SWOT Science Team Meeting 2025

1 NOAA
2 UC San Diego, Scripps Institution of Oceanography
3 National Geospatial-Intelligence Agency, United States of America
4 The University of Southern Mississippi
5 Johns Hopkins Applied Physics Laboratory
6 U.S. Naval Research Laboratory
7 The University of Newcastle Australia
8 DTU

Bathymetry Prediction from SWOT derived gravity using Machine Learning

Bjarke Nilsson[8], Biao Lu[8], Farshad Salajegheh[7], Benjamin Phrampus[6], Jonathan Kirby[8], Paul Elmore5, Xiaoli Deng[7], James Beale[3], Jamie Roberts[3], Luis Altamirano[4], Yao Yu[2], Walter HF Smith[1], Ole B. Andersen[8], David Sandwell[2]

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Bathymetry Prediction from SWOT derived gravity using Machine Learning

How we can use SWOT to support global efforts to map the sea floor?

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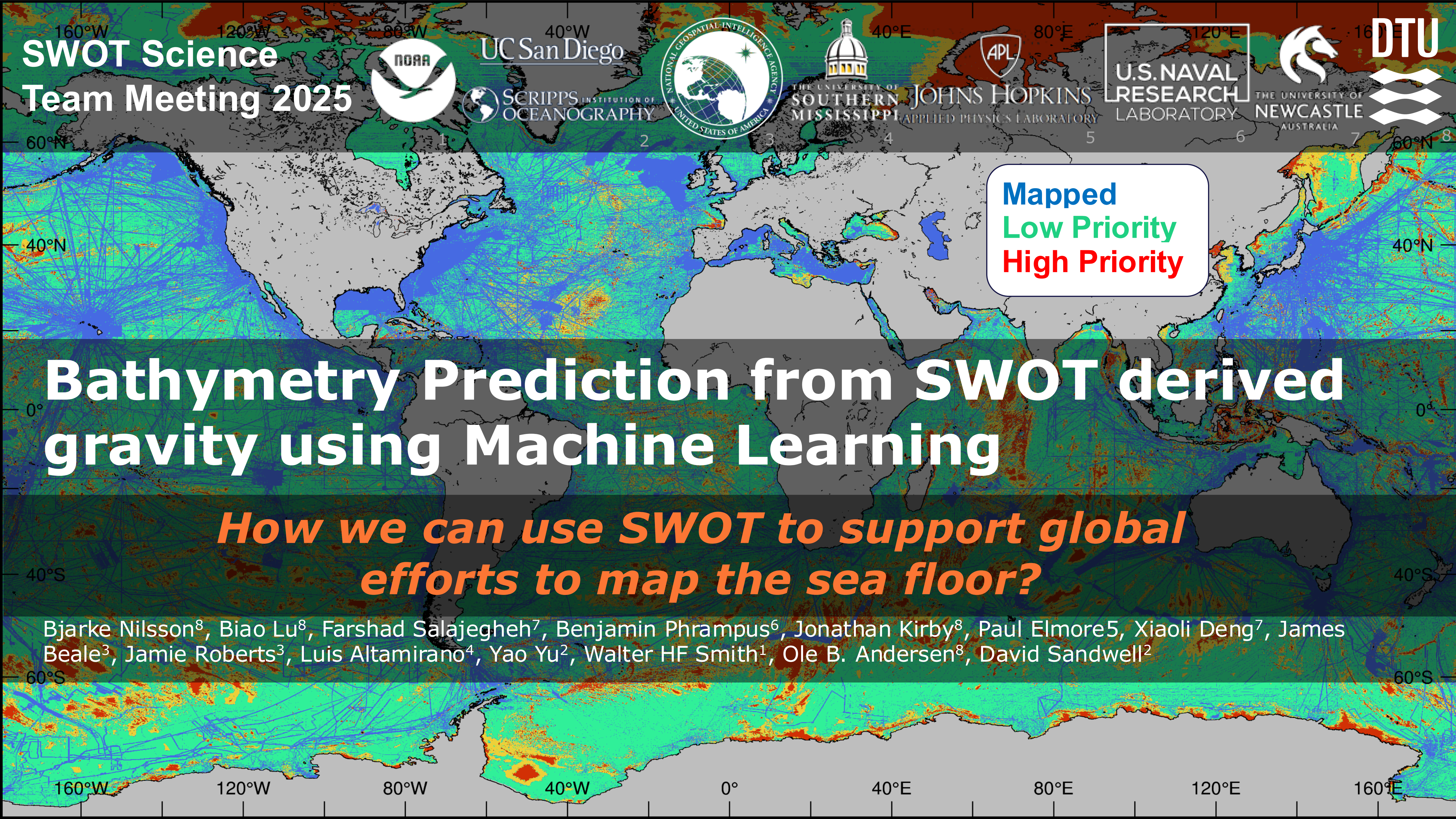
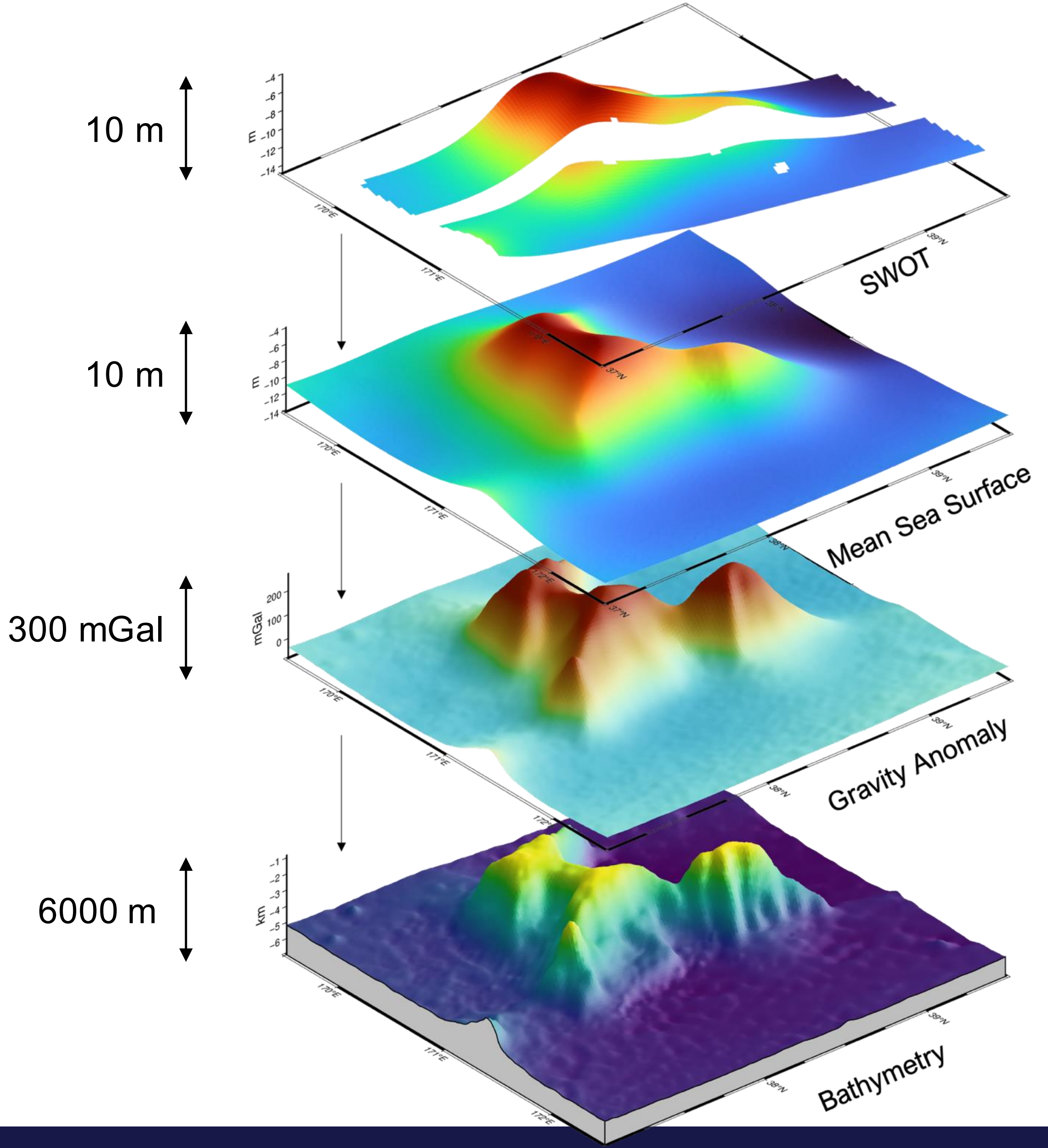


Bathymetry from SWOT

- ➢ Band-passed gravity is highly correlated with bathymetry
- ➢ ~98% of the signal in the MSS is gravity
- ➢ Gravity at the sea surface is attenuated at ~4 km

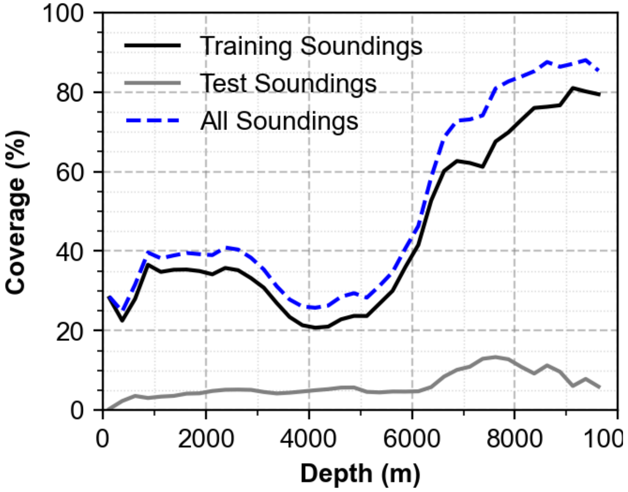
Decrease in SSH error has huge impact on bathymetric prediction!

