This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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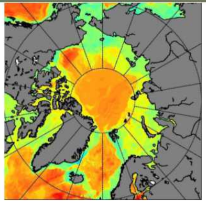
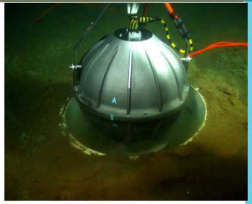
SAND2018-6430C

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





FY19: $388K FY20: $398K FY21: $414K

Proposed manager: Lori Parrott

PRESENTED BY

Jennifer M. Frederick, 08844

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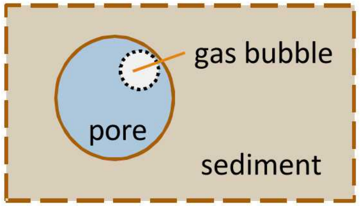
Gas Has a Huge Effect on the Speed of Sound



$$V = \sqrt{\frac{B}{\rho}}$$

bulk modulus → B

density → ρ

compressional wave velocity (speed of sound) → V

B_{air} = 142 kPa
B_{water} = 2.2 Gpa
$B_{sediment}$ = 40 GPa

The "hot chocolate" effect.

Navy submarine near Prudhoe Bay, Alaska

- 2018: The Naval Arctic Strategy now includes "blue water operations," such as anti-submarine warfare, mine warfare, etc., requiring accurate navigation and sonar performance.
- The Arctic seafloor is more prone to contain gas than non-Arctic regions.
- Current SONAR algorithms do not consider gas in sediments.

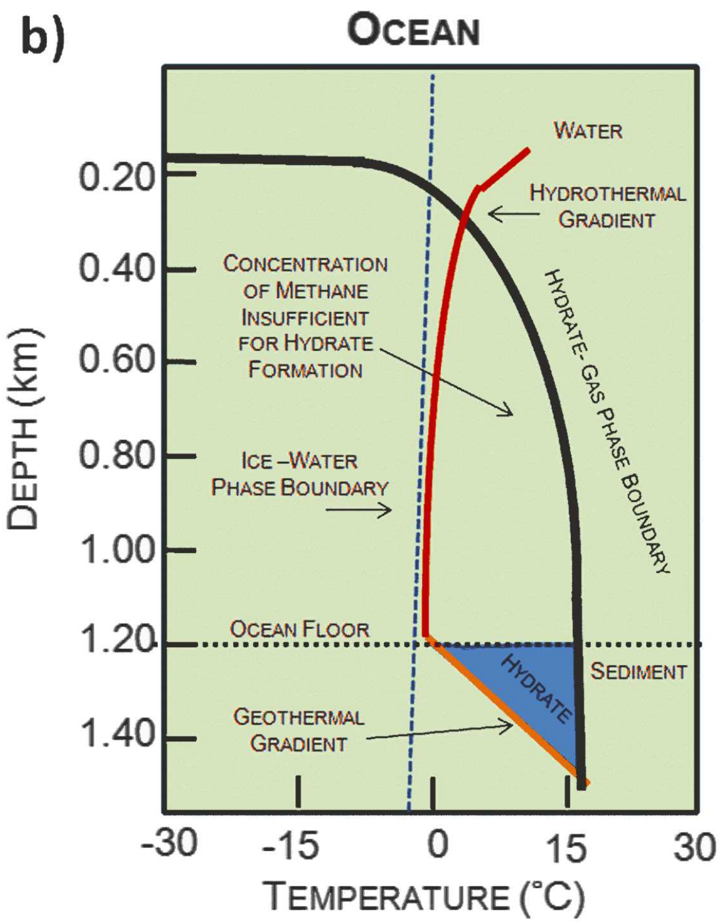
Predicting the Gas Phase is Complicated

Why can't we just add gas to the SONAR algorithms and fix the problem?

- Methane gas can occur as dissolved, free gas, or as solid (gas hydrate):

We need to know:

