AI4Ocean Workshop 2026 Report

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Bottom line: Machine learning can materially improve how ocean data are analyzed, accessed, and used — but realizing this potential requires domain-science leadership, robust validation, and community-driven model development.

https://ai-for-ocean.github.io/workshop2026

A partial group photo

July 20–31, 2026 | University of Washington | Seattle, WA

This intensive two-week convening focused on advancing AI/ML applications within the ocean sciences. The program featured three days of cross-disciplinary research presentations, followed by a week-long, project-driven hackathon and career-focused roundtable sessions with experts from industry and national laboratories.

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Executive Summary

Ocean observations including in situ, airborne and spaceborne are essential for understanding ocean circulation, biogeochemistry, and climate. Traditional methods for converting these raw observations into gridded, analysis-ready products are reaching their limits as data volumes grow. New scientific questions demand finer resolution and multi-variable synthesis. Applications further need prompt information flow derived from realtime data. Machine learning (ML) offers complementary approaches that can compress, denoise, interpolate, and interrogate these datasets in ways that traditional methods cannot.

The AI4Ocean Workshop 2026 held July 20–31 at the University of Washington School of Oceanography, brought together 52 participants from 23 institutions spanning academia, NASA headquarters and centers, national laboratories, and industry. The workshop combined invited talks, lightning talks, and a week-long student hackathon with daily lectures on machine learning, remote sensing, and geophysical fluid dynamics, culminating in eight team projects.

The workshop identified three levels of AI readiness for in situ and satellite remote sensing (Section 5). **Demonstrated capabilities** included compact ML representations of observations, noise reduction, and learning relationships across different variables. **Emerging applications** included LLM-queryable data products and ML extensions to traditional statistical methods, empirical parameterizations, and ocean state estimation, although these require further validation. **Long-term opportunities** include using LLMs to answer increasingly complex scientific questions as AI systems gain access to and learn from Earth-observation datasets.

Recommendations (Section 6) emphasize several aspects of practicing ML for ocean sciences.

1. Robust uncertainty quantification is essential for ML product utility.
2. Domain scientists including oceanographers, remote sensing specialists, atmospheric scientists should lead defining the objectives.
3. Student training should be incentivized in NASA grants in an era of AI replacing white-collar jobs to ensure the generational continuity in ocean sciences.
4. Foundation model development should be community-driven and experimental rather than top-down.
5. Clear pathways from products to operations must be defined. Funding agencies should create incentives to bridge the persistent gap between scientific findings and implementable, science-driven applications (e.g., the "Earth Data to Action" pathway).

AI cannot drive scientific discovery on its own (at least at the time of this writing in August 2026). The workshop concluded that realizing the potential of AI for ocean remote sensing depends on investing in people and practices as much as in algorithms. The workshop format itself, i.e., bringing together students and researchers deep in ocean science and in AI applications in an intensive, collaborative setting, proved to be an effective platform for facilitating the connection between scientific discovery and implementable, science-driven applications. Sustaining and expanding this kind of cross-disciplinary convening is itself a recommendation: the bridge between science and action is built by people working together, not by technology alone.

1. Introduction

1.1 Motivation

Machine learning is rapidly transforming the landscape of oceanography. Satellite observations from missions such as NASA SWOT (Surface Water and Ocean Topography) and PACE (Plankton, Aerosol, Cloud, ocean Ecosystem) together with high-resolution numerical simulations and increasing in situ ocean interior observations such as the broad coverage by Argo floats and high-frequency measurements from Ocean Observing Initiative (OOI) — are revealing ocean variability at unprecedented spatial and temporal scales. This convergence creates a unique opportunity to rethink how we observe, model, and understand the ocean as an integrated system.

However, applying AI/ML to oceanography presents distinctive challenges: ocean data are sparse, noisy, and high-dimensional; physical constraints must be enforced; and model interpretability is essential for scientific discovery but less mature in the ML approach. There is a pressing need to build a community of researchers fluent in both ocean dynamics and modern AI methods, and to establish best practices that ensure ML outcomes are physically consistent and scientifically meaningful.