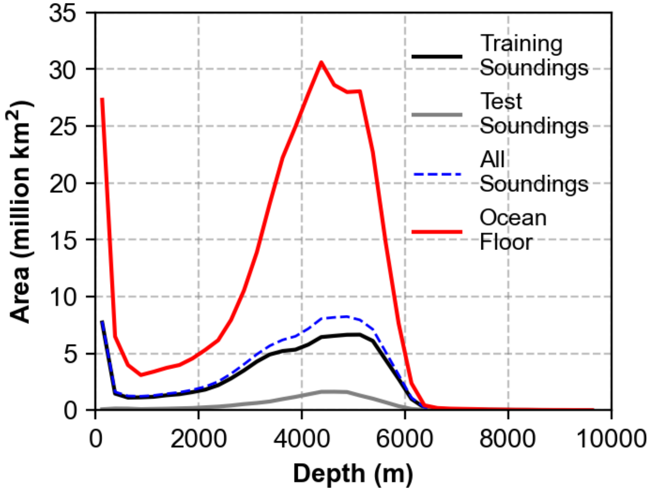


Status of global ocean-floor mapping

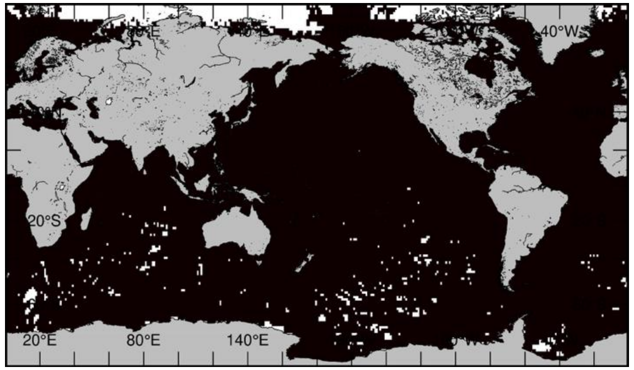
Ships cover 26% of the global ocean

- ➢ SeaBed2030 has made great progress (~6% to 27%)
- ➢ The abyssal plains make up > 50% of the sea floor, yet only 25% of this is mapped
  - This is the region with best gravity-inversion performance
- ➢ Traditional regions of interest are best mapped
  - We want to spend ship-hours wisely
  - **Current speed is ~1% mapped per year**

