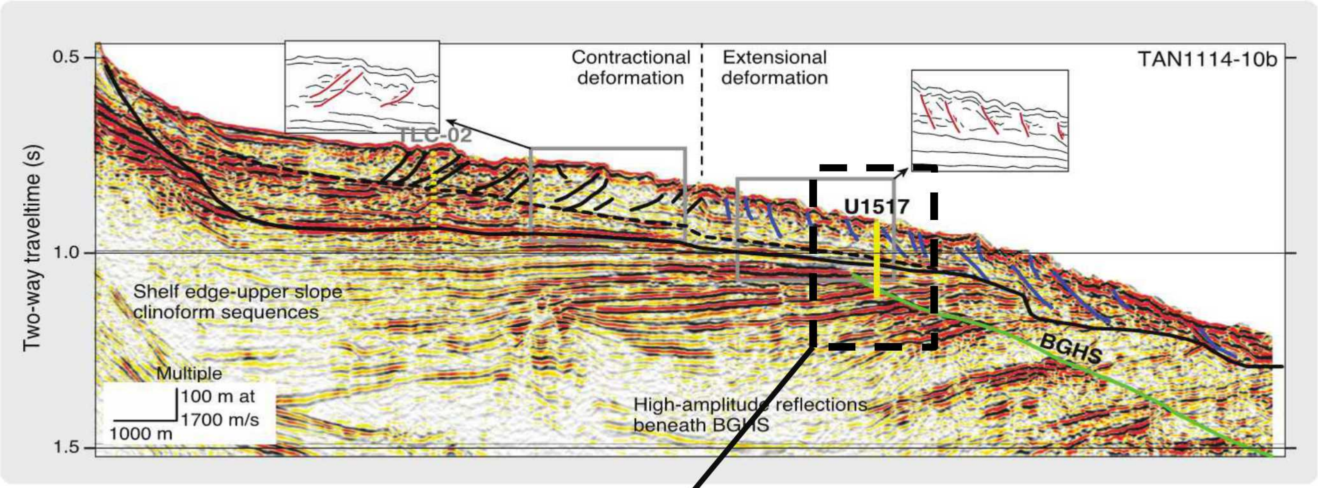
IODP 372 Preliminary Report

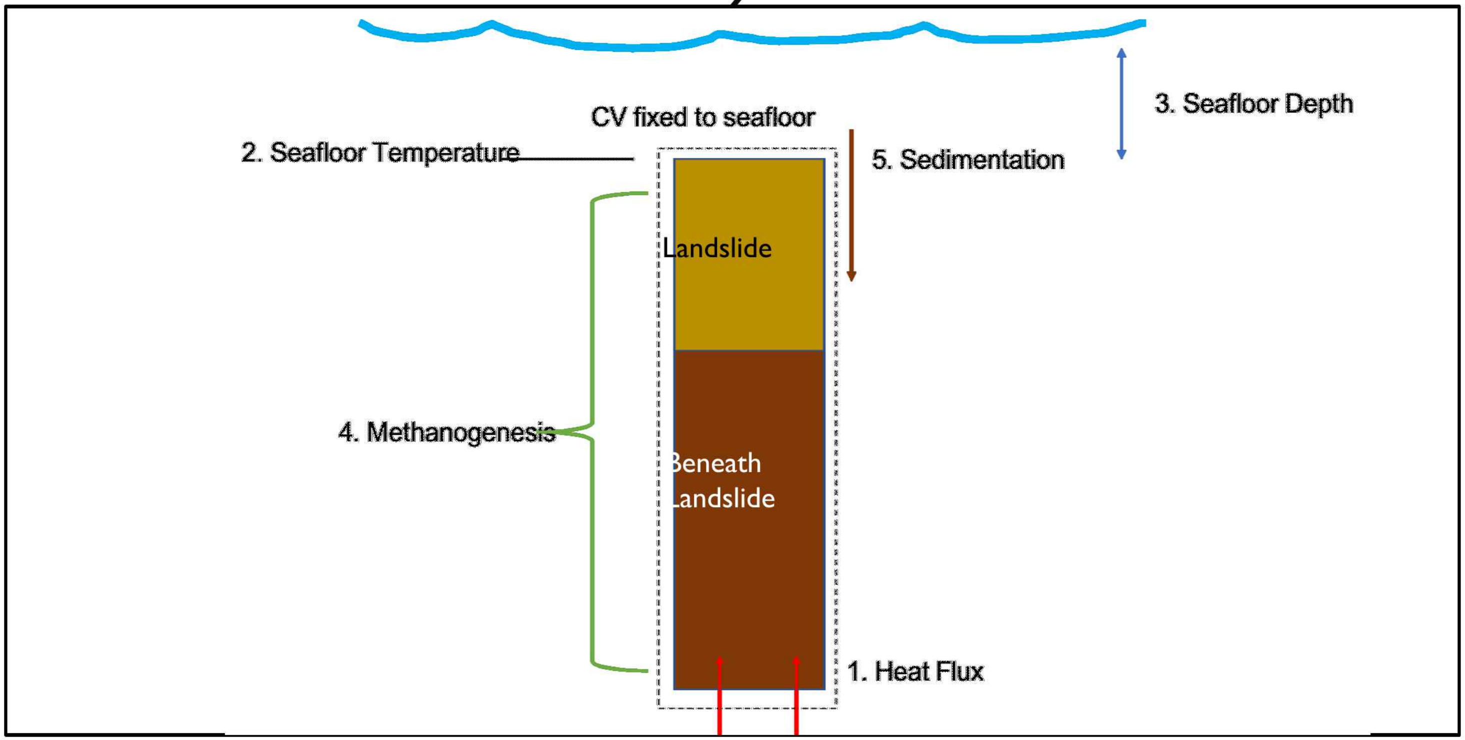
Applying the Framework: IODP 372

Gas hydrate was observed at ~150 mbsf. What can we say about the system and how it might be trending in the future?



Applying the Framework: IODP 372





Applying the Framework: Sampling

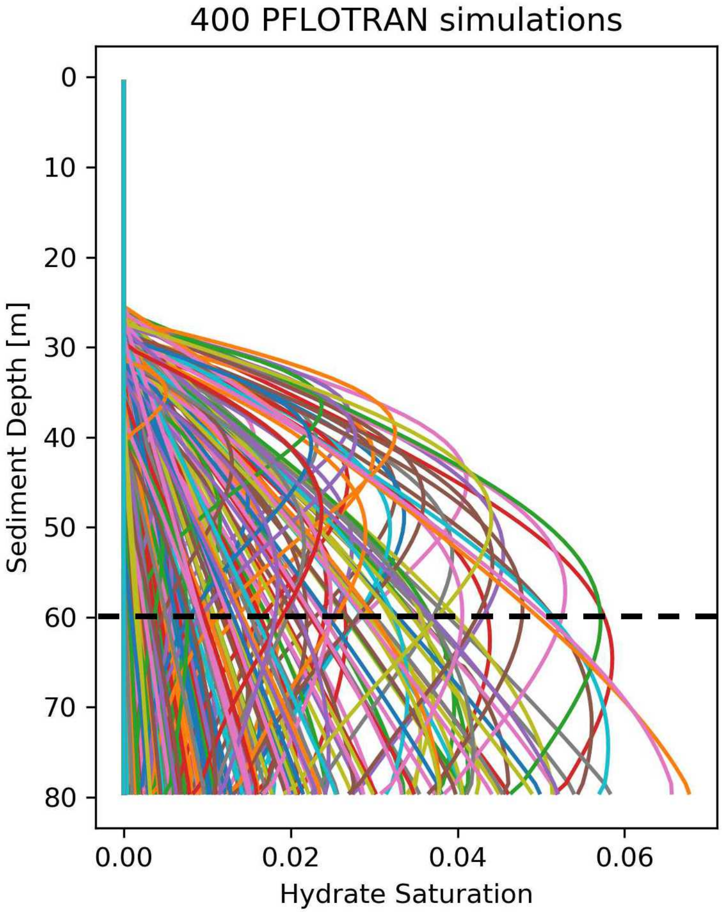
Parameter	Distribution	Min	Max	Current (approx.)
Seafloor Depth (m)	Uniform	690	790	725
Seafloor Temperature (C)	Uniform	1	8	6
Geothermal Gradient (°C/km)	Uniform	0.005	0.05	0.038
Sedimentation Rate (mm/yr)	Log-uniform	1×10^{-5}	1×10^{-2}	8×10^{-4}
Seafloor Organic Carbon Fraction (%)	Uniform	3×10^{-3}	1×10^{-2}	unknown
Rate of Methanogenesis (s^{-1})	Log-uniform	1×10^{-15}	1×10^{-13}	unknown