1.2 Workshop Objectives

The AI4Ocean Workshop 2026 was designed around three core goals:

1. **Build an Ocean-AI community.** Foster a cross-disciplinary community with a shared vision of advancing ocean science through innovative data science and AI technologies. Promote collaboration across domains, institutions, and career stages.
2. **Establish scientifically rigorous pathways for AI in oceanography.** Define clear machine learning practices to ensure research outcomes are consistent with known ocean dynamics. Ensure that AI methods contribute meaningfully to scientific understanding rather than producing black-box results.
3. **Enable optimal future ocean observations through AI innovation.** Identify where AI can transform ocean observing systems, data assimilation, and predictive capabilities. Lay the groundwork for future observing system concepts and strategic ocean-AI integration.

2. Workshop Design and Participation

Program Structure and Agenda

The workshop was structured as an intensive two-week program.

Week 1 — Presentations and Community Building (July 20–22)

The first three days were dedicated to research presentations and community formation:

Day 1 (Monday, July 20): Opening remarks by the three organizers, followed by invited talks by Dr. Luke Van Roekel (Los Alamos National Laboratory) on "Ocean AI/ML development at DoE" and Dr. Zhiwen Fan (Texas A&M University) on "Ocean Foundation Model Architecture." Four lightning talks covered adjoint-based stochastic parameterization, exponential scaling for ocean processes, SWOT for ice mélange detection, and deep learning for ice-ocean interactions. The day concluded with self-introduction slides from all participants (round-robin, ~1.5 min each) and the initiation of project ideas via a shared slide deck.

Day 2 (Tuesday, July 21): Invited talks by Dr. Kelsey Bisson (NASA Headquarters) on "Biodiversity from Space: Challenges and Opportunities" and Dr. Ian Fenty (NASA JPL) on "NASA ECCO Development and Challenges for ML." Eleven lightning talks spanned topics including MITgcm DINO configurations, probabilistic sea-ice velocity prediction, diffusion models for altimetry, ocean front detection with Gaussian Mixture Modeling, SSH-based current estimation, decadal oxygen variability, optimal state-space representation, SWOT object detection models, Arctic sea ice forecasting and freeboard gap filling, and SSH-to-subsurface flow mapping. The day ended with project formation and team scoping.

Day 3 (Wednesday, July 22): Invited talk by Martin Kolster (Ph.D. student, University of Colorado Boulder) on "Spatiotemporal Machine Learning Representations of Satellite Altimeter Measurements." Twelve lightning talks covered marine nitrous oxide emissions, MOM6 regional emulation, subgrid vertical mixing ML, wave-current interactions, synthetic cloud generation, heat transport inference, glider-based current reconstruction, metagenomics and environmental data, Southern Ocean sea ice velocities, and more. The afternoon featured a project pitch session (5 min per team), team finalization, and an evening movie night.

Week 1–2 Transition — Hackathon Period (July 23–29)

Daily schedule during the hackathon:

Time	Activity
9:00–10:00	Morning lecture (1 hour)
10:00–10:30	Project check-in (all teams)
10:30–12:00	Project work
12:00–13:30	Lunch
13:30–16:00	Project work / hackathon
16:00–17:00	Afternoon check-in (all teams)
17:00	Optional informal discussion

Morning Lecture Schedule:

- Thursday, July 23 — Dr. Georgy Manucharyan (UW) — "Fundamentals of Machine Learning for Oceanography"

- Friday, July 24 — Dr. Steve Nerem (University of Colorado) — "Introduction to Satellite Altimetry and Satellite Gravity for the Oceans"
- Monday, July 27 — Dr. Justin Stopa (University of Hawaii at Manoa) — "Introduction to SAR and Its Applications"
- Tuesday, July 28 — Tatsu Monkman (New York University) — "Using Diffusion Models for Multivariable Satellite Data Fusion"
- Wednesday, July 29 — Eugenio Cutolo (Atalaia AI) — "Introduction to Transformers"
- Thursday, July 30 — Dr. Jinbo Wang (TAMU) — "Let's Go Nonlinear with SWOT"

Weekend (July 25–26): No formal sessions. Participants worked independently or explored Seattle. Some activity photos can be accessed here: https://ai-for-ocean.github.io/workshop2026/activities/

Week 2 — Final Presentations and Wrap-up (July 30–31)

Final project presentations by the eight teams, with 20–30 min per team including Q&A.