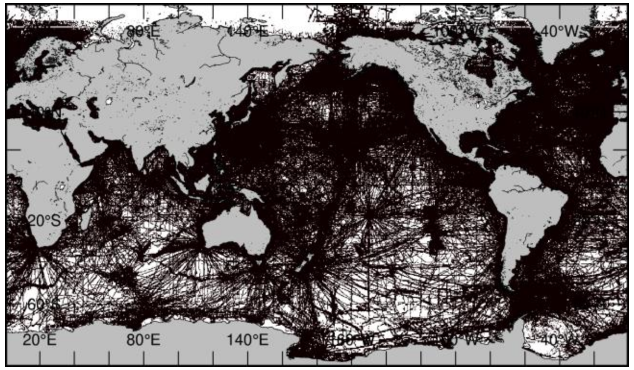




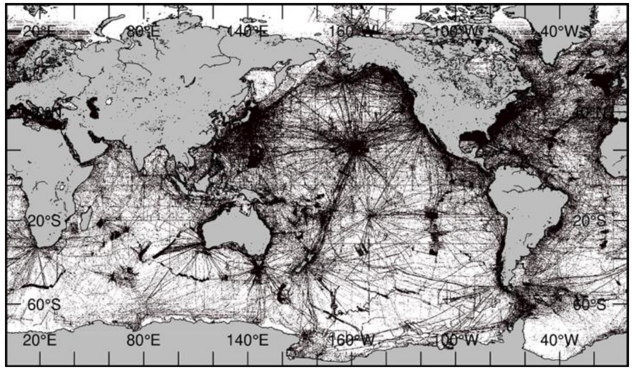
Ship Coverage at 100 km resolution



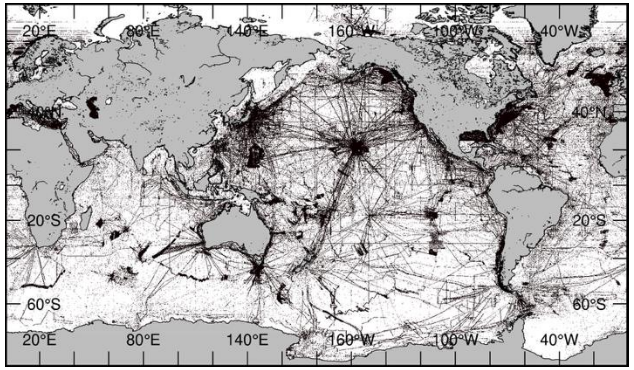
Ship Coverage at 25 km resolution



Ship Coverage at 5 km resolution

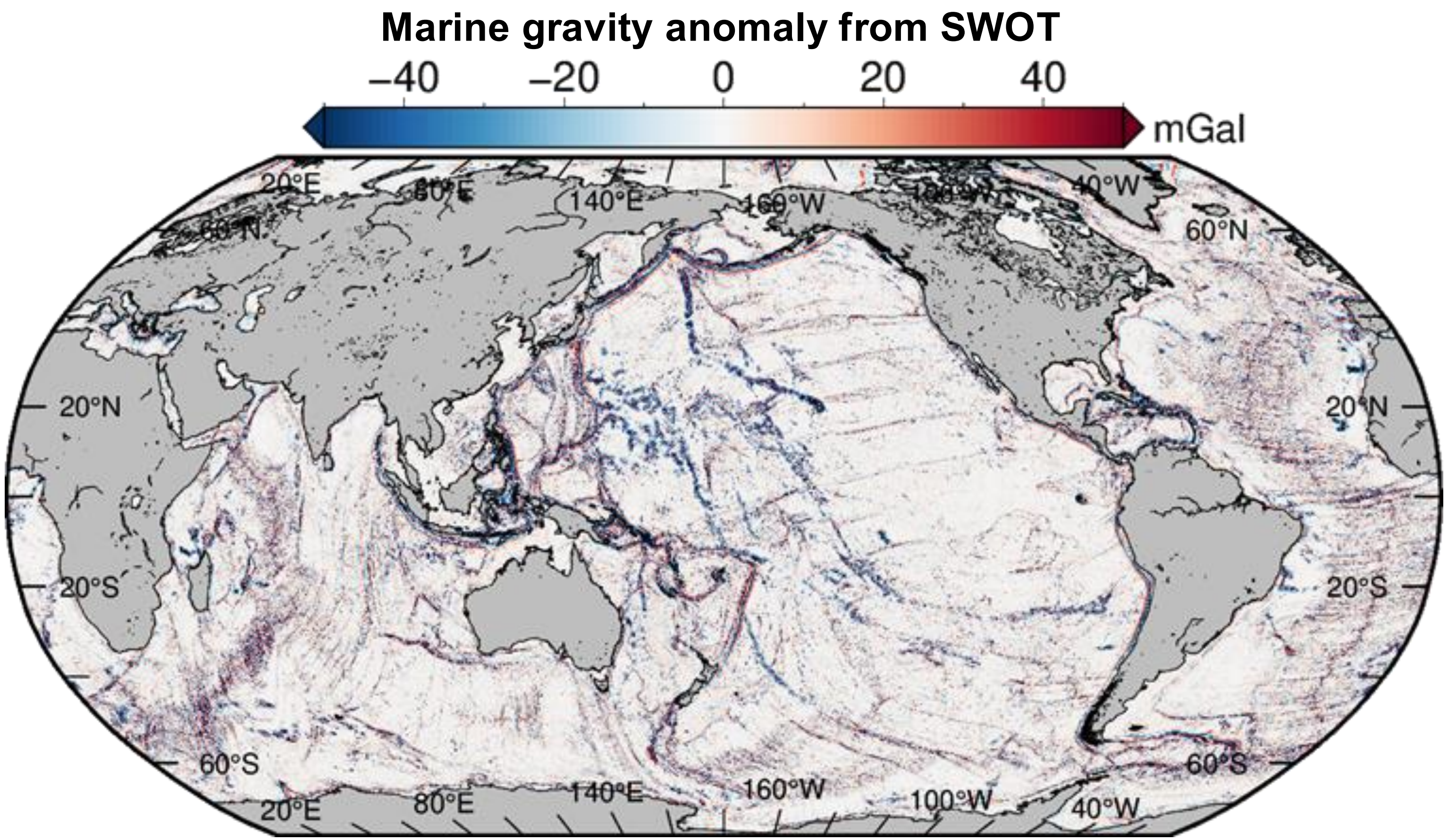


Ship Coverage at 2 km resolution



Status of global ocean-floor mapping

SWOT covers ~98% of the ocean surface



Status of global ocean-floor map

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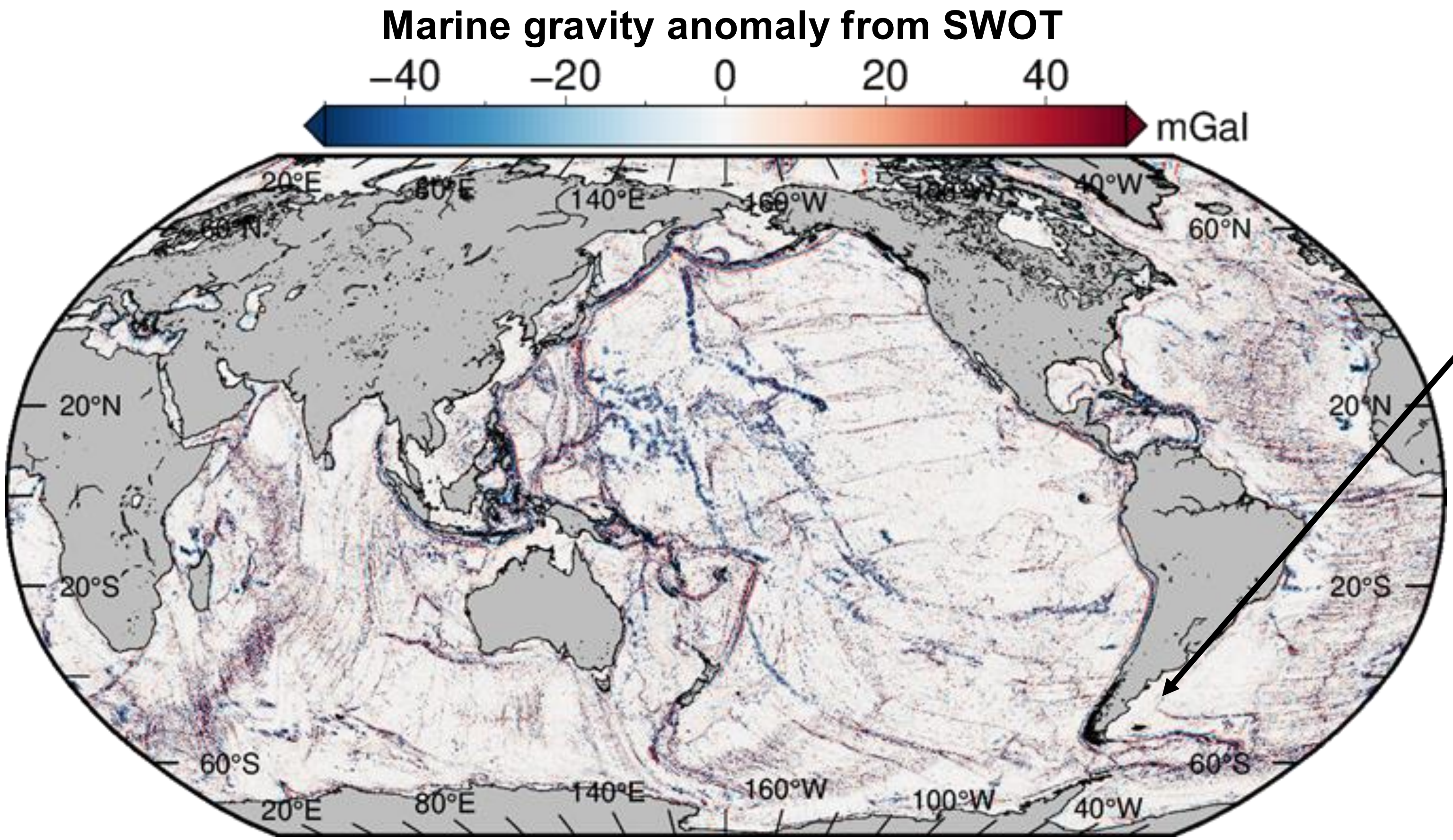
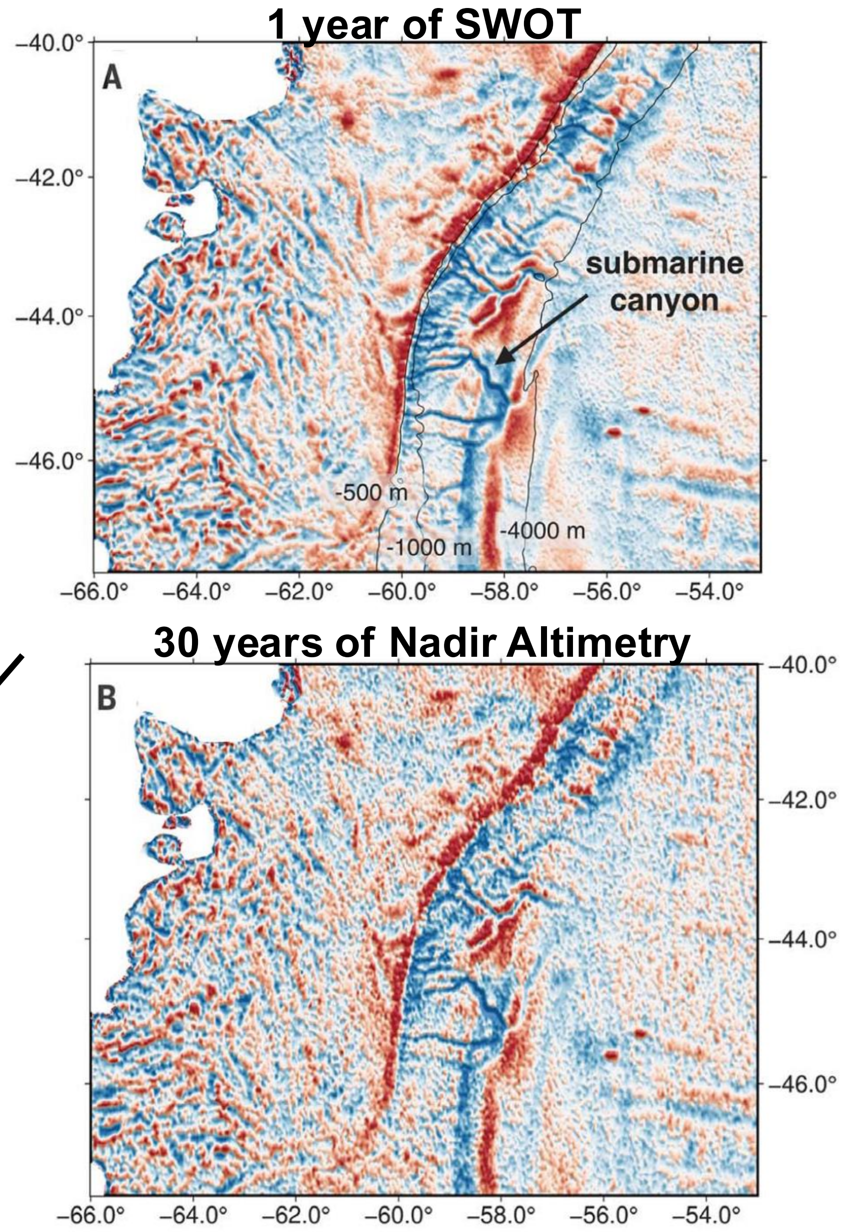
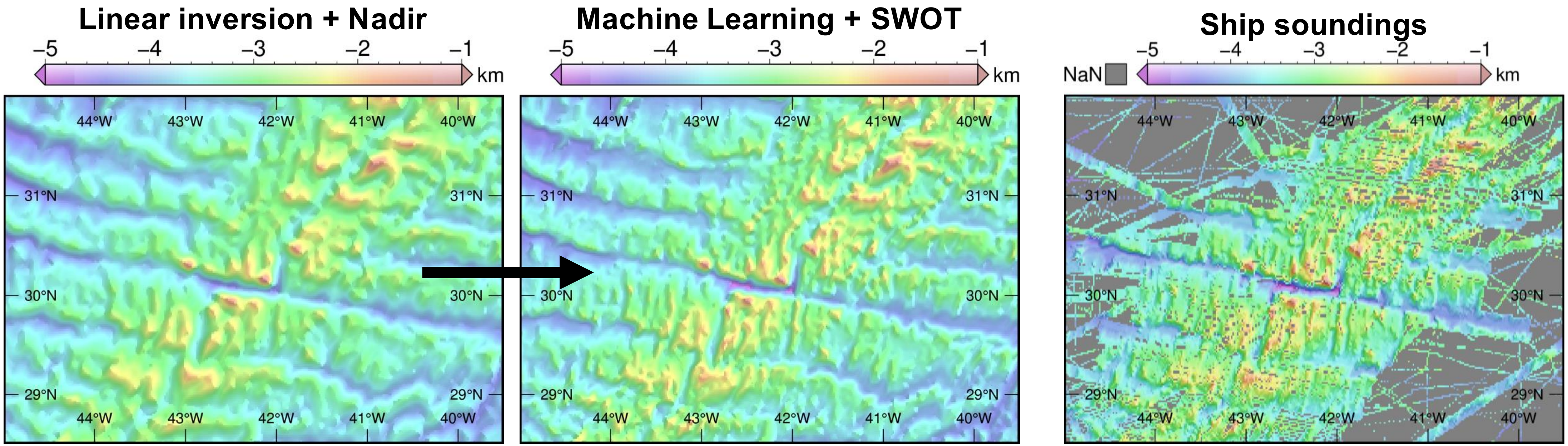




Yu, Y., Sandwell, D. T., & Dibarboure, G. (2024). Abyssal marine tectonics from the SWOT mission. Science, 386(6727), 1251–1256.

Optimal utilization of SWOT for bathymetric inversion

- **Goal**: Provide the best bathymetry map, **from SWOT data**, **utilizing Machine Learning**
- **Setup**: Five groups working with the same data, with five different methods
  - 2xDTU, SIO, NCU and NRL
- **Combination:** combine individual models in order to provide the optimal solution
- **Evaluation**: withheld data used to evaluate all five models



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1. **DTU-DNN**: Deep Neural Network
2. **SIO-DNN**: Deep Neural Network
3. **NCU-DNN**: Deep Neural Network

First talk of the session

4. **DTU-DKL**: Deep Kernel Learning
5. **NRL-CNN**: Convolutional Neural Network

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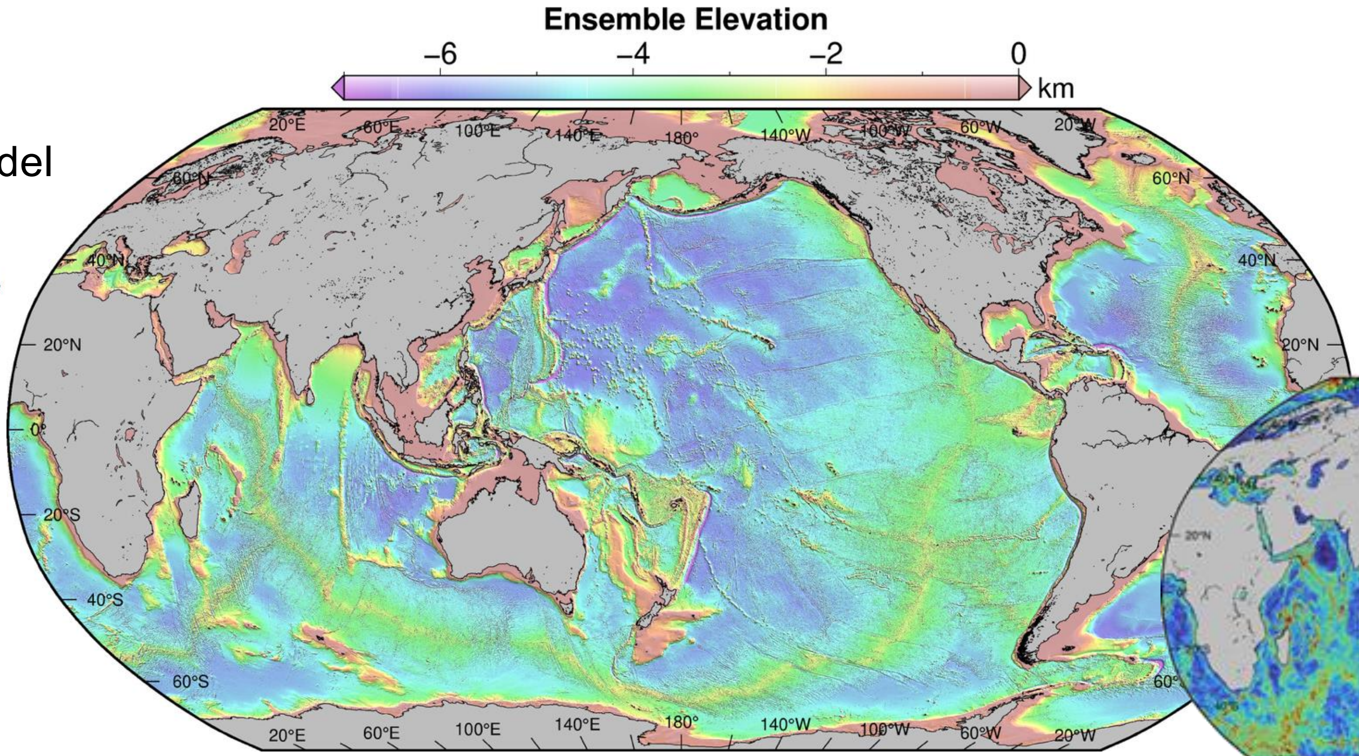
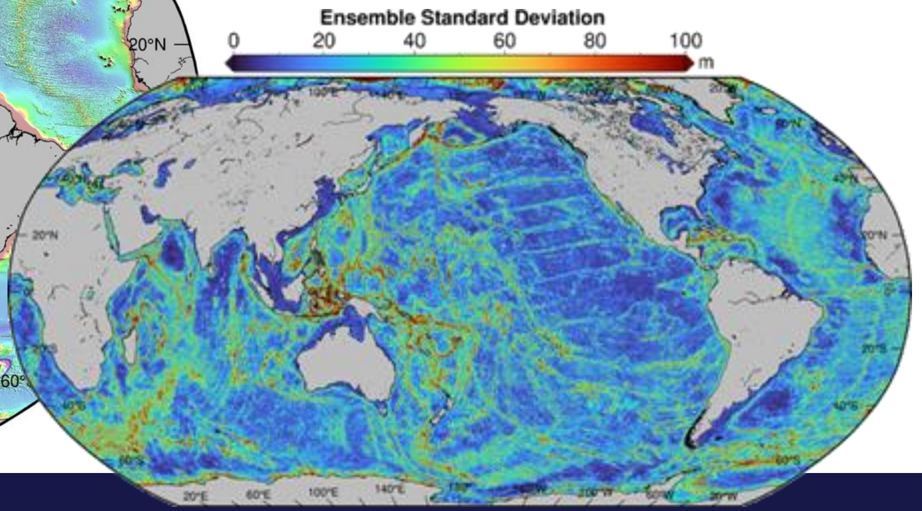
Simple ensemble model

