# Leveraging Ocean Data and Models: Building the Data Infrastructure, Workforce, and Modeling Capacity to Synthesize Earth's Ocean Observations

*A response to the Request for Information for the Decadal Survey for Earth Science and Applications from Space 2028–2037 (ESAS 2028)*

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*This version posted September 2026.*

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## A Cross-Cutting Data Systems and Modeling Strategy for the 2028–2037 Decadal Survey

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NASA Earth System Science Research Sphere: Biosphere (Aquatic Ecosystems), cross-cutting in direct support of the Atmosphere, Cryosphere, Geosphere, and Hydrosphere spheres

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## Executive Summary

NASA's aquatic and marine research enterprise within the overarching NASA Biosphere Program is entering an era of unprecedented data abundance. MODIS and the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) mission already generate ocean color data at rates that strain legacy processing and archiving workflows, and forthcoming missions will add further volume and complexity. These satellite streams are joined by rapidly growing in situ networks (e.g., BGC-Argo), suborbital campaigns, genomic surveys, citizen science, and increasingly high-resolution numerical models. The result is a Big Data regime in which the volume, variety, and acquisition rate of ocean relevant Earth system data exceed the capacity of legacy processing, storage, and synthesis approaches. An important goal is to fully integrate observing workflows, understanding, and models across the terrestrial, aquatic, and atmosphere domains to fully enable understanding of life and the realization of improved information to manage uses of ecosystem services.

This white paper addresses Leveraging Ocean Data and Models, a cross-cutting Grand Challenge that underlies and enables progress on the four other foundational grand challenges under the NASA Biosphere, Atmosphere, Cryosphere, and Hydrosphere framework - Global Biosphere, Carbon and the Elements of Life, Interface Habitats, and Transient Events - each of which depends on the ability to acquire, harmonize, and synthesize disparate satellite, suborbital, in situ, and model data streams. We recommend a decadal strategy built on two complementary pillars: Access and Utility of Ocean Observational Data, covering tiered cloud-based facilities, workforce training, international data sharing, and machine learning; and Numerical Models and Data Assimilation, covering mechanistic and statistical models, coupled physical-biogeochemical assimilation, hybrid approaches, mission emulators, and a NASA Digital Twin Ocean. Without concerted, proactive investment in this cross-cutting infrastructure, the scientific and societal returns on the coming decade's expanded observing system will be substantially diminished.


## 1. Introduction: The Science Question and Societal Challenge

NASA's ocean biology and biogeochemistry program has entered an era in which the acquisition rate of Earth observing data is increasing exponentially. MODIS on Aqua and Terra each generate roughly 30 TB of operational ocean color data annually, and PACE alone generates some 800 TB per year. Historically, NASA's Ocean Biology Distributed Active Archive Center (OB.DAAC) stored these data on physical servers at the NASA Goddard Space Flight Center; these holdings have since migrated to the Earthdata Cloud [1]. As additional missions are approved and launched over the coming decade, data volume and diversity will continue to expand, placing the Ocean Biology and Biogeochemistry (OBB) community squarely within the Big Data regime [2,3], in which the amount, variety, and acquisition rate of data exceed the capacity of traditional data processing software and workflows. Satellites are only one part of this expansion. Data volumes have grown as sharply from suborbital and airborne campaigns, from autonomous platforms such as BGC-Argo floats and gliders, genomic and other 'omics' surveys of marine microbial communities, citizen science programs, and from the output of numerical models run at steadily finer resolution; the ocean data repositories that hold them have expanded correspondingly in number, volume, and heterogeneity [4,5]. These streams differ from one another not only in volume, but in kind, with each measuring different quantities over different scales and with uncertainties that are characterized to very different degrees. This paper draws substantially on NASA's Ocean Biology and Biogeochemistry Science Vision [6], the community assessment it seeks to translate into an implementable decadal strategy.

This abundance of incoming data represents a scientific opportunity, but realizing its value requires new techniques and expertise for capture, storage, sharing, usability, and analysis. Combining the complementary strengths of these disparate observational and modeled data streams, rather than treating them as isolated products, will improve understanding of marine ecosystems and biogeochemistry, enable three-dimensional and time resolved characterization of the ocean, and support quantification of uncertainty across multiple, independent estimates of common properties (e.g., carbon biomass). However, owing to the heterogeneous nature of different data streams, and their frequent incompatibility, it remains unclear how best to combine them in an effective, systematic, and reproducible manner. This is an instance of the multimodal data fusion problem, which the data sciences treat as a first-order methodological challenge in its own right [7].