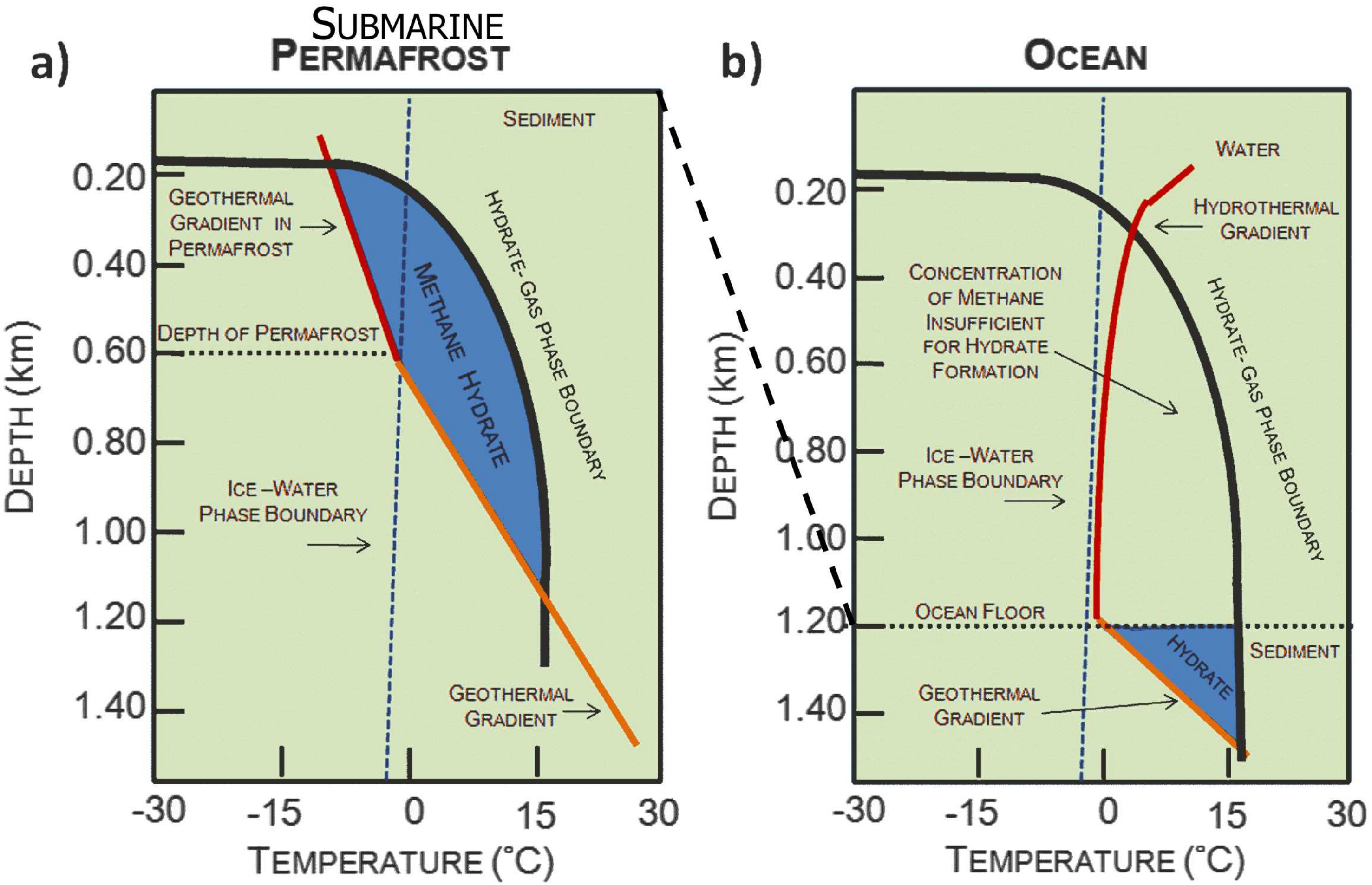
- temperature (assume a typical geotherm)
- pressure (assume its hydrostatic)