$$\langle T \rangle = \frac{1}{N} \sum_{n}^{N} T_n$$



Model dissagreements

$$\sigma^2_{\langle T \rangle} = \frac{1}{N} \sum_{n}^{N} \left(T_n - \langle T \rangle \right)^2$$



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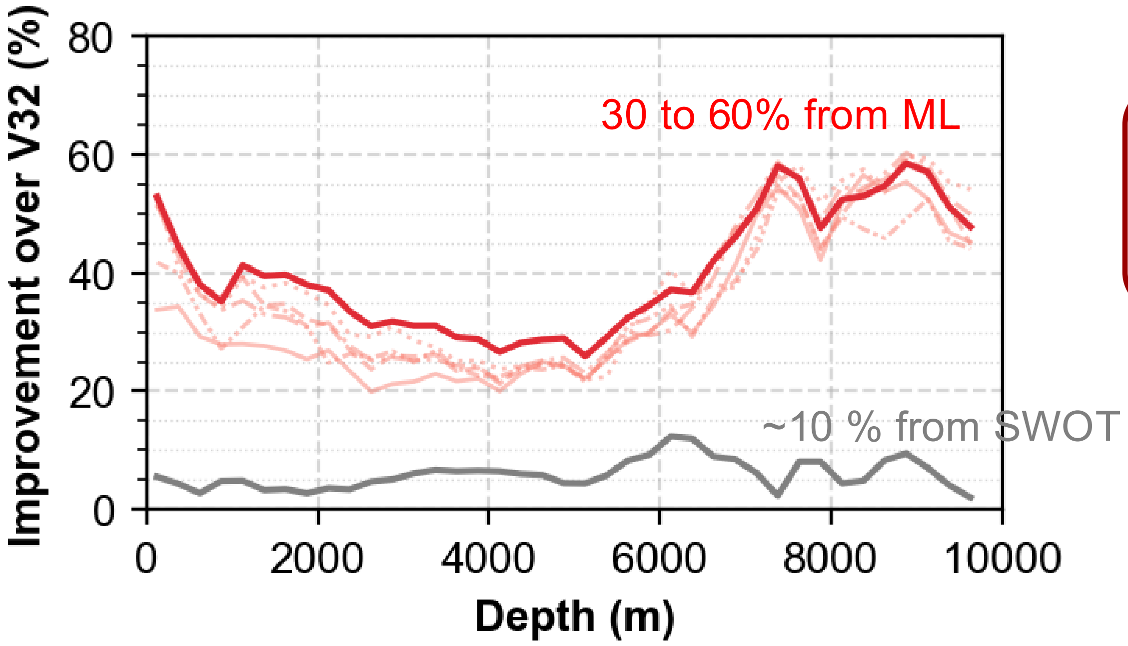
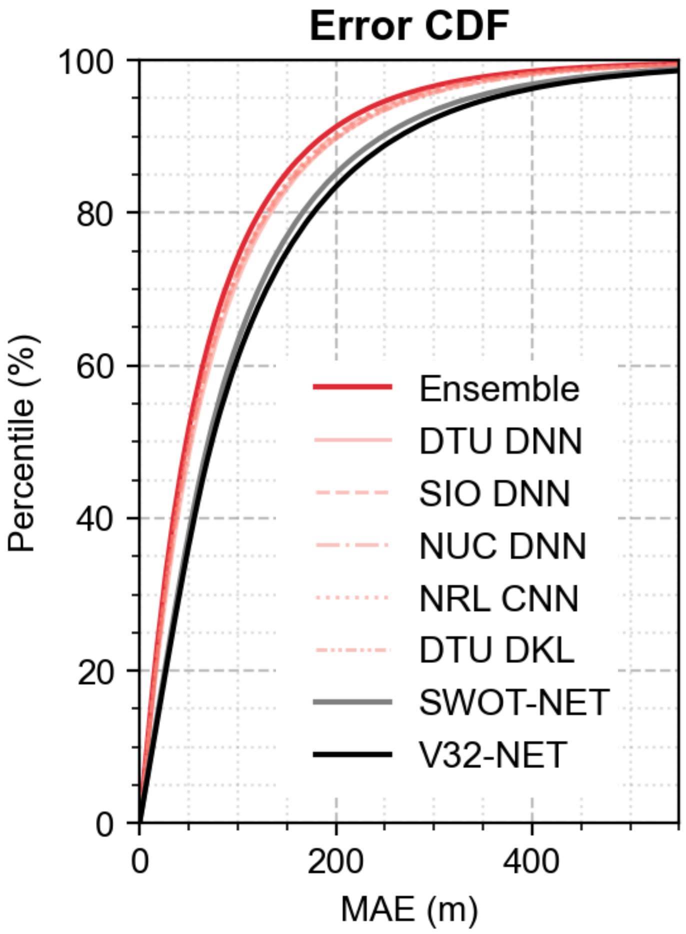
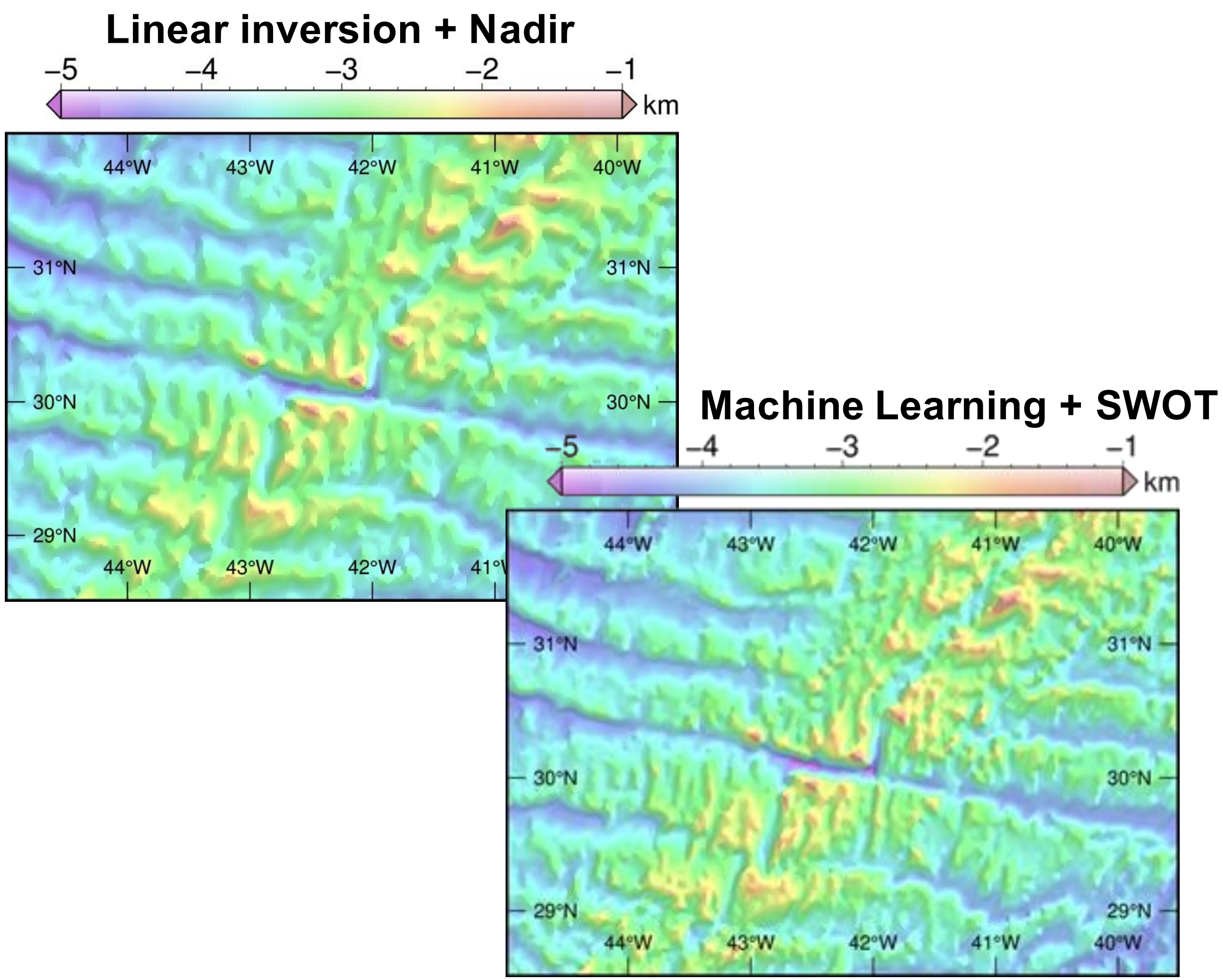
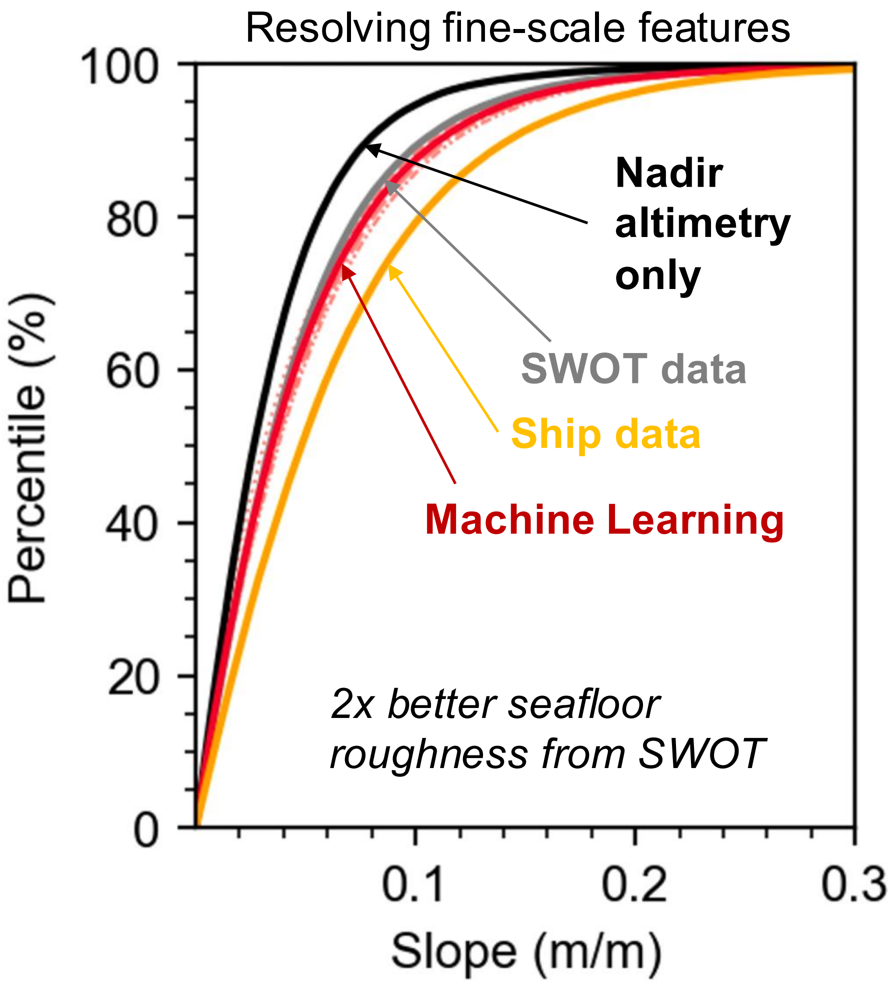