Social Events and Lab Tours:

- Movie Night — July 23, 7:00–9:00 PM
- Argo Lab Tour — July 28
- Karaoke Night – July 29, 7:00–9:00 PM

Venue: School of Oceanography, Ocean Science Building, University of Washington.

3. Workshop Curriculum

The workshop curriculum was designed to provide both foundational knowledge and cutting-edge research exposure, structured across three pillars.

3.1 Invited Talks (20 min + 20 min discussion)

Invited talks anchored the presentation days, featuring senior researchers from NASA, national laboratories, and universities:

1. Dr. Luke Van Roekel (Los Alamos National Laboratory) — "Ocean AI/ML Development at DoE"
2. Dr. Zhiwen Fan (Texas A&M University) — "Ocean Foundation Model Architecture"
3. Dr. Kelsey Bisson (NASA Headquarters) — "Biodiversity from Space: Challenges and Opportunities"
4. Dr. Ian Fenty (NASA JPL) — "NASA ECCO Development and Challenges for ML"
5. Martin Kolster (University of Colorado Boulder) — "Spatiotemporal Machine Learning Representations of Satellite Altimeter Measurements"

3.2 Lightning Talks (10 min + 10 min discussion)

Over 25 lightning talks were delivered across the three presentation days, covering a broad spectrum of topics:

- **SWOT and satellite altimetry:** SSH-to-subsurface flow mapping, SWOT object detection models, sea ice velocity from SWOT, altimetry data gridding with diffusion models, spatiotemporal observability in geostrophic turbulence
- **Sea ice and polar oceans:** Probabilistic deep learning for sea-ice velocity, ice mélange detection, glacier melt simulation, Antarctic sea ice transport
- **Air-sea interaction:** Air-sea heat flux from satellite imagery, wave-current interactions, SAR applications
- **Ocean parameterization:** Adjoint-based stochastic parameterization, MOM6 regional emulation, subgrid vertical mixing, diffusion models for ocean state reconstruction
- **Biogeochemistry:** Marine nitrous oxide emissions, metagenomics and environmental data, ocean color/fluorescence, carbon export estimation
- **ML methods:** Generative diffusion models, transformer architectures, foundation models, Gaussian Mixture Modeling for front detection, synthetic cloud generation

3.3 Morning Lectures (Hackathon Period)

Six morning lectures provided foundational and methodological training during the hackathon:

1. Dr. Steve Nerem — Introduction to satellite altimetry and satellite gravity for ocean applications
2. Dr. Georgy Manucharyan (University of Washington) — Fundamentals of machine learning for oceanography
3. Dr. Justin Stopa — Introduction to SAR (Synthetic Aperture Radar) and its applications
4. Dr. Tatsu Monkman — Using diffusion models for multivariable satellite data fusion
5. Dr. Eugenio Cutolo — Introduction to Transformer architectures
6. Dr. Jinbo Wang — Nonlinear approaches to SWOT data analysis

3.4 Self-Introduction Session

All participants prepared self-introduction slides (~1.5 min each) on Day 1, providing a rapid overview of backgrounds, research interests, and collaboration goals. This session was critical for team formation and identifying complementary expertise.

4. Collaborative Projects and Technical Outcomes

4.1 Project Scoping and Team Formation

Project formation followed a structured process inspired by the ECCO Summer School format:

1. **Day 1 (July 20):** A shared Google Slide deck was introduced for participants to post project ideas and identify potential collaborators.
2. **Day 2 (July 21):** Dedicated project formation session for team organization and scoping.
3. **Day 3 (July 22):** Each team pitched their project (5 min each), followed by team finalization and plan confirmation.

4.2 Hackathon Projects

Eight teams worked collaboratively on the projects listed below. All produced comprehensive full project reports. Double-blind reviews were conducted by three anonymous reviewers. The reviews were used for selecting a hackathon winner.