Without a proactive strategy for addressing this challenge, the sheer volume, accumulation rate, and disparate nature of data streams and model output will significantly hamper the community's ability to realize the science goals described for the Global Biosphere, Carbon and the Elements of Life, Interface Habitats, and Transient Events Grand Challenges [8–11] over the coming decade. As such, we identify Leveraging Ocean Data and Models as a Grand Challenge, and an RFI priority, in its own right, requiring concerted and targeted investment in research, technology, and workforce training.

This challenge is explicitly cross-sphere: the Atmosphere, Cryosphere, Geosphere, and Hydrosphere communities represented in this Decadal Survey face analogous growth in data volume, diversity, and model complexity, and stand to benefit from shared investment in common infrastructure, interoperable standards, and a jointly trained workforce. The challenge, therefore, is to:

> *Leverage advanced data harmonization, interoperability, synthesis, integration, and mining strategies; train next-generation scientists to maximize the value of satellite, suborbital, and modeled data streams to facilitate better understanding of ocean life, biogeochemistry, ecosystems, and their dynamic processes.*

## 2. State of the Science: Achievements and Limitations

For three decades, the NASA Ocean Biology Processing Group (OBPG) has maintained continuous, cross calibrated ocean color climate data records across a succession of sensors, even as individual missions have been launched and decommissioned. This is a sustained achievement in data continuity and community stewardship with few close analogs elsewhere in Earth science [12,13]. Over the same period, autonomous in situ observing has expanded dramatically, notably through the Biogeochemical (BGC)-Argo float array [14,15], an extension of a global Argo array that now numbers close to 4,000 active floats [16], while numerical modeling of ocean biogeochemistry has matured from simple box models to global ocean biogeochemical models (GOBMs) and fully coupled Earth system models (ESMs) capable of representing interactions among ocean physics, biogeochemistry, and the broader climate system [17]. Assimilation of physical ocean properties (e.g., temperature, salinity, sea surface height) into circulation models is well advanced [18], and biogeochemical data assimilation (i.e., incorporating chlorophyll and nutrient observations) is following a similar trajectory [19]. Machine learning methods, already transformative in image recognition, language processing, and other Big Data domains, are beginning to be applied to ocean color [20–22] and biogeochemical problems [23], offering a new and complementary tool for extracting information from large, heterogeneous datasets. These advances notwithstanding, three limitations stand between the community and the full scientific value of the data it now holds.

First, ocean data streams remain heterogeneous, frequently incompatible, and inconsistently characterized in terms of uncertainty. Chlorophyll concentration, for example, is derived from spectral ocean reflectance by passive ocean color sensors [24], from fluorescence on in situ platforms [25], and from attenuated backscattering by lidar [26]. Each approach carries its own algorithm dependent uncertainty, and pixel to pixel error estimates for satellite retrievals remain challenging to produce [27]. Compounding this issue, most mechanistic biogeochemical models are formulated in units of carbon (or nitrogen) concentration, while the common "currency" for comparing models with satellite observations is chlorophyll. The combined uncertainties introduced by derivation of chlorophyll from reflectance on the observational side and carbon-to-chlorophyll conversion on the modeled side can be large enough to make model-satellite comparisons difficult to interpret [28]. No consensus currently exists on the optimal approach for comparing and combining such disparate currencies.

Second, current ocean biogeochemical and ecosystem models remain limited by incomplete process representation and coarse resolution [29]. Many models lack explicit representation of bacteria and viruses [30], include only a limited number of phytoplankton functional types or trophic levels, and stop well short of the fish and upper trophic consumers at which ecosystem change is most visible to society. Additionally, models omit micronutrients beyond iron and rely on crude parameterizations of poorly observed processes [29]. GOBMs and ESMs typically operate at horizontal resolutions of one-quarter to one degree, precluding representation of the small-scale turbulence and convective processes that structure ecosystems [31]. This contributes to persistent difficulty in capturing features such as the deep chlorophyll maximum [32] and oxygen minimum zones [33–35]. These limitations manifest as substantial, and persistent, inter-model discrepancies, and differences amongst ESMs in projected changes to net primary production over the twenty-first century [36] have not narrowed appreciably between model intercomparison exercises conducted roughly a decade apart [37–39]. Statistical, data-driven models face a related, but distinct, limitation in that their skill in extrapolating to undersampled regions and future ocean states, precisely where predictive power is most needed, remains difficult to independently verify [40].