Applying the Framework: Responses of Interest

- Hydrate saturation
- Gas saturation
- Temperature
- Pressure
- Dissolved methane concentration

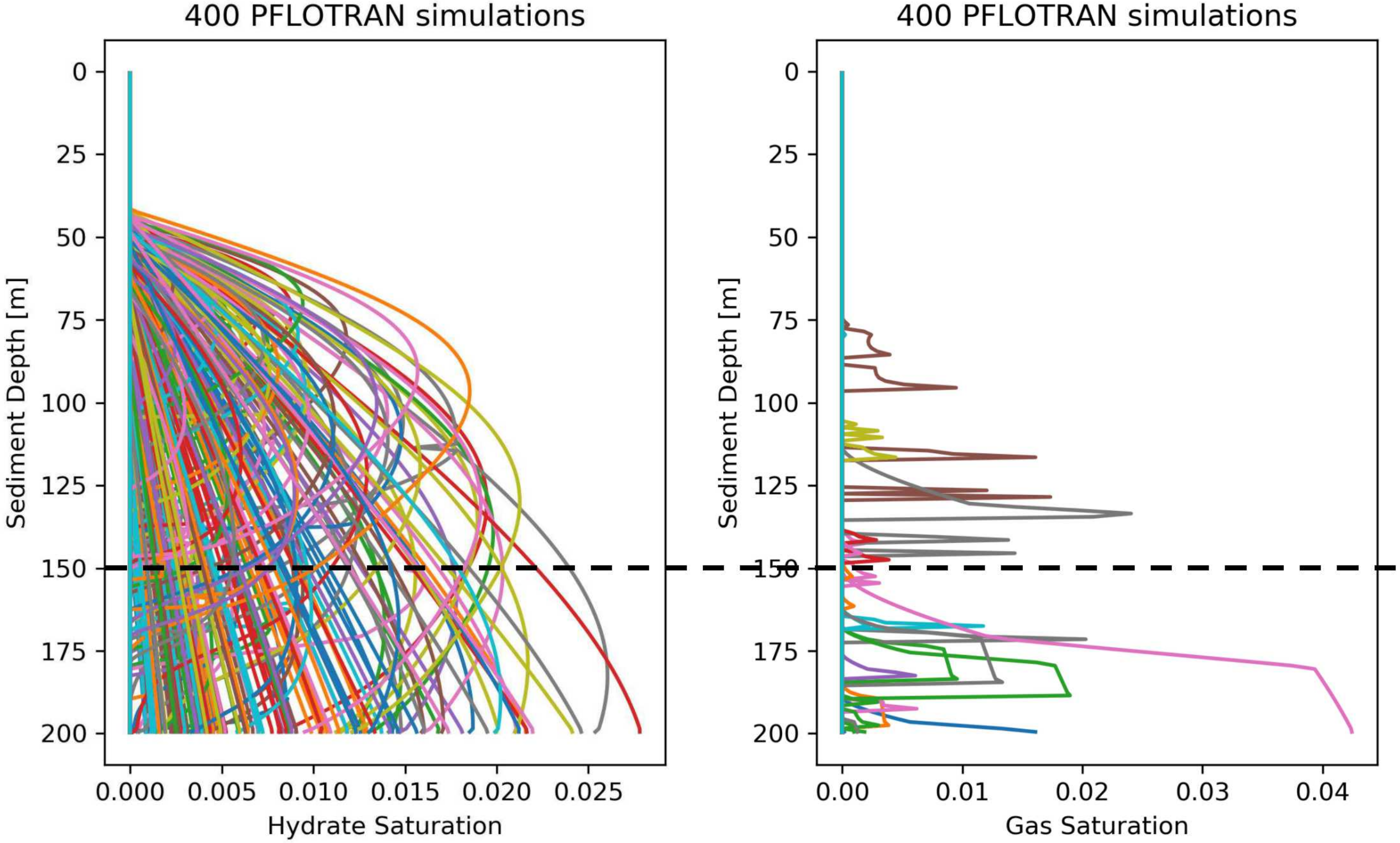
Simulate to 100 kyrs

Within Landslide



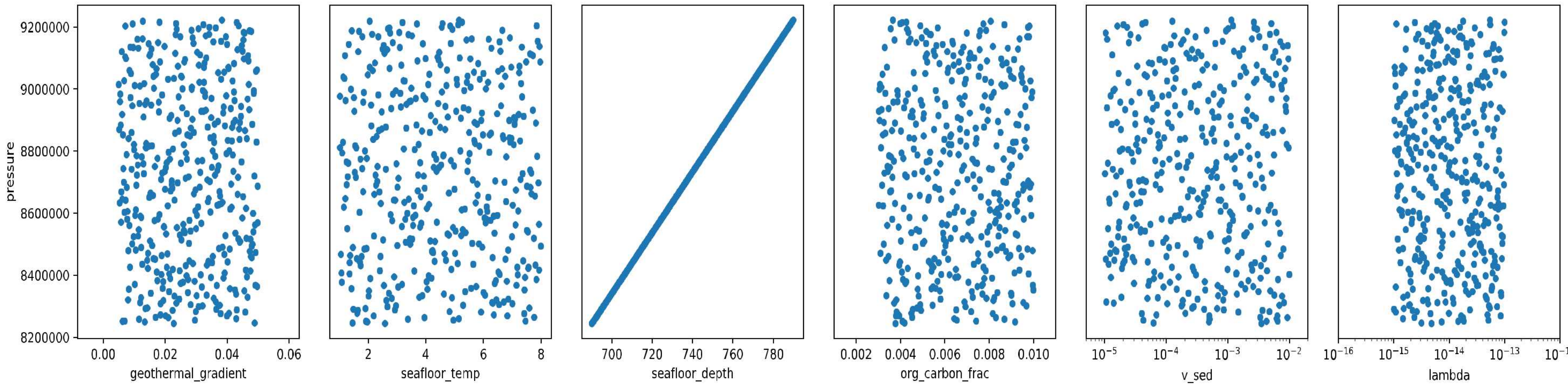
196/400 simulations produce hydrate at 150 mbsf