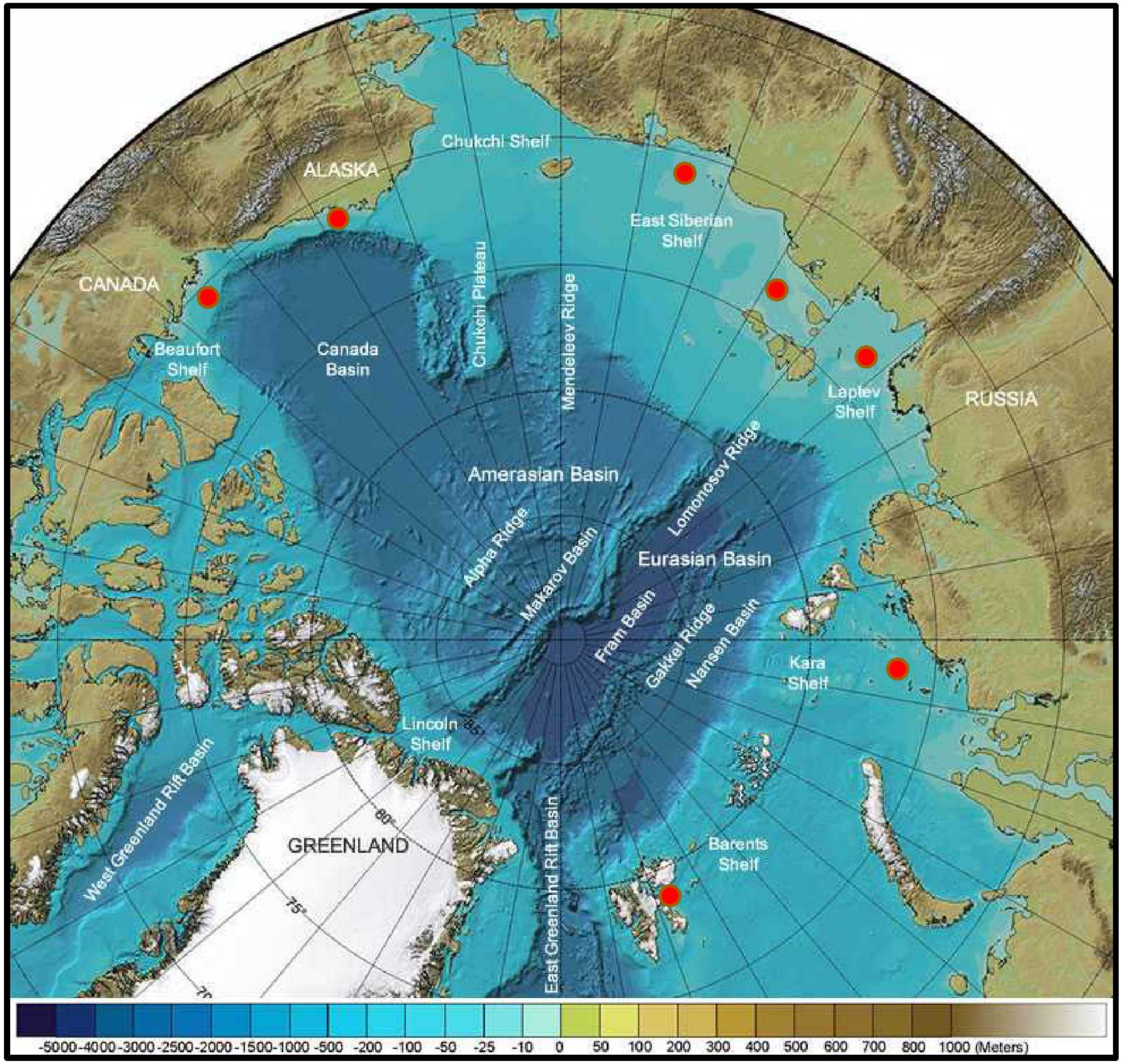
Predicting the Gas Phase is Complicated

Regions of submarine permafrost perturb the temperature profile. . .

- A non-trivial thermal model is needed
- Need to model temperature, thus we need: ρ, C_p, K, θ,

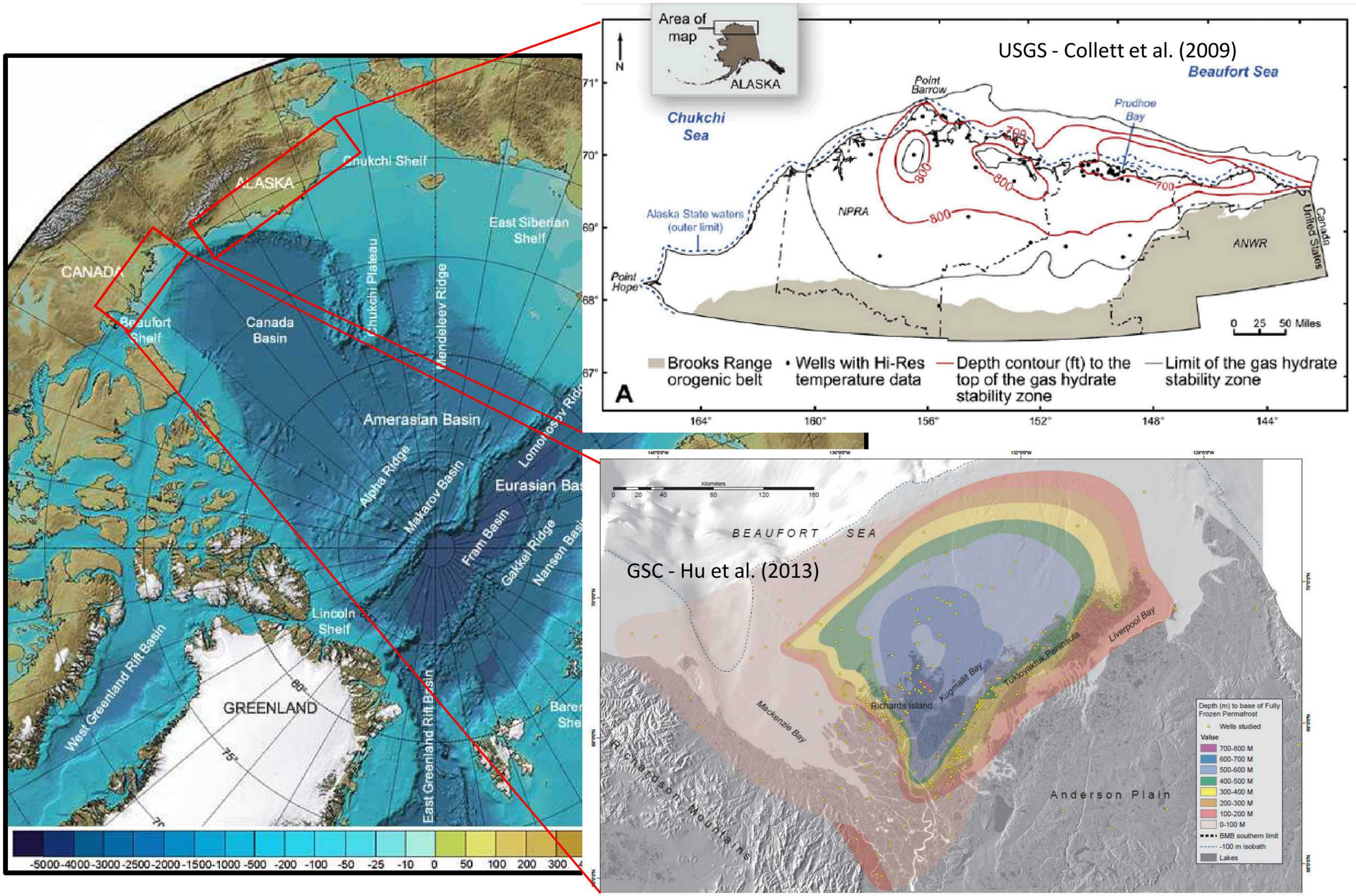


The Arctic is a Data-Sparse Region



● examples of individual studies for methane gas hydrate stability and/or submarine permafrost

The Arctic is a Data-Sparse Region



If it’s so important, why doesn’t the Navy collect more data?