Third, the infrastructure, workforce, and institutional coordination required to fully exploit available data and models remain underdeveloped. Many existing data archives are not yet structured for the tiered, cloud-scale computational and storage access that Big Data synthesis will require [41]. However, in 2025 OB.DAAC announced that all mission data were fully migrated to the Earthdata Cloud environment [1]. Cloud-based strategies are being realized but more coordination and funding is required to achieve a community wide transition. Additionally, unique data streams produced by different agencies and countries are not always shared through mechanisms that support their combined use [41]. Meaningful, cross-disciplinary synthesis of satellite, in situ, ‘omics, and model data requires teams that combine oceanographic domain expertise with computer science, statistics, machine learning, and cyberinfrastructure skills. These skill sets have not historically been central to OBB research and take substantial time and sustained funding to mature into effective collaborations. Similarly, coupled data assimilation - the simultaneous assimilation of physical and biogeochemical observations - remains particularly difficult, with early attempts sometimes producing worse results for one or both components than assimilating either alone [42,43], underscoring the developmental stage of this critical capability.

## 3. Proposed Data and Modeling Strategy

Addressing the Leveraging Ocean Data and Models Grand Challenge requires simultaneous progress along the two complementary fronts identified in the OBB Science Vision [6]: 1) Access and Utility of Ocean Observational Data, which concerns the computational infrastructure, tools, and trained workforce needed to process, understand, and visualize Big Data; and 2) Numerical Models and Data Assimilation, which concerns advanced model development and the assimilation of observations into models. The eight elements below outline a coordinated approach spanning both.

### 3.1 Tiered, Cloud-Based Data Infrastructure and Open Access

Synthesizing ocean color, lidar, and other satellite data with in-water sensor data requires steady growth in computational and storage capacity at national facilities. Housing the data is only the first step; making disparate streams easily accessible to a broad community of researchers without overwhelming users of vastly different technical capacities is equally critical. Taking the Modern-Era Retrospective analysis for Research and Applications (MERRA-2 [44]) project in atmospheric science as our model, we recommend development of a tiered hierarchy of networked computational and data facilities linking oceanographers, aquatic scientists, computational scientists, cyberinfrastructure professionals, and end-user stakeholders. Enhanced regional facilities, sufficient to support modeling and analysis at multi-petaflop and multi-petabyte scales, and infrastructure supporting fast, intuitive, user-centric data access, processing, and discovery tools (not merely raw data), are both necessary.

### 3.2 Interdisciplinary Workforce Development and Training

Data utility depends not only on technological infrastructure but on the availability of tools and a trained workforce capable of using them. Across the biological sciences, training in integrating multiple data types and in scaling analyses to cloud and high-performance computing is consistently reported as the largest unmet need [45], and cloud-native, analysis-ready repository design is now a well-developed model for meeting it [46]. Dedicated, transdisciplinary research collaborations between oceanographers, computer scientists, and cyberinfrastructure specialists, supported by course development and training programs, are needed to prepare the next generation of OBB data users and stakeholders across research, industry, and government to efficiently access, analyze, and synthesize large and disparate data products.

### 3.3 International Data Sharing and Community Coordination

Because unique and important data streams are produced by different agencies and different countries, improved international community data access and information sharing agreements are essential. International organizations such as the International Ocean-Colour Coordinating Group (IOCCG) [47] provide an existing avenue for fostering two-way data sharing discussions and ensuring that data are provided in forms standardized and usable by the tiered computational and data facilities described above.