1. **PIXC-IE**: PIXel Cloud-Identifying phase Errors
2. One run instead of twenty: a deep-learning ensemble-mean emulator for eddy-permitting ECCO
3. **WAVES**: WAVe and geostrophic Extraction with Supervised learning
4. **MARLIN**: Machine-learning Analog Retrieval for LINking satellite observations with ocean reanalysis
5. **SLeD**: SWOT Lead Detection in the Southern Ocean
6. Waves to Surface Flow
7. **NOISY SALMON**: Neural Ocean Imaging for SWOT, Yielding Smoothed Altimetry through Learned Mapping of Ocean Noise
8. **ORCA**: Ocean Representation learning for a Coupled Atmosphere

5. Key Findings: AI for Oceanography

The workshop demonstrated that AI can provide multiple paths for improving the analysis and use of satellite remote sensing data. Findings are grouped by readiness level — what was demonstrated at the workshop, what is emerging and promising, and what remains aspirational.

Demonstrated at the workshop

1. **ML representations of satellite data.** ML models can produce compact representations of satellite datasets that are easier to use than the originals and may provide better temporal and spatial interpolation than traditional optimal interpolation (OI) — the statistical method widely used to map sparse satellite observations onto regular grids.
2. **Noise reduction.** ML can reduce noise in satellite remote sensing measurements, improving data quality for downstream applications.
3. **Cross-variable relationships.** ML can identify and model complex relationships between different remotely sensed variables (e.g., between ICESat-2 and SWOT, SWOT backscatter and surface current etc.), providing a new technique for exploring interactions in the Earth system.

Emerging and promising

4. **LLM-queryable data products.** ML models can be structured so that Large Language Models (LLMs) can query them, expanding commercial and public access to NASA's satellite remote sensing archives. This approach was explored in workshop projects and shows strong potential but is not yet operational.
5. **Extending traditional methods.** ML offers new approaches that extend traditional statistical methods and empirical parameterizations in numerical models and ocean state estimation. Early workshop results were encouraging, but broader validation is needed.

Long-term and aspirational

6. **Progressive LLM capability.** As LLMs learn from the use of these datasets, they may eventually answer increasingly complex scientific questions. This pathway is forward-looking and was not demonstrated at the workshop.

6. Recommendations

Robust uncertainty quantification ML products without uncertainty estimates are of limited use for scientific applications or operational decision-making. All ML-derived ocean products should include rigorous, quantified uncertainty, validated against independent observations.

Domain-science leadership of interdisciplinary teams Many opportunities exist at the interface of oceanography and machine learning, but these are best exploited on multi-disciplinary teams where oceanographers, remote sensing scientists, atmospheric scientists, and Earth scientists take a leading role, i.e., “let the nails emerge before looking for the hammer”. Domain experts are necessary to identify the key scientific questions and should not over-emphasize the role of computer science. Without domain science, we often face the problem of lacking applications and adoptions of a technology. This resembles NASA’s tradition in building space missions: driven by science quests before building the hardware.

Student training and hypothesis-driven education AI has strong potential to accelerate scientific discovery, but achieving tangible progress requires domain experts to formulate valuable hypotheses and design adequate methods to test them. The workshop recommends promoting student training focused on domain-specific scientific knowledge with direct connections to AI as an incentive in NASA grants, with a focus on creative and hypothesis-driven education and training — ensuring that the next generation of researchers can formulate scientific questions and use AI as a tool to answer them, rather than treating AI as an end in itself.

Foundation model development governance Foundation models (large-scale ML models trained on broad data that can be adapted to many downstream tasks) should be developed through community involvement. This is inherently a research project — it is experimental by nature and should proceed through natural selection of approaches rather than a centrally directed process. The community should be involved before finalizing any single foundation model with transparent evaluations.

Operations transition pathway Workshops can produce algorithms and products, but someone must take on operations — transitioning research-grade ML outputs into sustained, operational data services. This handoff must be planned from the outset.

Connecting scientific findings to implementable applications A persistent gap exists between ocean scientific findings and implementable, actionable applications — the "Earth Data to Action" pathway. Too often, scientifically rigorous results remain in the research domain and never reach the operational or decision-support communities that could benefit from them. The workshop recommends that funding agencies create incentives to bridge this gap, supporting translational efforts that connect scientific discovery to real-world applications. Critically, these applications must be science-driven: the scientific question should lead, and AI/ML should serve as a tool to answer it, not the reverse. Incentive structures should reward proposals that explicitly articulate both the scientific motivation and the implementation pathway, and should support the validation, stakeholder engagement, operational transition work that is currently underfunded.