USNS *Pathfinder* oceanographic survey ship

6 Navy survey ships operating 365 days/yr

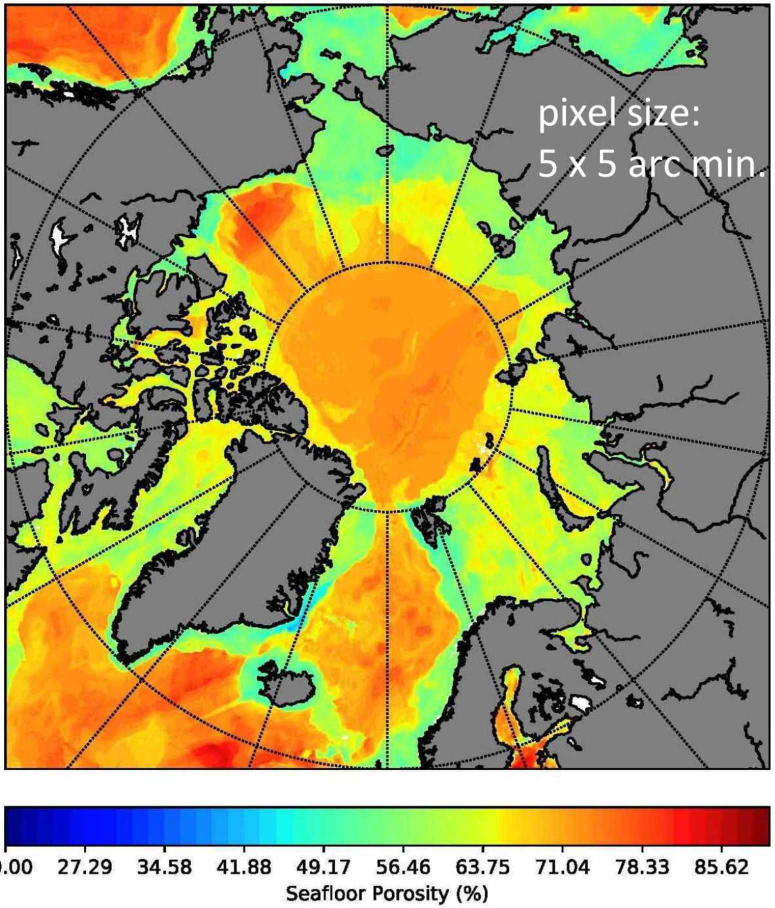
- ~ $60k/day
- current focus is in W. Pacific

Sea ice makes operations difficult!

We are stuck with data sparsity in the Arctic for the time being.

Geospatial Machine Learning

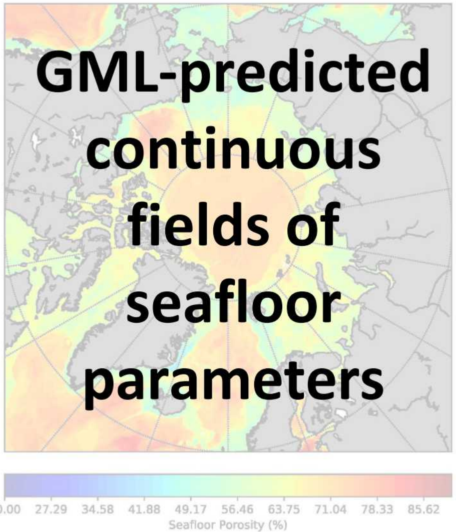
The first ever prediction/map of Arctic seafloor porosity, using geospatial machine learning at the Naval Research Lab (2015).



Martin et al. (2015)

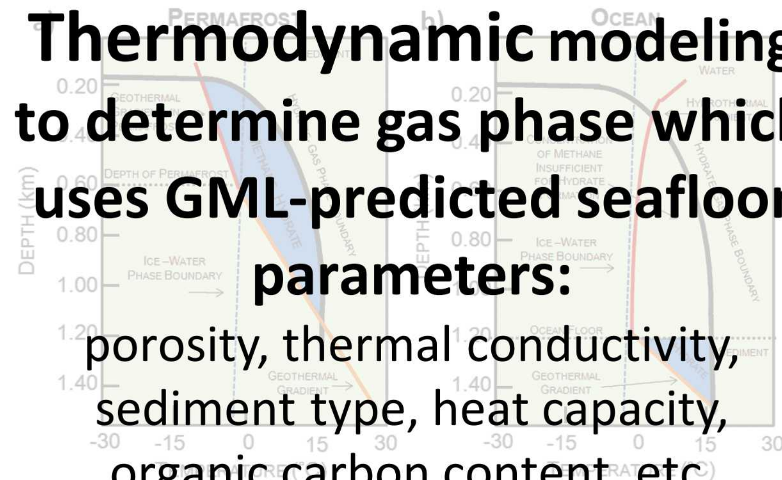
- Interpolation is ill-suited if data is sparse
- NRL is beginning to specialize in *geospatial machine learning:*
  - uses everything we know about the seafloor to make intelligent predictions
  - predictions are based on the proximity in multi-dimensional, geologic predictor space, rather than solely using geospatial proximity
    - e.g., bathymetry, distance from shore, surrogate pairs
  - relationship between predict*ors* and the predict*and* need not be known a priori
  - current algorithms include K-Nearest Neighbor (KNN), Random Forests, etc.
  - predictors are validated (feature selection) via 10-fold validation method
  - geologically similar areas outside the Arctic contribute to prediction within the Arctic