### 3.4 Cross-Stream Synthesis and Common Currency Standards

Even after infrastructure and workforce gaps are addressed, meaningful synthesis across heterogeneous, multi-dimensional data types (e.g., satellite observations, 'omics data, and model output) will remain a central and long-term challenge. Progress requires both the cross training of individual scientists across disciplines and, importantly, the deliberate assembly of teams with dedicated specialists for each major data stream, sustained across multiple funding cycles. Precedents include Science Investigator-led Processing Systems (e.g., the NASA Ocean Biology Processing Group) and discipline spanning Centers of Excellence, which, alongside data synthesis, provide leadership, best-practice recommendations, and training that will develop accessible and broadly usable synthesis tools as a lasting legacy. NASA's Multisource Integrated Observatory (MIO), whose multisource Data, Applications, Research and Technology teams are organized around cross-cutting challenge themes rather than single missions [48], and the Integrated Modeling Virtual Institute (IMVI), which pursues the equivalent unification across NASA's modeling portfolio [49], are the agency's current expressions of this model.

### 3.5 Machine Learning Integration Across the OBB Enterprise

Machine learning, a subset of artificial intelligence directed at extracting patterns from large data volumes, is a natural tool for OBB's Big Data challenge, having already proven highly effective in pattern and image recognition and language processing. We recommend enhanced investment in machine learning and deep learning (ML\DL) training and embedding of ML\DL experts and statisticians directly within ocean biology and biogeochemistry research teams to maximize the technique's utility while safeguarding scientific rigor. These endeavors should be a close collaboration between domain specialists and data scientists as naïve application of machine learning risks incorrect assessments and misleading science [21,50].

### 3.6 Statistical and Mechanistic Models: Complementary Tools for Synthesis

Two particularly important classes of mathematical model warrant continued, parallel investment. Statistical (data-driven) models apply correlative relationships to spatially and temporally extrapolate sparse observations of an ocean property of interest using environmental covariates that can be more easily observed. For example, species distribution models have long been used in terrestrial ecology and have more recently been applied to estimate distributions of key phytoplankton species from sparse observations [51–53]. Care must be taken, however, in extrapolating these models to regions with no data and in using them to make future, non-analog predictions [40]. Mechanistic models, by contrast, use discretized systems of differential equations to provide synthetic laboratories for understanding processes and perturbations (e.g., warming) even where observations remain sparse or absent. The approaches range from idealized box models designed to isolate specific processes, to GOBMs, Lagrangian models that track individual water parcels, and fully coupled ESMs. Both model classes, and hybrid configurations that combine them, underpin our ability to understand the ocean's long-term role in regulating climate through the cycling of carbon and other life sustaining elements [54,55], and both require sustained development as part of this Grand Challenge.

### 3.7 Advanced Numerical Modeling, Coupled Data Assimilation, and Hybrid Approaches

Continued development of both statistical (data-driven) and mechanistic ocean biogeochemical models is required, alongside coordination among modeling groups to understand and reduce disparities driven by differing parameterizations, resolution, and complexity. Priority areas include improved representation of phytoplankton diversity [56], viral and bacterial processes [57], additional trophic levels [58], and Lagrangian tracking of particles, pollutants, and water parcels using data from the growing float and glider network [59]. Extending trophic representation upward is a distinct requirement [60], since end-to-end model configurations that carry variability from phytoplankton through zooplankton and fish to upper-trophic consumers are what link satellite observable properties to the fisheries and protected species outcomes on which management decisions rest. The fish and ecosystem models capable of this have largely developed in a separate community, so coupling them is as much an interoperability problem as a modeling one. A further requirement is the length of the model record. Much of the variance in the ocean record is organized by recurrent climate modes (e.g., El Niño-Southern Oscillation, North Atlantic Oscillation, Pacific Decadal Oscillation) rather than by trend. Attributing an observed anomaly to natural variability or to forced change — rather than merely describing it — therefore requires reanalysis-quality biogeochemical hindcasts spanning the full satellite era, at resolutions that capture the ocean's response to those modes [61–64]. Better quantified uncertainties in satellite and in situ observational products, including seasonal and regional bias assessments, are needed to support both model evaluation and formal data assimilation. Sustained investment in combined physical–biogeochemical data assimilation, building on successes in other disciplines such as atmospheric science, should be prioritized alongside exploration of hybrid approaches that combine mechanistic equations for well-understood processes (e.g., ocean physics) with machine learning for less well-constrained biogeochemical and ecological processes.