Global error
Bias: 14 m
Uncertainty: 130 m



SWOT resolves small scale features

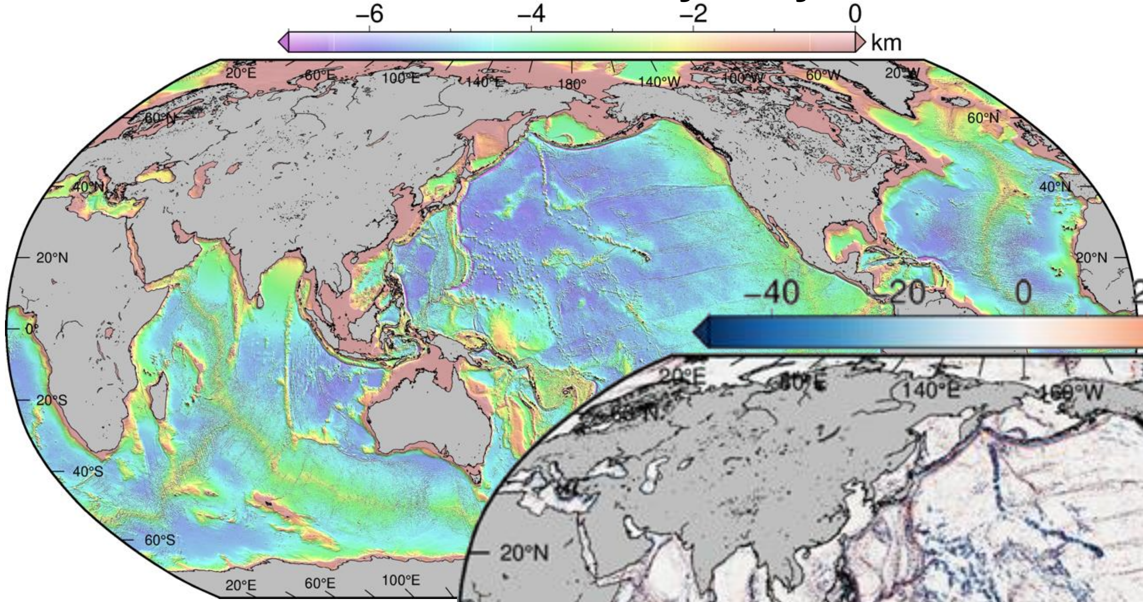




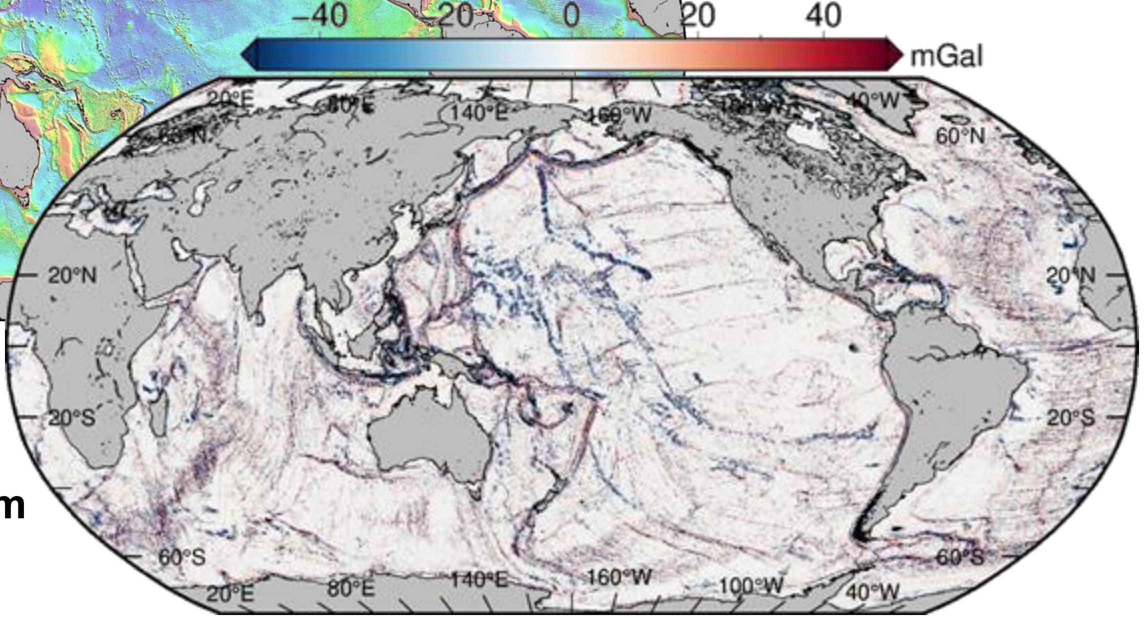
How SWOT can help identify areas of interest

Global dataset of gravity anomalies

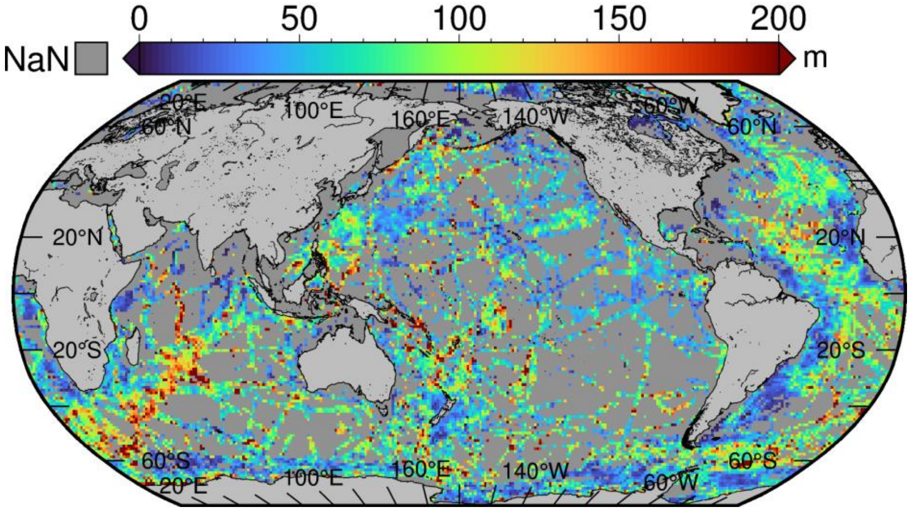
Predicted Bathymetry



Gravity from SWOT



Ensemble Absolute Test error



Establish features that could influence prediction error

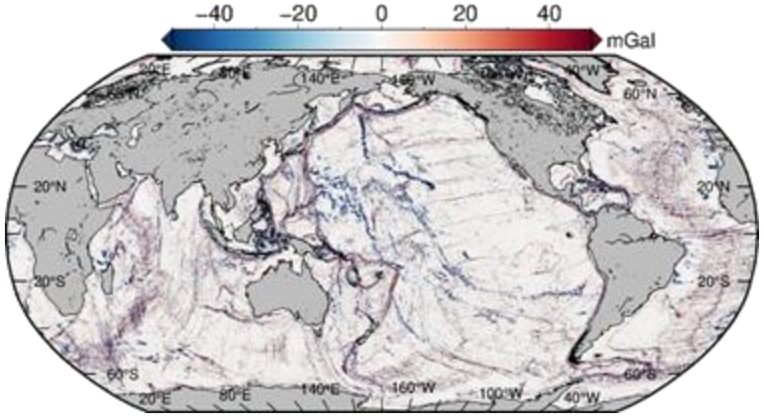
Residual analysis

Estimating errors in order to prioritize ship mapping

➢ Establish features that could **explain prediction error**

Trained-on features

Gravity + gravity derivatives



Location (lat/lon)
Depth

ML builds upon drawing from distributions: we compute out-of-distribution estimates from features