We Propose a Novel Integration of Geospatial Machine Learning and Thermodynamic Modeling

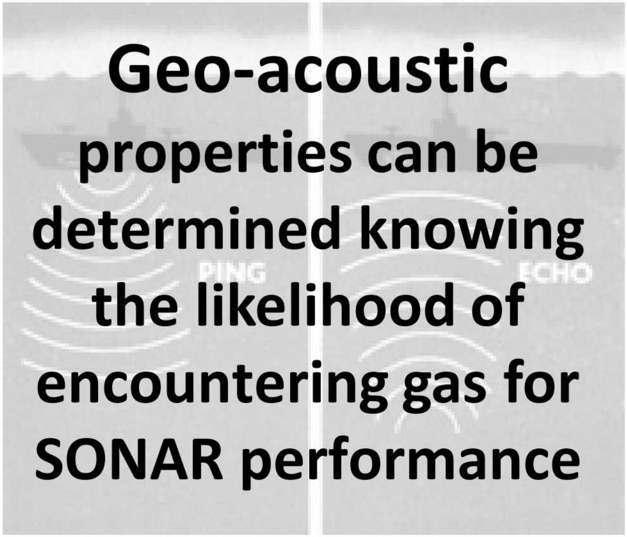


GML-predicted continuous fields of seafloor parameters

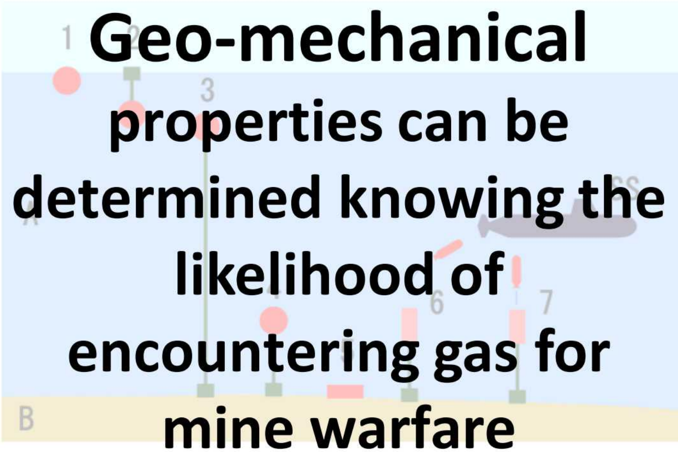
+



Thermodynamic modeling to determine gas phase which uses GML-predicted seafloor parameters:
porosity, thermal conductivity, sediment type, heat capacity, organic carbon content, etc.

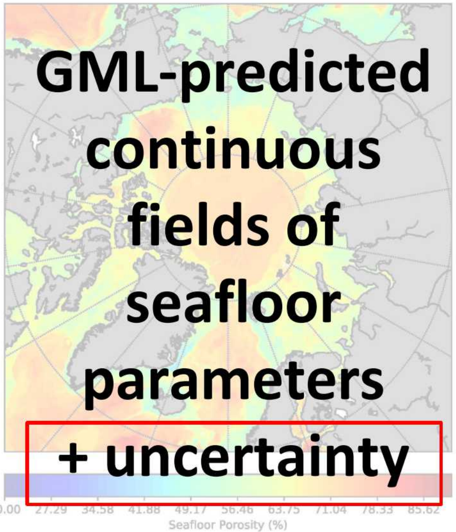


Geo-acoustic properties can be determined knowing the likelihood of encountering gas for SONAR performance



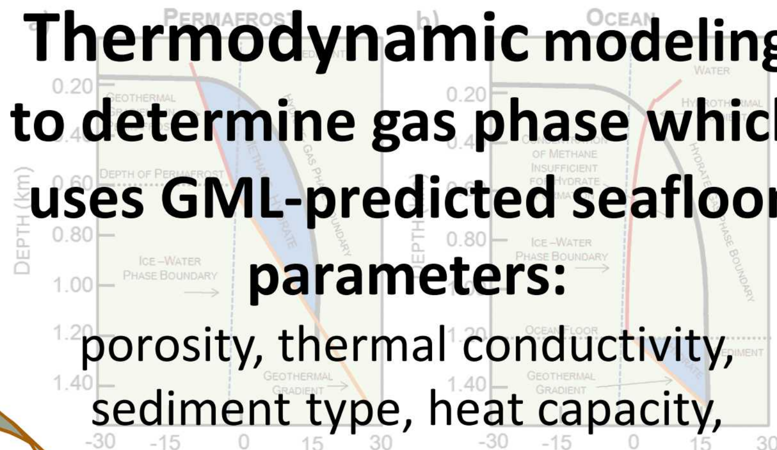
Geo-mechanical properties can be determined knowing the likelihood of encountering gas for mine warfare

We Propose a Novel Integration of Geospatial Machine Learning and Thermodynamic Modeling