### 3.8 Satellite Mission Emulators and a NASA Digital Twin Ocean

As models increasingly incorporate inherent and apparent optical properties and radiative transfer, they become valuable as emulators for ocean color satellite mission planning, as already demonstrated for PACE mission planning [65] and sensor drift tolerance analysis [61]. Continued development, improvement, and maintenance of such simulators/emulators, including representation of additional optical constituents and processes, is recommended, along with their use in Observing System Simulation Experiments (OSSEs) to inform future mission design. These capabilities, together with the modeling and assimilation advances described above, position NASA to pursue a Digital Twin Ocean, paralleling the European Union's Earth Digital Twin initiative [66,67]. This would be a data-assimilative model system ingesting near-real time, multi-stream observations at sufficient global, vertical, and coastal resolution to link the Global Biosphere, Climate and the Elements of Life, Interface Habitats, and Transient Events Grand Challenges, ultimately supporting actionable predictions for ecosystem management, hazard response, and policy.

## 4. Key Measurement and Data Requirements

Realizing this strategy requires the following capabilities:

Storage and throughput capacity sufficient to accommodate multi-petabyte annual data volumes (e.g., PACE's ~800 TB per year, growing with future missions) at multi-petaflop processing scale, with cloud-based elasticity to absorb episodic surges in demand.

Latency appropriate to application: near-real time (hours) for hazard response and data assimilative applications, and routine reprocessing cycles sufficient to preserve climate data record consistency.

Formal detection and attribution requires gap-free ocean climate data records, reprocessed to a common calibration across the full multi-sensor era and long enough to separate recurrent climate modes from forced change.

Interoperable data standards and metadata, e.g., common file formats, documented uncertainty fields, Findable, Accessible, Interoperable, and Reusable (FAIR) aligned discovery tools, enabling cross-agency and cross-national synthesis.

Quantified, product level uncertainty estimates, including pixel level satellite retrieval errors and regional/seasonal bias characterization, for all major data streams entering model evaluation or assimilation.

Model resolution sufficient to resolve mesoscale and sub-mesoscale ocean processes (finer than the current one-quarter- to one-degree standard for most GOBMs/ESMs), together with adequate vertical resolution to capture subsurface features such as the deep chlorophyll maximum.

Coupled physical–biogeochemical data assimilation capability, extending beyond current physical-only or biogeochemical-only assimilation systems.

End-to-end model coupling, linking biogeochemical models to fish and upper trophic level models through common gridding, forcing, and uncertainty conventions, so that variability observed at the phytoplankton base can be propagated to fisheries- and protected species-relevant outcomes.

Effective cross-disciplinary collaborations take longer to build than a single grant period, so OBB research teams require embedded machine learning, statistics, and cyberinfrastructure specialists sustained beyond the standard three-year award.

## 5. Feasibility and Implementation within the Decadal Time Frame

Much of the foundational technology and precedent for this strategy already exists, positioning it for substantial progress within the decadal time frame. NASA has already migrated OB.DAAC data storage, hosting, and access to cloud-based resources, and the atmospheric science community's MERRA-2 reanalysis project demonstrates a workable model for community scale data access. The Ocean Biology Processing Group's three-decade record of sustained, cross-mission data continuity provides a proven institutional template for the dedicated, interdisciplinary teams recommended in this challenge, and the BGC-Argo float array, GOBMs, and ESMs already provide a substantial foundation of in situ data and model capability for near-term synthesis efforts.

The principal implementation risks lie less in individual technology readiness than in the sustained, cross-agency coordination and funding required to build durable, interdisciplinary teams. Assembling scientists who can effectively work across oceanography, computer science, statistics, and cyberinfrastructure requires significant time and stability that single funding cycles do not typically provide. Coupled physical-biogeochemical data assimilation will likely require dedicated, near- to long-term research investment before routine operational use. Similarly, a fully realized Digital Twin Ocean - one that ingests near-real-time, multi-stream data resolving both coastal and open-ocean processes and incorporates anthropogenic stressors such as fisheries and pollution - is a 10- to 25-year goal rather than a decadal-window deliverable. It should build incrementally on the nearer-term investments in infrastructure, models, and assimilation systems recommended above.

Because this challenge is fundamentally about people and infrastructure rather than any single new instrument, its feasibility depends on funding mechanisms built for multi-year, multi-institution teams rather than individual investigator awards. Within the decadal time frame, sustained support for centers modeled on the Ocean Biology Processing Group — coupled with cross-agency coordination (e.g., with NOAA and USGS, as encouraged elsewhere in this Decadal Survey) and international partnerships —

would substantially de-risk the tiered data infrastructure, workforce training, and modeling advances recommended here.