Aux features

Trained features

Bayesian ML

Model dissagreements

Residual analysis

Estimating errors in order to prioritize ship mapping

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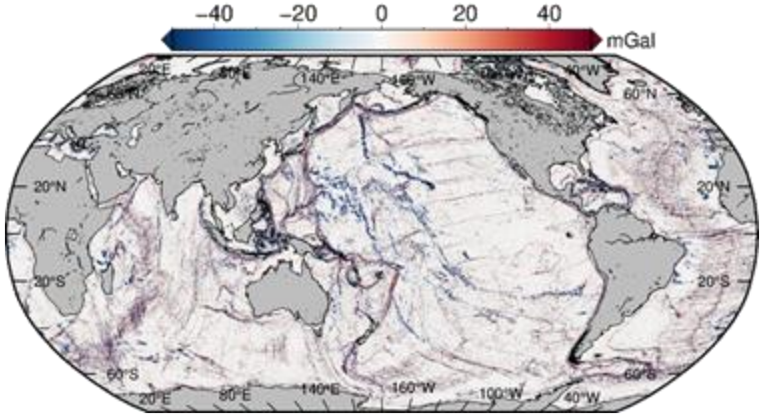

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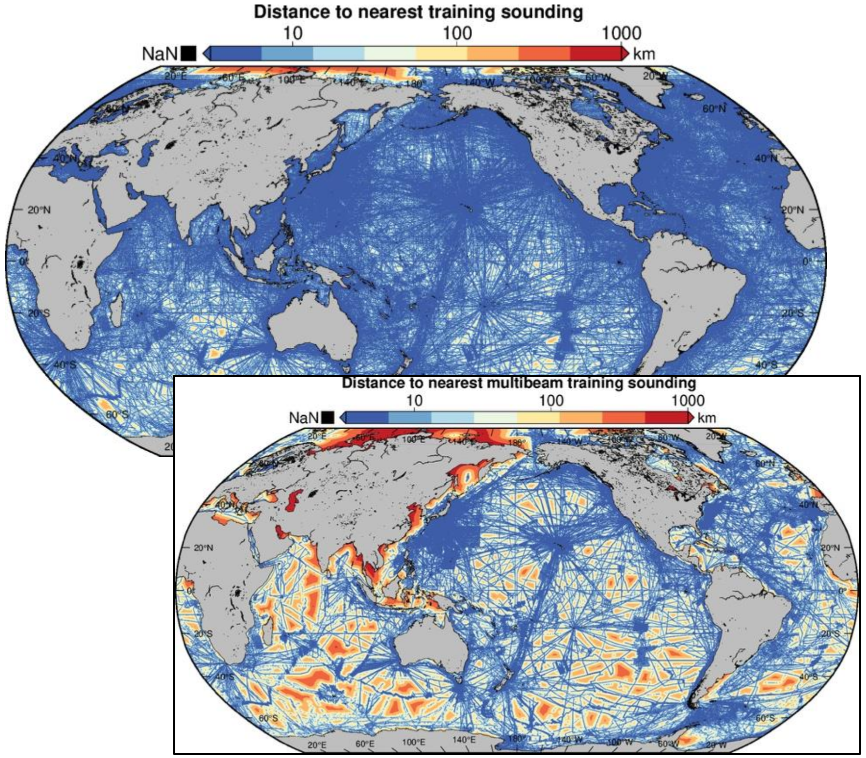

Trained features

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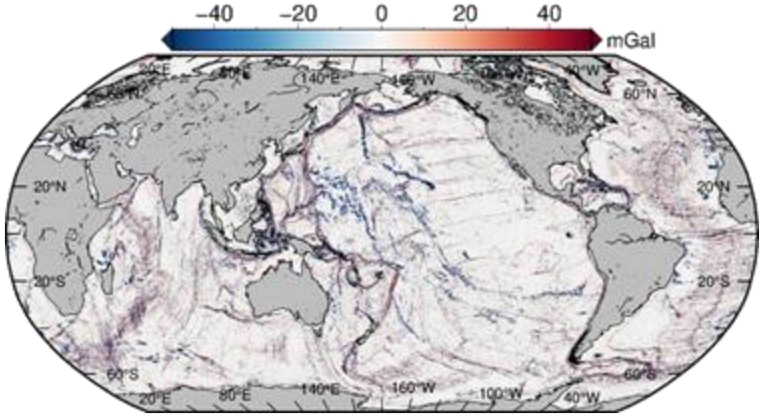

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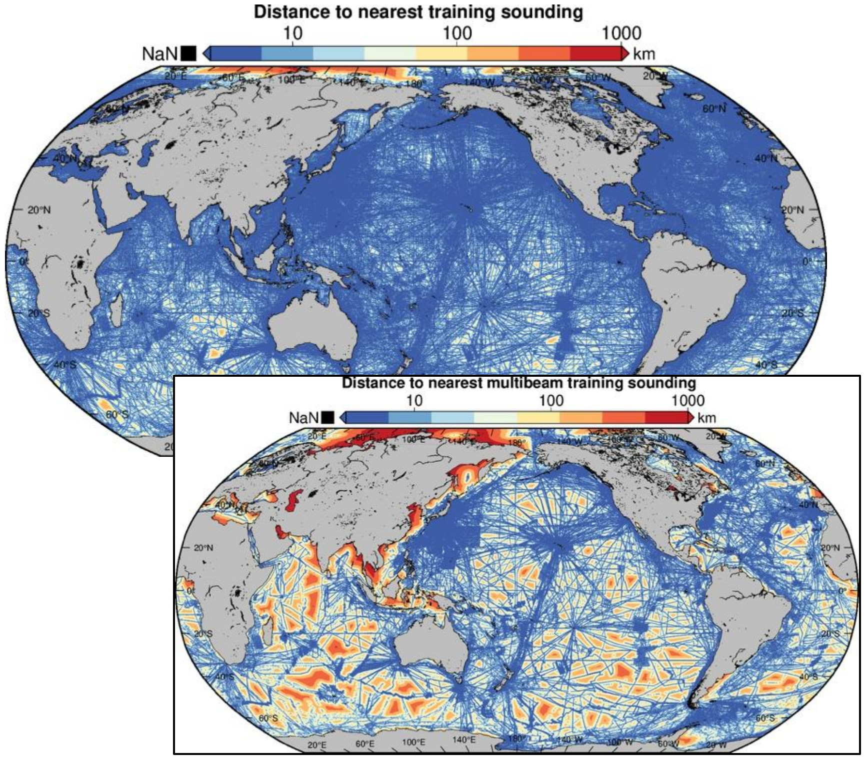
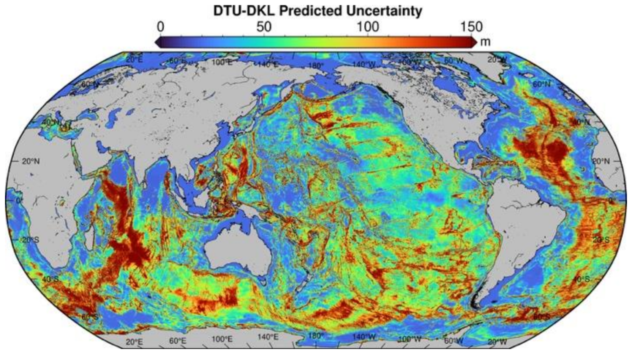


Trained features

Bayesian ML



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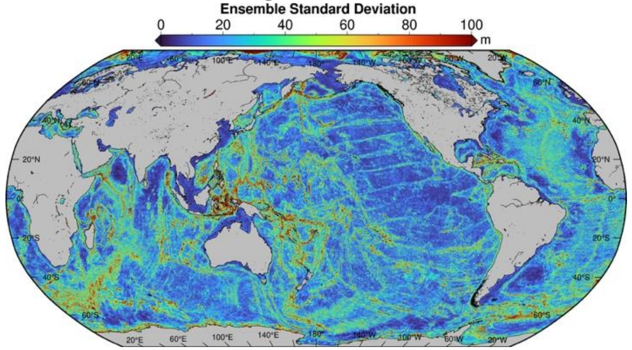
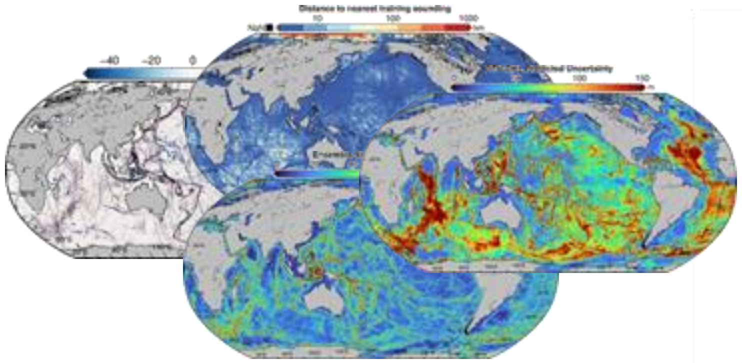
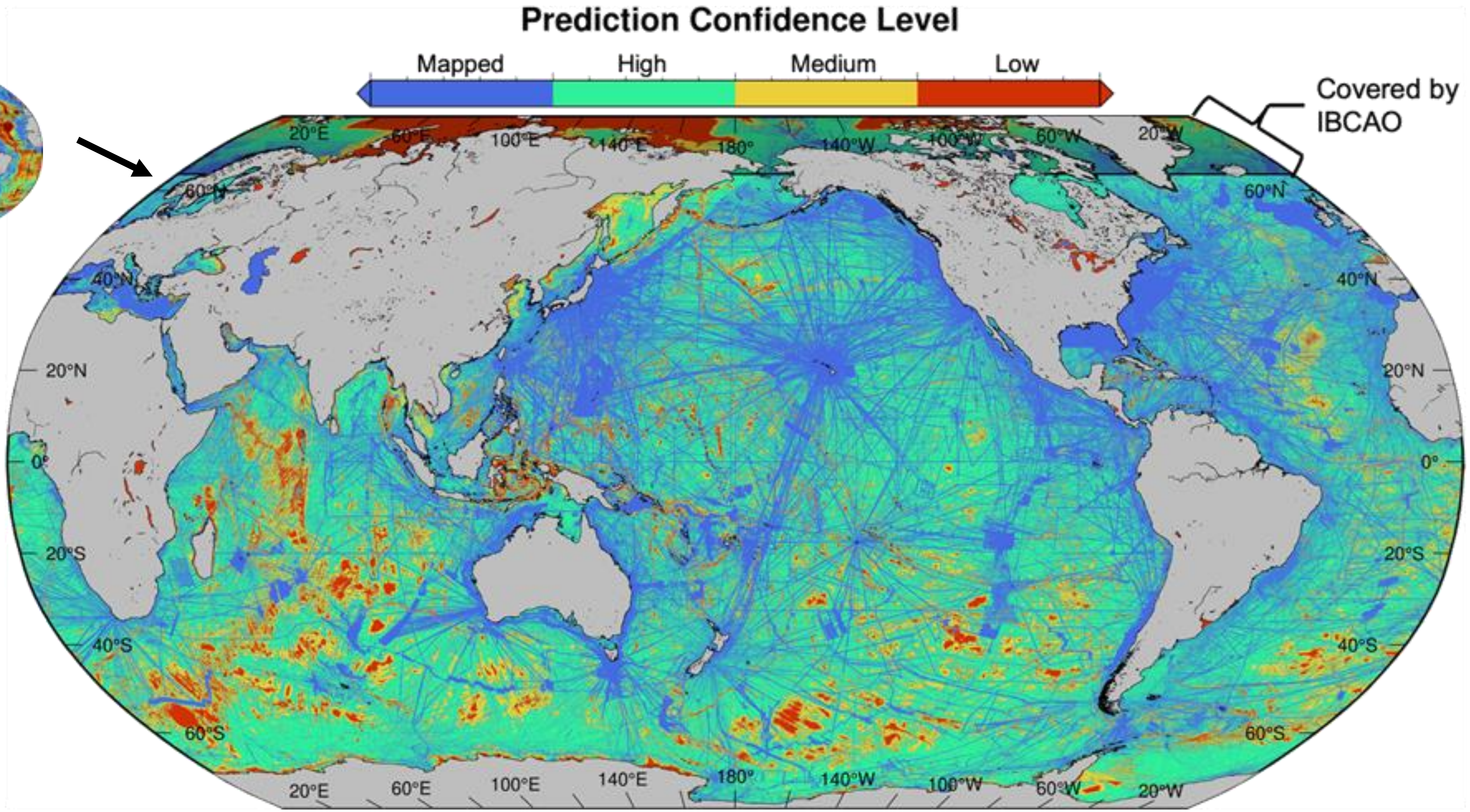