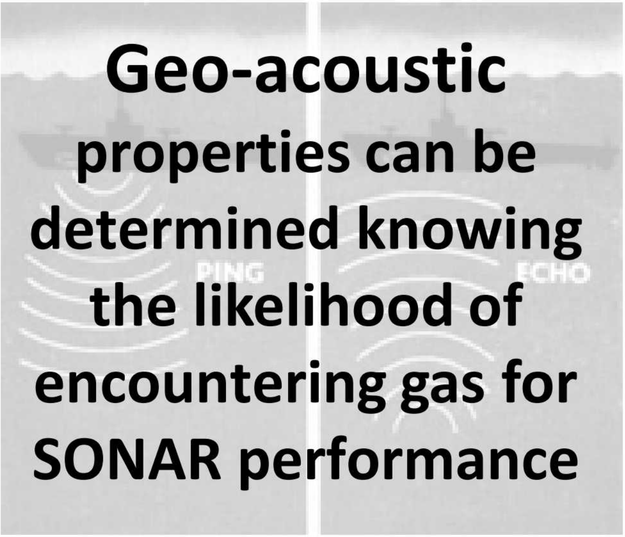
GML-predicted continuous fields of seafloor parameters + uncertainty

+

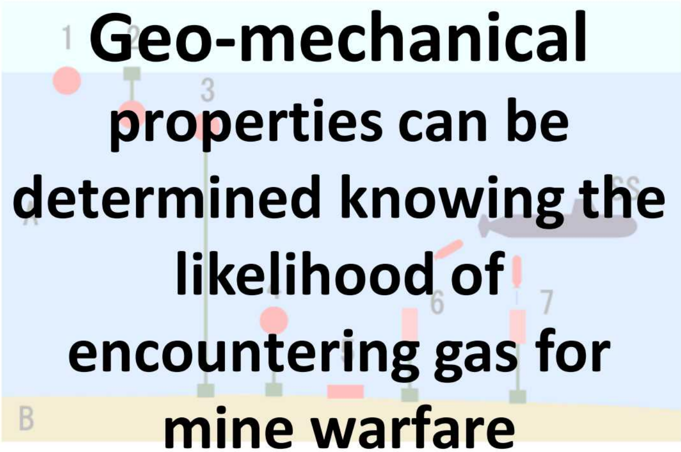


Thermodynamic modeling to determine gas phase which uses GML-predicted seafloor parameters:
porosity, thermal conductivity, sediment type, heat capacity, organic carbon content, etc.

uncertainty propagates into predictions



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



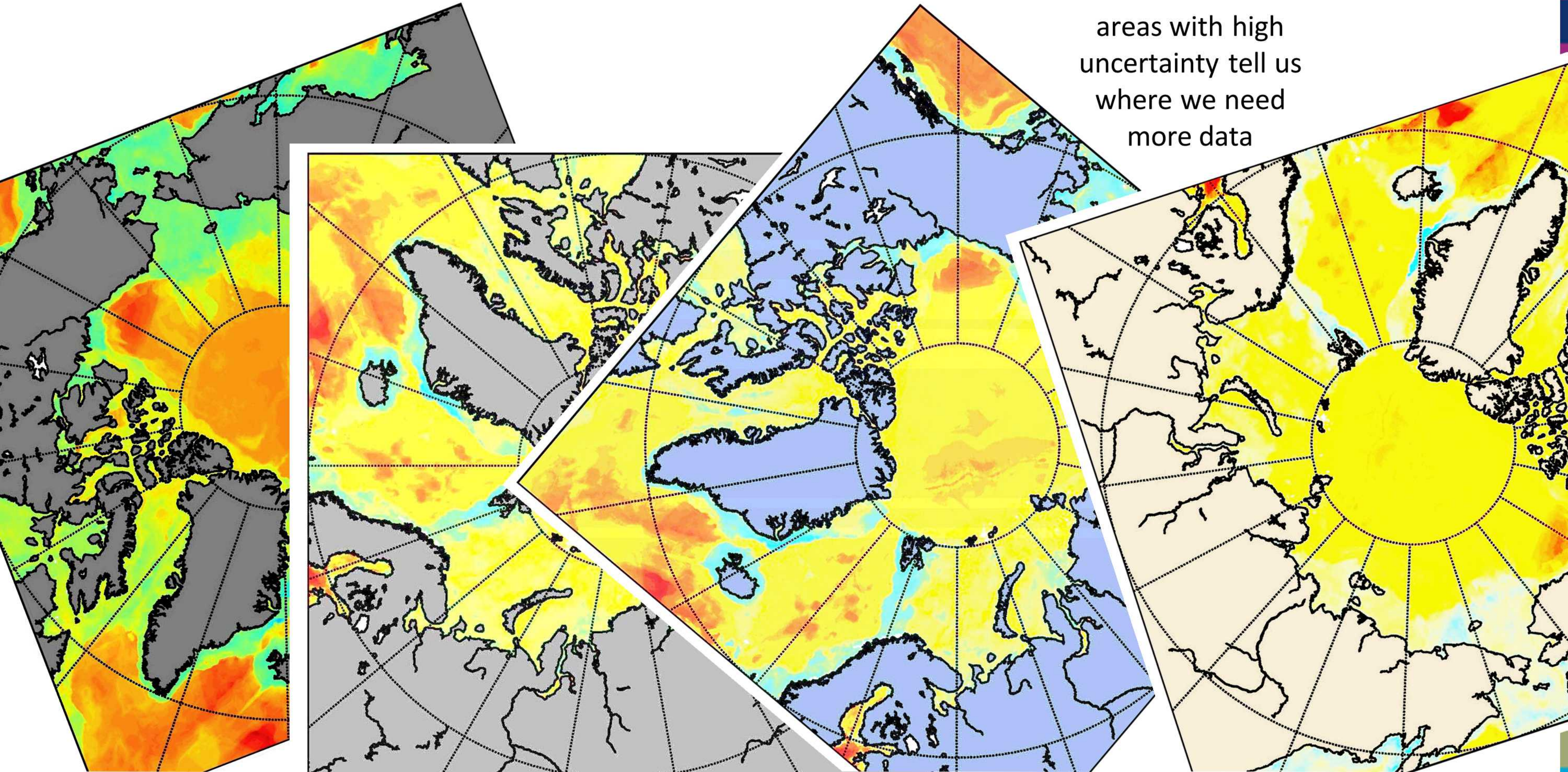
Geo-mechanical properties can be determined knowing the likelihood of encountering gas for mine warfare

Resulting in Probabilistic Maps

For any Navy-relevant quantity:

- speed of sound, seafloor bearing strength, etc.