## 6. Summary of Recommended Priorities

We recommend that the 2028-2037 Decadal Survey prioritize the following elements to address the Leveraging Ocean Data and Models Grand Challenge:

**1.** Interdisciplinary workforce and team building. Organize and sustain dedicated teams spanning oceanography, computer science, statistics, machine learning, and cyberinfrastructure, and invest in teaching these techniques so that ML/DL experts and statisticians are embedded within OBB research efforts rather than consulted at arm’s length. (immediate/near-term, then continued)

**2.** Advanced computing infrastructure and technology. Develop a tiered hierarchy of networked computational and data facilities linking cross-disciplinary science and applications communities, and advance the underlying technologies for cloud-based computing and cross-stream data synthesis. (immediate/near-term)

**3.** Next-generation modeling and data assimilation. Develop models that explicitly resolve remotely sensed ocean properties, reducing ‘common currency’ mismatches between models and satellite data; invest in assimilation systems that ingest physical and biogeochemical streams simultaneously; and pursue hybrid modeling approaches together with satellite mission emulators for mission planning and OSSEs. (immediate/near-term)

**4.** Community engagement, access, and global co-design. Identify and coordinate with end users to ensure maximum utility of data products and models, including through workshops and summer schools, and enhance international data access, information sharing, and cross-pollination of modeling advances. (continued)

**5.** A NASA Digital Twin Ocean. Build toward a digital twin that uses the full suite of observations and modeling capabilities described above, linked explicitly to the Global Biosphere, Climate and the Elements of Life, Interface Habitats, and Transient Events Grand Challenges. (long-term)

## 7. Conclusion

NASA's Ocean Biology and Biogeochemistry program is entering a period of unprecedented observational capability. Data volume alone, however, is not understanding. The scientific and societal value of this expansion will be realized only if matched by equally ambitious investment in data infrastructure, computational capacity, modeling and assimilation systems, and workforce training. Leveraging Ocean Data and Models is therefore not a peripheral or purely technical concern but a cross-cutting Grand Challenge in its own right - and its resolution is a precondition for progress on the other four OBB Grand Challenges (Biosphere, Atmosphere, Cryosphere, and Hydrosphere) described elsewhere in this white paper series. We urge the 2028–2037 Decadal Survey to prioritize it accordingly, ensuring that the coming decade's growth in ocean-relevant Earth system data translates into commensurate growth in scientific understanding, environmental stewardship, and benefit to the nation.

## Figures

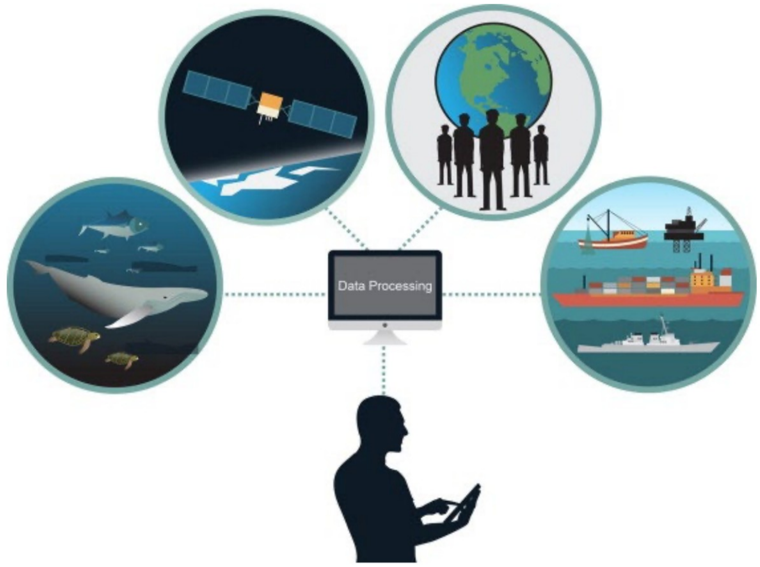


*Figure 1. Multiple, disparate data types, including biological, remotely sensed, and socio-economic streams, must be integrated to support decision-relevant data processing and dynamic ocean management. Reproduced from Maxwell et al. [68], as presented in the OBB Science Vision report [6].*

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