A compounding problem is that existing institutional structures provide weak incentives for operational adoption of scientifically validated data products or algorithms. The path from research prototype to sustained operational use is unclear — a researcher who develops a successful ML-based ocean product has little institutional or funding motivation to navigate the transition to operations, and operational centers have limited incentive or resources to adopt community-developed tools. The workshop recommends that NASA and partner agencies reduce the barrier by establishing clear transition pathways, creating funding mechanisms that explicitly support the operational handoff, and building incentive structures that reward both the scientists who develop validated products and the operational centers that adopt them.

The workshop itself demonstrated a practical mechanism for addressing this disconnect. The workshop format brought together researchers deep in ocean science and researchers deep in AI and applications, in an intensive collaborative setting that naturally facilitated the connection between scientific discovery and implementable applications. Cross-disciplinary convenings of this kind — where domain scientists, ML practitioners, and potential operational users work side by side on shared problems — reduce the social and intellectual barrier that normally separates these communities. The workshop recommends sustaining and expanding this model as a low-cost, high-impact mechanism for bridging the science-to-action gap, including its use as a platform for operational stakeholder engagement and transition planning.

7. Targeted Physical Oceanography Research Opportunities

The following opportunity areas were identified at the intersection of AI, physical oceanography (PO), and satellite oceanography:

1. **AI + physical oceanography + satellite oceanography.** Broad opportunities exist for ML to improve the analysis, interpolation, and interpretation of satellite-derived physical ocean variables (sea surface height, temperature, salinity, winds).
2. **Surface-to-subsurface inference.** Satellites observe the ocean surface; ML offers a path to infer subsurface ocean structure (temperature, salinity, currents) from surface observations — a longstanding challenge in physical oceanography.
3. **Foundation models as data compression.** Foundation models can compress vast satellite datasets into compact, queryable representations. However, the information that is lost in this compression must be identified and quantified. Use cases are needed, including physics-oriented, domain-specific foundation models for prognostic ocean variables (variables that evolve in time according to physical equations, such as temperature and velocity), with clearly defined evaluation metrics. The workshop recommends a proposal call for evaluation of such models.
4. **Validation of ML.** ML models must be validated against independent data, not the same observations used for training. Robust, independent validation is essential for scientific credibility and operational adoption. The community needs to design a framework that validates AI-generated products following conservation laws and known physics.

8. Synthesis and Future Strategic Outlook

8.1 Roundtable Discussions

Throughout the workshop, informal roundtable discussions emerged around several cross-cutting themes:

- **Data quality and accessibility:** One of the major challenges in applying ML to ocean data is the data readiness. Once a dataset is ready for training, ML development and implementation are usually fast. Data cleaning, however, is not a glorious task; domain scientists often avoid it whenever possible. This creates a gap in the available AI-ready oceanography datasets.
- **Trustworthiness (AI ethics):** This discussion was led by a student and focused on the topics of responsibility, explainability, robustness, and transparency in using LLMs to perform scientific research. Concerns and best practices were shared among attendees, including data privacy and identifying AI hallucinations.
- **Foundation models for ocean science:** We are still at the beginning of exploring the concept of foundation models. There were discussions about what are foundation models. It is understood that we likely need multiple FMs before a final model that ‘understands’ the entire Earth system, which will certainly require enormous amounts of computation. Smaller foundation models for certain tasks, missions, variables will be practical in the near future, such as denoising, gap-filling etc.
- **Career pathways:** Scientists at various career stages were present, including professors, a startup CEO, a scientific AI researcher from the private sector, and a full-time research scientist. The discussion centered on questions from students and topics included the motivation for pursuing different career pathways and what skills are most relevant for pursuing each of these pathways. Many senior scientists are concerned about the future of

their graduate students given the rapid development of AI. Much of the conventional work students perform in their research could be replaced by AI, leaving them at risk unless unique roles can be identified for them. Some senior scientists encourage students to pursue industry jobs if possible.