These maps will provide the <u>best</u> calculated estimates of continuous seafloor properties to date.

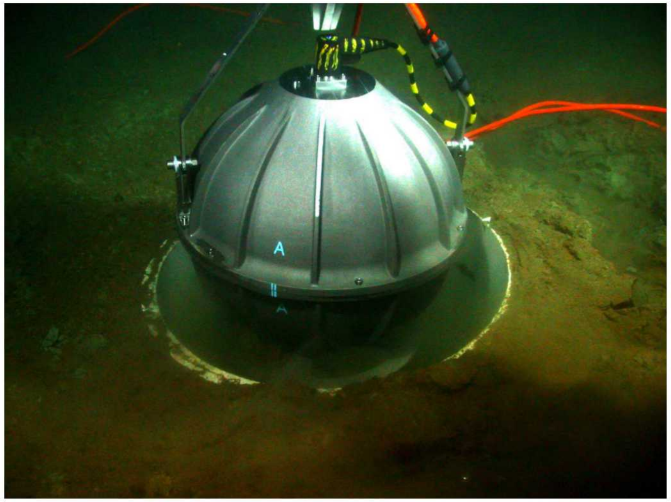


Focus on National Security

Defense (US Navy)

- Arctic is a new theater of operations for the Navy (now includes blue water ops such as anti-submarine and mine warfare)
- The probabilistic maps of shallow sediment properties can improve sonar performance, guide mine placement
- <u>Most reliable form of environmental input to tactical decision aids</u>

Nuclear Treaty Compliance Detection & Monitoring



ocean bottom seismometer

- The seafloor presents a vast area for the placement of ocean bottom seismometers
- Requires accurate models of tomographic structure describing the transmission of seismic waves
- The probabilistic maps of shallow sediment properties can help constrain shallow tomography models

Project Plan & Milestones

Black text = SNL tasks; Blue text = NRL tasks

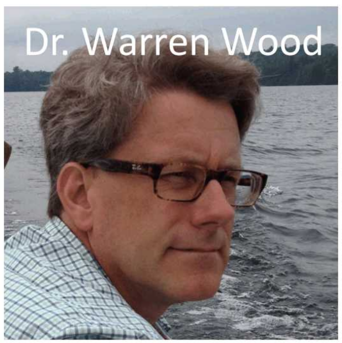
	Activities & Milestones	Measurable Outcomes	Risk Mitigation/No-go Pts.
FY19: Q1, Q2	• Develop the theoretical physical relationships and required seafloor parameters for thermodynamic (TD), methanogenesis (M), geomechanical (GM), geoacoustic (GA), and tomographic (TG) calculations.	Theoretical groundwork for TD, M, GM, and GA calculations is established. The required data (seafloor parameters) for use in GML is defined.	No-go: If theoretical groundwork cannot be established (unlikely).
FY19: Q3, Q4	• Gather and enter required data into NRL GPSM software framework (gridded datasets). • Explore a range of GML algorithms (including surrogate-pairs) to optimize for level of data sparsity.	Data is obtained and ready for use within the GML software framework. Most promising GML algorithms for the Arctic are identified for further pursuit.	No-go: Time consuming – data assimilation may not represent all available data.
FY20: Q1, Q2	• Conduct feature selection for GML predictors that maximize correlations with predictands. • Numerically implement the theoretical physical models and equations for TD, M, GM, GA, and TG calculations.	The selected GML algorithms are fully optimized for Arctic data sparsity and desired predictands. A common software framework is chosen for physical model implementation.	Coordinate numerical implementation of physical models using a single software framework to minimize data passing. No-go: Poor quality, or untrustworthy data
FY20: Q3, Q4	• Demonstrate validation of GML algorithm using 10-fold validation technique. • Numerical implementation of physical models is complete.	The chosen GML methodology is validated for Arctic data. Physical models are numerically implemented in a single software framework.	No-go: If validation of the optimized GML methodology fails. No-go: If physical model implementation fails.
FY21: Q1, Q2, Q3	• Integrate the GML predicted fields with physical modeling to produce probabilistic maps for geoacoustic and geomechanical properties, and tomography. • Demonstrate the impact of gas on geoacoustic parameters used for SONAR performance, mine warfare tactical decision aids.	The GML methodology and physical models can produce reliable, probabilistic maps of Navy-relevant quantities. Project outcome has a demonstrated relevance to national security issues.	Uncertainty may be so large, as to cause resulting maps to be inconclusive. No-go: If probabilistic maps do not show relevance to national security issues.
FY21: Q4	• Complete the required final SAND report.	A new capability is documented and citable for future, follow-on work.	Publications on annual progress can aid writing the final report.