Combining prediction-features to estimate errors

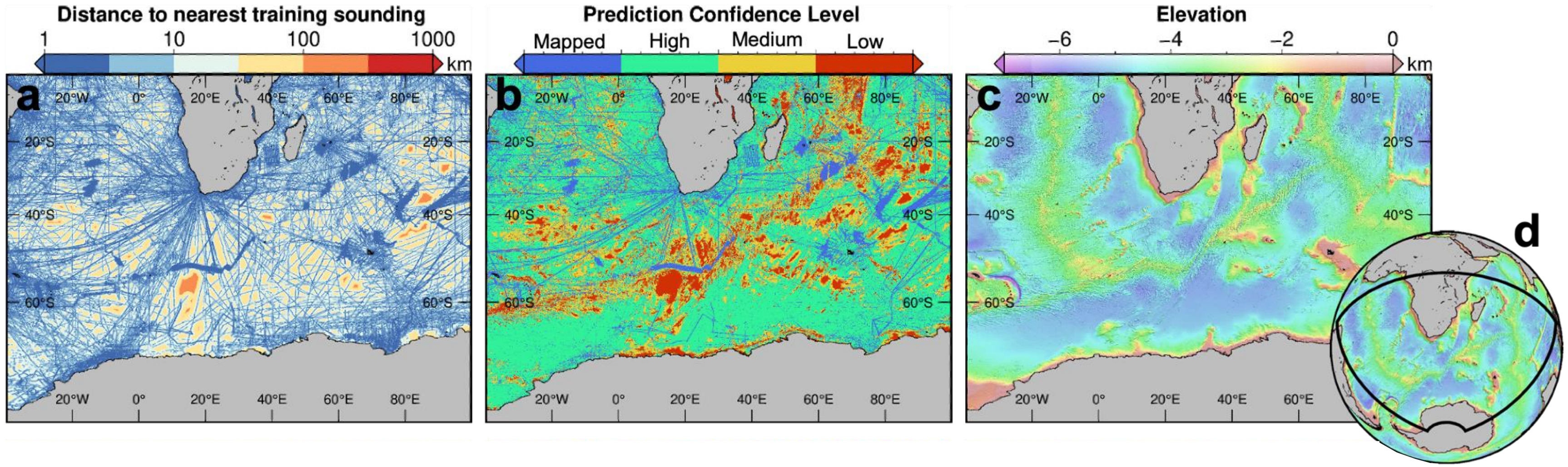


	Correlation
Geographical Distance	0.16
Features Distance	0.32
DKL SD	0.38
CNN SD	0.43
Ensemble SD	0.44
Multivariate Regression	0.54



Inspecting features of interest

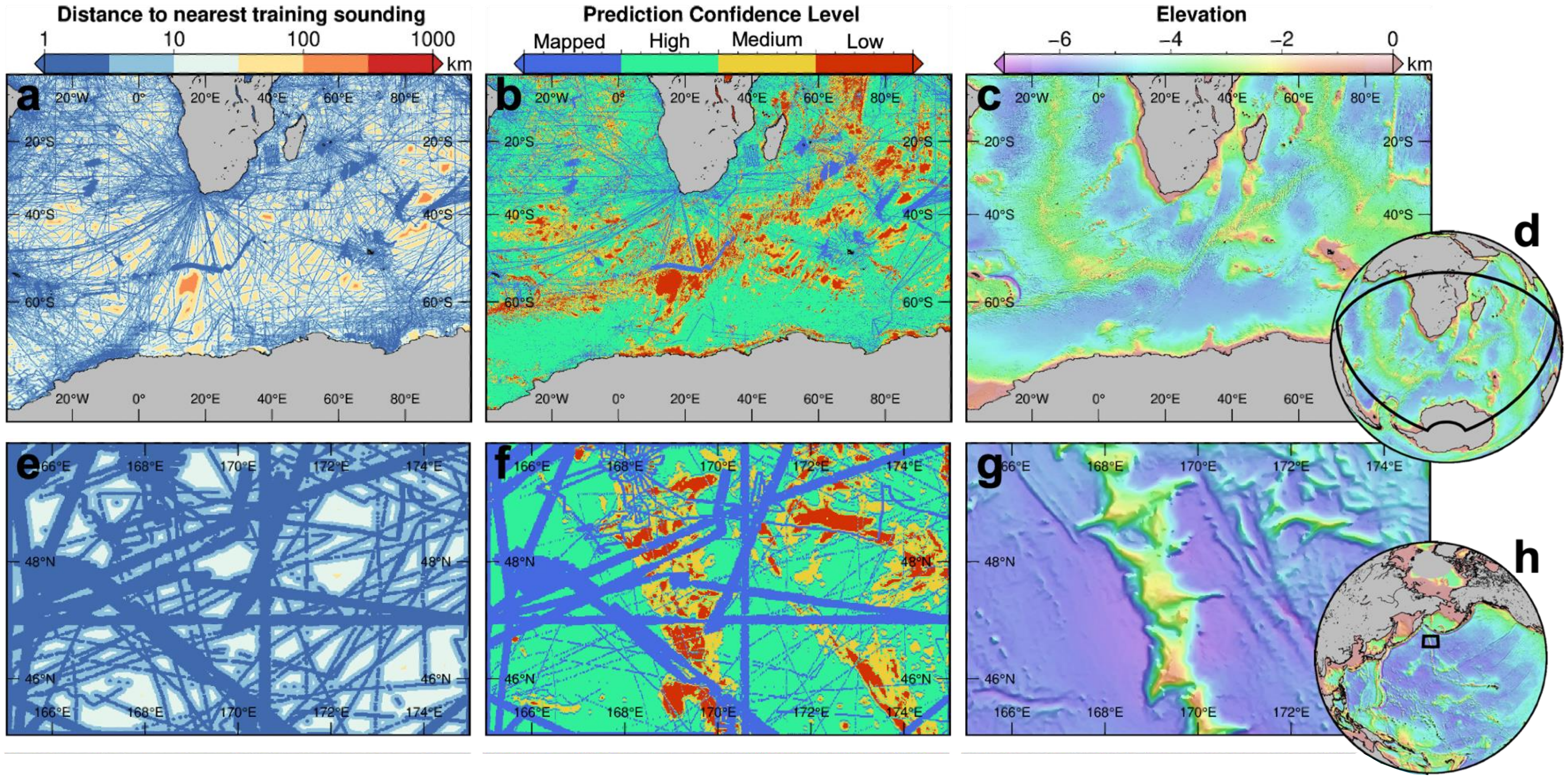
Higher uncertainty due to data gaps in the southern ocean



Inspecting features of interest

Higher uncertainty due to data gaps in the southern ocean

Large features causing large uncertainty next to swaths (emperor seamounts)