8.2 Proposal Development Strategies

- **NASA ROSES proposals:** Several teams identified NASA Research Opportunities in Space and Earth Sciences (ROSES) program elements relevant to their project topics.

- **NSF cross-directorate funding:** Several members discussed the pathway to an NSF proposal responding to NSF 26-512 Unlocking dataset value for AI-enabled scientific discovery (AI datasets)
- **DoE and national laboratory collaborations:** Connections with Los Alamos National Laboratory opened pathways for DoE-funded climate and Earth system modeling collaborations.
- **Industry partnerships:** A round table discussion was conducted for students and postdocs on career development particularly between academia and industry. Dr. Martin, a recent PhD graduate from physical oceanography hired by Nvidia, shared his experience of transitioning to the private sector.

8.3 Future Directions and Community Building

1. **Sustained community infrastructure:** Maintaining the workshop Slack workspace, GitHub repositories, and website as persistent community resources beyond the workshop duration.
2. **Recurring workshops:** Building AI4Ocean into a recurring annual or biennial event, potentially rotating host institutions. The organizers will need to secure a sustained funding source to support student and early-career participation.
3. **Data challenges and benchmarks:** Developing standardized ocean ML benchmarks (analogous to computer vision benchmarks) to enable fair comparison of methods across research groups.
4. **Cross-mission data fusion:** Advancing ML methods that integrate multiple satellite missions (SWOT, PACE, ICESat-2, Sentinel-6, NISAR), Argo, drifters, OOI-moorings, for holistic ocean characterization.
5. **Education and training:** Expanding the lecture and tutorial content developed for this workshop into openly available educational resources for the broader community.
6. **Support students and early careers:** Continuing to support graduate student travel grants and broadening participation across institutions and career stages. This is becoming particularly important in this era when AI can easily surpass students in research.

9. Conclusion

The AI4Ocean Workshop 2026 demonstrated that machine learning offers concrete, demonstrable pathways to improve how NASA's satellite ocean remote sensing data are analyzed, accessed, and used, from compact ML representations that rival or exceed traditional optimal interpolation, to noise reduction and cross-variable relationship. The eight collaborative hackathon projects, spanning analog forecast of loop current eddies, sea ice lead identification, and SWOT noise removal, provided tangible proof of concept that interdisciplinary teams can produce scientifically meaningful ML results within a workshop setting.

The workshop also made clear that realizing this potential at scale depends on factors beyond algorithm development. Domain scientists must lead interdisciplinary teams to ensure that ML outcomes are physically consistent instead of generating datasets that risk misleading downstream analysis, whether scientific or applied. Robust, independent validation and uncertainty quantification are prerequisites for operational adoption. Foundation model development should remain community-driven and experimental, guided by use cases and evaluation metrics defined by the science community. *Sustained investment in student training in hypothesis-driven science and applications, incentivized through grant programs, is essential to build the current and more importantly future workforce capable of bridging ocean dynamics and AI at the scale NASA's observational enterprise demands.* Finally, the persistent gap between scientific findings and implementable, science-driven applications must be addressed through dedicated incentives to translate science to action.

The single most important recommendation from this workshop is that *NASA should invest in ocean-AI research as a jointly scientific and computational endeavor, where progress is measured by physical understanding through peer-reviewed science papers and observational impact in large-impact data products rather than by model performance metrics alone.* The workshop format itself, convening researchers deep in ocean science alongside those deep in AI and applications, proved to be an effective platform for bridging the science-to-action gap, and sustaining this convening model should be part of NASA's strategy as well as NSF. The AI4Ocean community formed at this workshop, 52 participants across 23 institutions, spanning career stages from Master's students to senior researchers, provides a ready foundation.

Appendix

1. Team

Organizers:

- Dr. Jinbo Wang — Associate Professor, Department of Oceanography, Texas A&M University
- Dr. Georgy Manucharyan — Associate Professor, School of Oceanography, University of Washington
- Dr. Nadya Vinogradova Shiffer — Program scientist, Physical Oceanography, NASA Headquarters

Steering Committee

- Dr. Luke Van Roekel – Scientist, Los Alamos National Laboratory
- Dr. Ian Fenty – Scientist, Jet Propulsion Laboratory
- Dr. Steve Nerem – Professor, University of Colorado Boulder
- Dr. Justin Stopa – Associate Professor, University of Hawaii
- Dr. Xavier Prochaska – Professor, University of California Santa Cruz
- Dr. Andrew Thompson – Professor, California Institute of Technology
- Dr. Sarah Gille – Professor, Scripps Institution of Oceanography, University of California – San Diego

2 Participant Demographics

The workshop attracted 60 total registrants, 52 of whom participated.