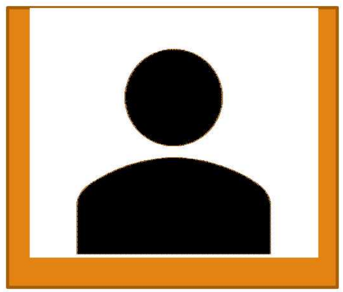
Budget and Team

SANDIA

+ ML staff

NRL





Dr. Ben Phrampus

Item	FY19 $K	FY20 $K	FY21 $K
Labor	$277.5	$284.5	$295.5
Purchases	$0	$0	$0
Subcontracts	$97.1	$101.5	$105.5
Travel	$13.4	$12	$13
TOTAL	$388	$398	$414

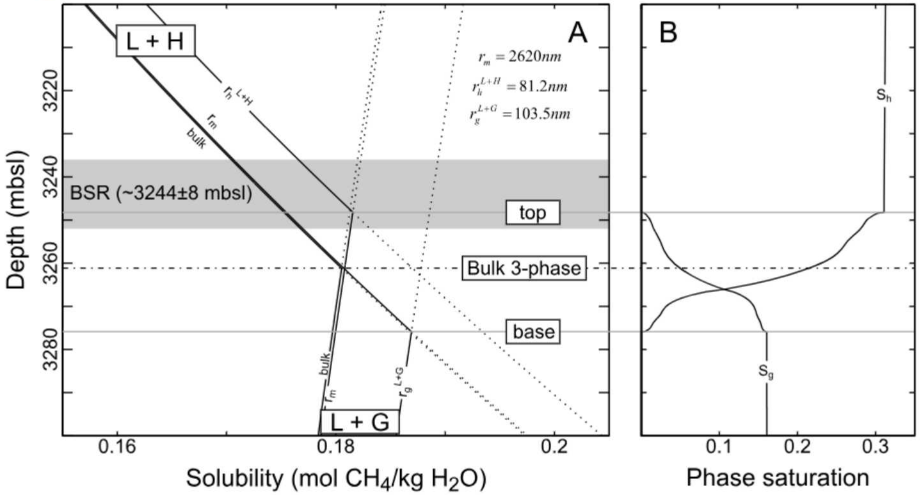
Name	Org	FTE			Role
		FY19	FY20	FY21	
Jennifer M. Frederick	8844	0.25	0.25	0.25	Principal Investigator; Thermodynamic sediment modeling
Kenneth Sale	8614	0.15	0.15	0.15	Biogenic methanogenesis model development
Brian Young	8343	0.15	0.15	0.15	Seismology, detection/monitoring, national security
Hongkyu Yoon	8864	0.15	0.15	0.15	Geomechanics, pore scale phenomena
Dr. Warren Wood and Dr. Benjamin Phrampus	NRL	see below	see below	see below	Naval Research Laboratory collaborator, machine learning, geoacoustics
Professor Hugh Daigle & fully funded grad. student	UT – (AA)	see AA budget	see AA budget	see AA budget	UT-Austin Academic Alliance collaborator, sediment physics and gas hydrate stability zone expert

Benefits and Impact at Sandia

- Establishes a new collaboration with the Naval Research Laboratory
- Potential follow-on funding from DoD or DOE
- Future collaborations funded under ONR
- Expands the Geoscience Research Foundation's portfolio into oceanography
- Supports the growth of Sandia's Arctic Science and Security Initiative

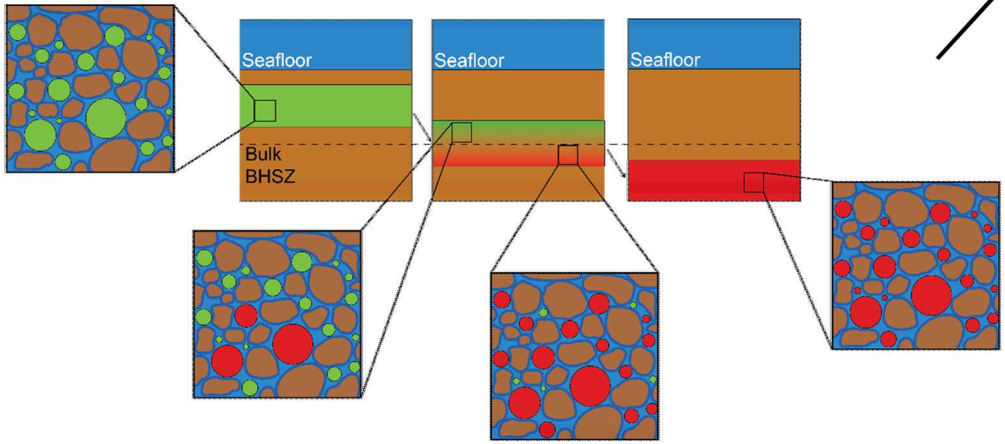
Back-up Slides

Shallowest gas occurrence is often not where you would predict from bulk thermodynamics (10s of meters shallower)



Blake Ridge example; Liu and Flemings (2011)

This is due to pore size effects, which allow gas and methane to coexist in pores of different size



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Phone: (512) 471-3775
Office: CPE 5.174

How can we predict this behavior in Arctic sediments?

Median grain diameter and width of grain size distribution at seafloor from GML

Expected range of pore size distributions from random grain packs

Predict changes during burial

Sensitivity to P, T changes on seasonal to decadal time scales