Beneath Landslide

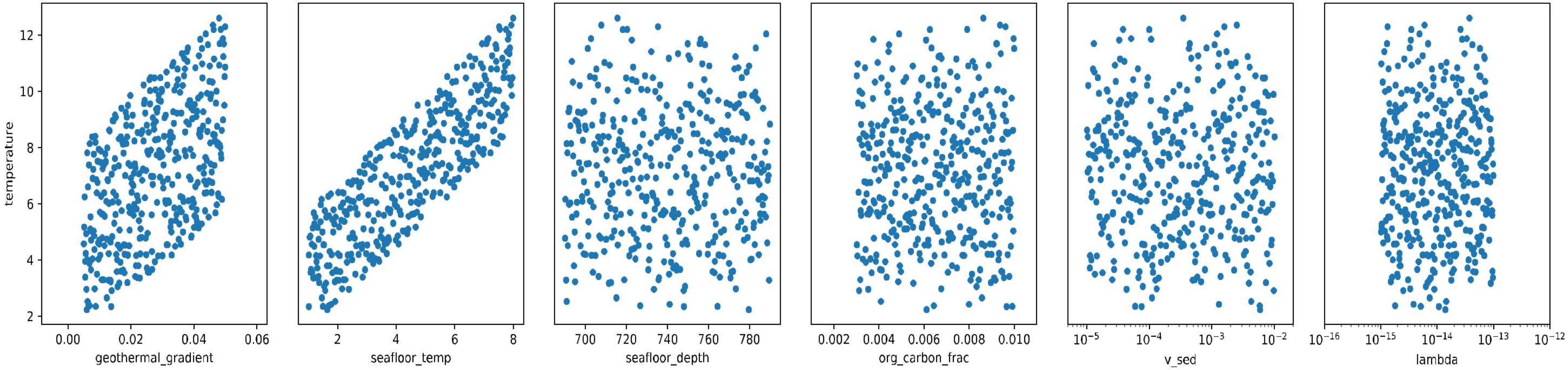


160/400 simulations produce hydrate at 150 mbsf

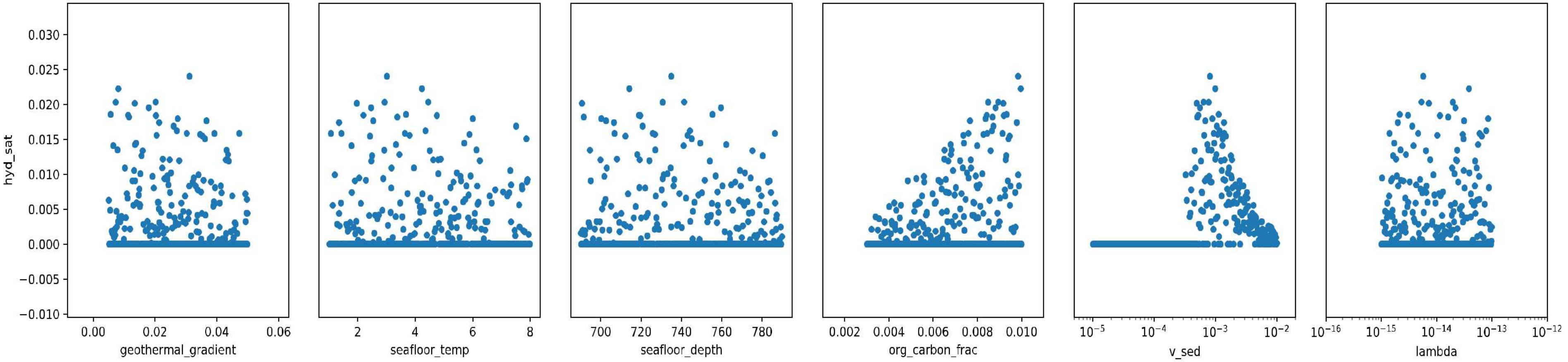
Beneath Landslide: 150mbsf



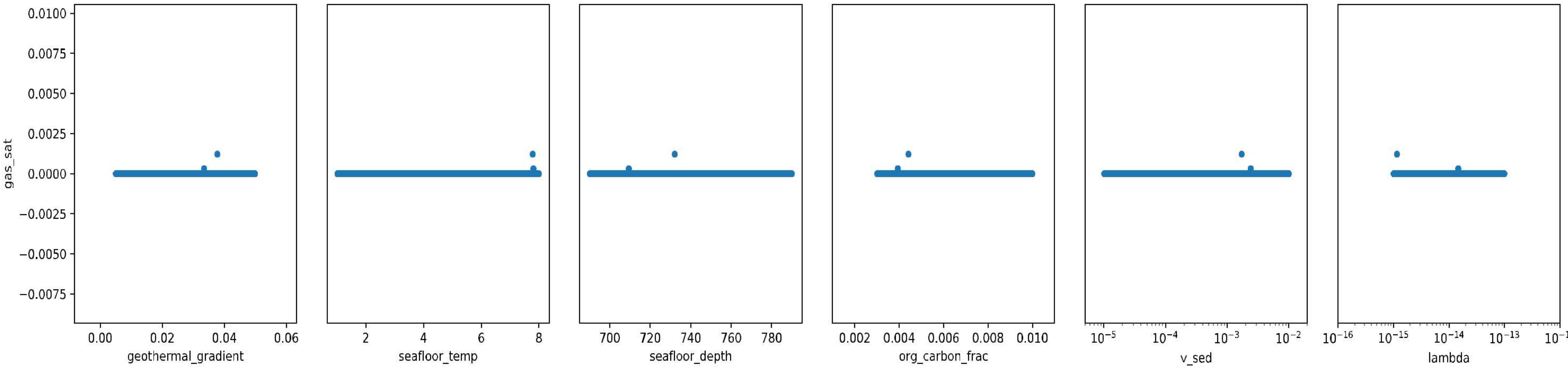
Beneath Landslide: 150mbsf



Beneath Landslide: 150mbsf



Beneath Landslide: 150mbsf



Only two simulations formed a free gas phase at 150 mbsf

Beneath Landslide: 150 mbsf