Presentation Participation:

- Lightning talk (10 min + 10 min discussion): 25 participants
- Invited talk (40 min): 8 participants

Institutional Representation (23 unique institutions):

Institution	Count
Texas A&M University	10
University of Hawaii at Manoa	4
Scripps Institution of Oceanography, UC San Diego	4
University of Washington	3
University of Texas at Austin	3

Institution	Count
University of Colorado Boulder	3
NorthWest Research Associates	3
NASA Jet Propulsion Laboratory	3
University of South Carolina	2
New York University	2
NASA Headquarters	2
Massachusetts Institute of Technology	2
UCAR / NCAR	1
U.S. Naval Research Laboratory	1
San Jose State University (Moss Landing Marine Labs)	1
Los Alamos National Laboratory	1
Columbia University	1
University of California, Santa Cruz	1
University of Maine	1
British Antarctic Survey / University of Cambridge (UK)	1
LOPS / Amphitrite (France)	1
Atalaia AI (Spain)	1

Career Stage Distribution (from 41 application responses):

Career Stage	Count
PhD student	14
Early career (< 10 years since highest degree)	16
Master's student	3
Mid-career (10–20 years)	2
Senior scientist (> 20 years)	1
Not specified	5

3. Sponsors

- NASA (via Grant 80NSSC25K7643)
- NSF (via the Data Science in Oceanography Undergraduate Summer Program)
- Texas A&M University
- University of Washington

4. Workshop Website

https://ai-for-ocean.github.io/workshop2026/

5. Complete Participant List

Aidan Janney (UCAR / NCAR), Allison Ho (University of Hawaii at Manoa), Arjit Seth (University of Texas at Austin), Brandon Castillo (San Jose State University / Moss Landing), Cim Wortham (NorthWest Research Associates), Daniel Neshyba-Rowe (NorthWest Research Associates), Dhruv Apte (University of Texas at Austin), Ethan Cruz (University of South Carolina), Feier Yan (Columbia University), Horim Kim (MIT), Inès Larroche (LOPS / Amphitrite), Jeffery Early (NorthWest Research Associates), Junwei Hua (Texas A&M University), Justin Stopa (University of Hawaii at Manoa), Kaden Jimenez (University of Hawaii at Manoa), Kelsey Bisson (NASA Headquarters), Lauren Harvey (SIO, UCSD), Levi Cai (University of Colorado Boulder), Luke Van Roekel (Los Alamos National Laboratory), Martin Kolster (University of Colorado Boulder), Maya Anjur-Dietrich (MIT), Natalie Stamper (University of South Carolina), Ou Wang (NASA JPL), Roy An (Texas A&M University), Saulo Soares (SIO, UCSD), Siobhán Johnson (BAS / Cambridge), Spencer Jones (Texas A&M University), Steve Nerem (University of Colorado), Tanvir Shahriar (UT Austin), Tatsu Monkman (New York University), Yannik Glaser (University of Hawaii at Manoa), Yingjun Zhang (SIO, UCSD), Yue (Luna) Bai (SIO, UCSD), Zhiwen Fan (Texas A&M University)
Andrei Medvedev (University of Washington), Eugenio Cutolo (Atalaia AI), Ian Fenty (NASA JPL), Krishna Calindi (Texas A&M University), Minghai Huang (Texas A&M University), Nayana Venukanthan (Texas A&M University), Robert Keenan Forney (U.S. Naval Research Laboratory), Scott Martin (University of Washington)

6. Acknowledgement

Some code provided by Dr. Ian Fenty the 2025 ECCO Summer School https://ecco-summer-school.github.io/ecco-2025/ were adopted for our workshop.

7. Team Projects

Collaborative team projects initiated during the workshop remain under active development. We will publish outcomes in a format of comprehensive reports or scientific publications in the future.