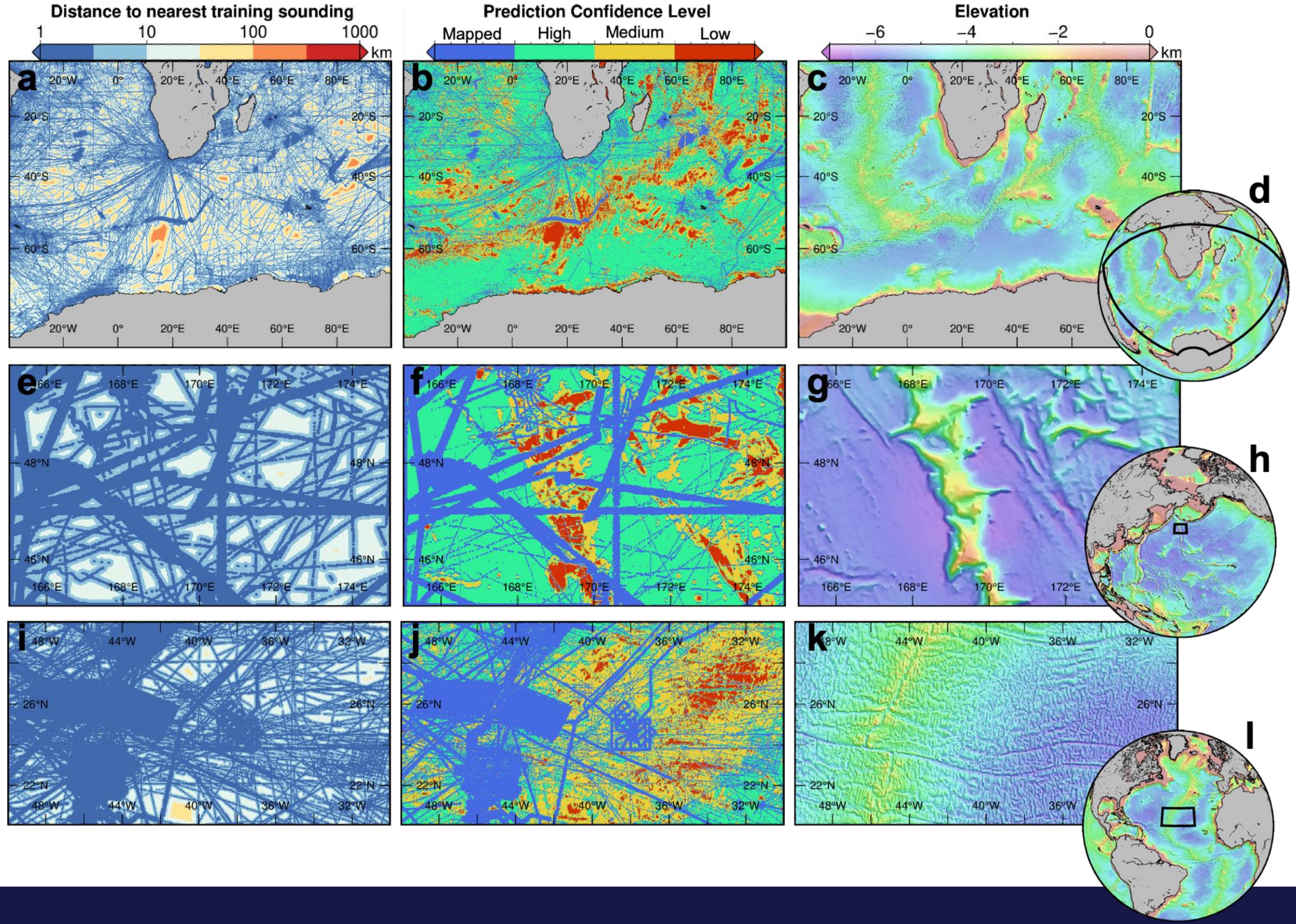


Inspecting features of interest

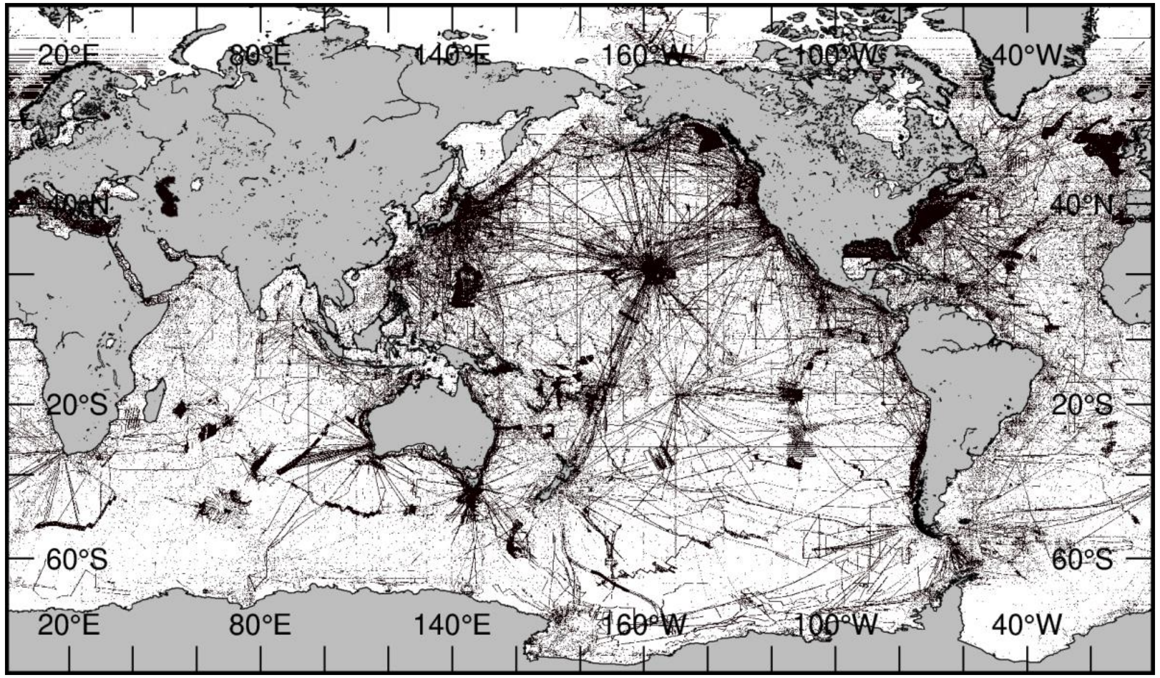
Higher uncertainty due to data gaps in the southern ocean

Large features causing large uncertainty next to swaths (emperor seamounts)

Large seafloor roughness causing overall higher uncertainty, while area of interest is mapped (Mid-ocean ridge)



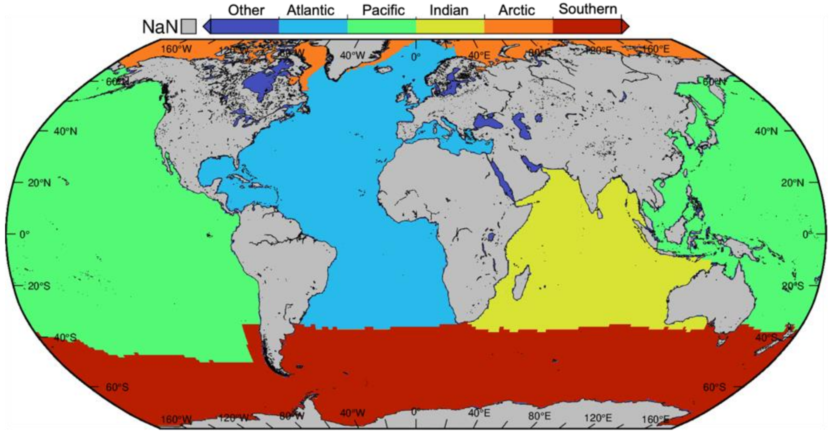
Reduction of “high-priority” areas by >50%



We can prioritise expensive ship-time

- Atlantic and Pacific are better mapped than Indian and Southern ocean
- We go from **~74% to ~7%** need for priority ship mapping
- Medium confidence is needed as areas around features is nessesary for overall mapping

Percentage Cover	Mapped	High Confidence	Medium Confidence	Low Confidence
Global Oceans	23.8	56.2	12.3	7.6
Pacific Ocean	33.7	55.2	7.5	3.6
Indian Ocean	20.3	53.8	16.0	9.8
Atlantic Ocean	32.7	56.5	8.8	2.0
Southern Ocean	13.8	60.7	18.0	7.6
Arctic Ocean†	12.7	44.5	15.8	26.9



Thank you for the attention!

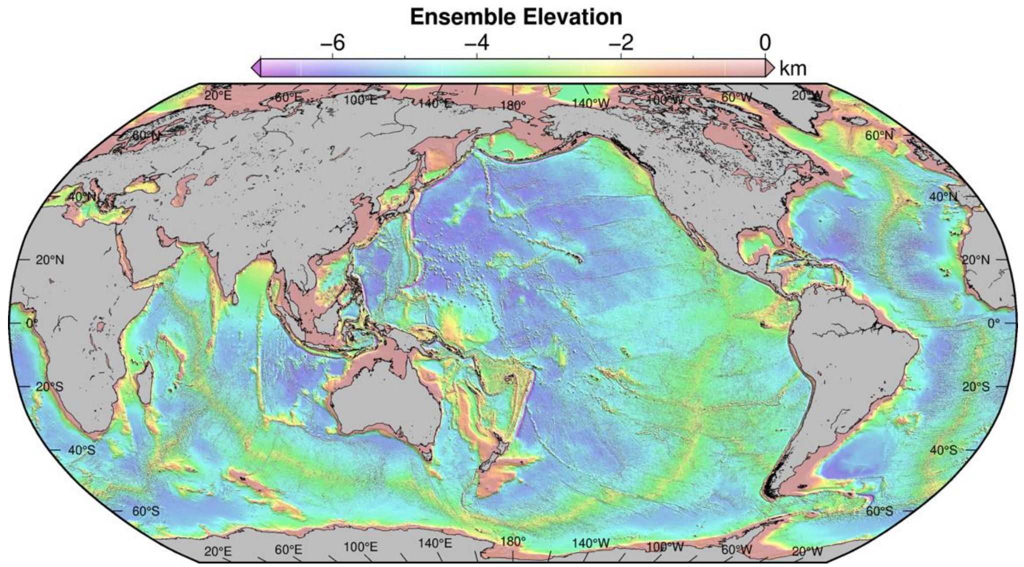
Questions?

Contact: Bjarke@space.dtu.dk

Conclusions

We can prioritise expensive ship-time

- Naive introduction of SWOT improves bathymetry estimates with ~10%
- Introduction of ML methods push this to **30-60% improvement**
- Inspection of features reduces needed ”mapping time” from 74 years to 7 years
- Ensemble model **will be available** for use

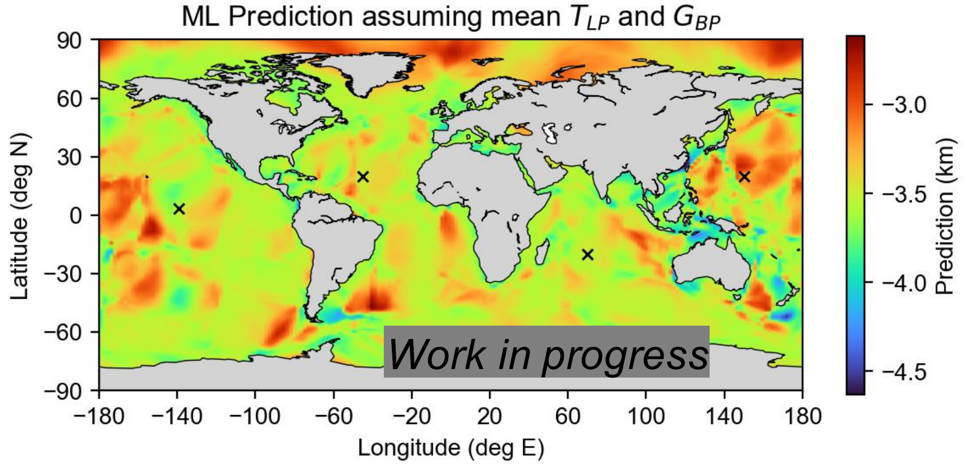


Current outlook on bathymetry prediction

And the impact of SWOT on marine geodesy

As bathymetry prediction reaches it's limit, the potential for "full" physical inversion increases

- ➢ Physics based ML method



SWOT

Gravity anomaly

Prop. Elastic plate thickness

Crustal thickness

$$\frac{\Delta G(\mathbf{k})}{T(\mathbf{k})} = 2\pi\gamma\left(\rho_c - \rho_w\right) e^{-2\pi|\mathbf{k}|s} \left\{1 - \left[1 + \frac{D\left(2\pi|\mathbf{k}|\right)^4}{g\left(\rho_m - \rho_c\right)}\right]^{-1} e^{-2\pi|\mathbf{k}|c}\right\}$$

Seafloor Topography

Mantle density

Crustal density

Ships / ML