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New Technologies for Monitoring Coastal Ecosystem Dynamics

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Abstract

In recent years, our view of coastal ecosystems has expanded and come into greater focus. We are currently making more types of observations over larger areas and at higher frequencies than ever before. These advances are timely, as coastal ecosystems are facing increasing pressures from climate change and anthropogenic stressors. This article synthesizes recent literature on emerging technologies for coastal ecosystem monitoring, including satellite monitoring, aerial and underwater drones, in situ sensor networks, fiber optic systems, and community science observatories. We also describe how advances in artificial intelligence and deep learning underpin all these technologies by enabling insights to be drawn from increasingly large data volumes. Even with these recent advances, there are still major gaps in coastal ecosystem monitoring that must be addressed to manage coastal ecosystems during a period of accelerating global change.

INTRODUCTION

By their nature, coastal ecosystems are highly variable in space and time. Coastal zones are influenced by dynamic physical processes that operate across a range of spatial and temporal scales, such as tides, ocean currents, waves, storm surges, and climate cycles. Climatic gradients are steep and climate variability is high around coastlines due to interactions between land and ocean. Furthermore, coastal ecosystems are being particularly impacted by climate change and other anthropogenic stressors (Doney et al. 2012, He & Silliman 2019). Because they are at the interface of land and ocean, coastal ecosystems experience many different aspects of climate change, including sea level rise, ocean acidification, increases in air and sea temperatures, changes in precipitation, and changes in storm frequency and intensity. Coastal ecosystems are also experiencing increased direct human impacts such as overfishing, pollution, habitat loss due to urban or agriculture development, and saltwater intrusion from groundwater extraction (He & Silliman 2019).

Increasing pressures on the coastal zone are threatening these ecosystems and the many services that they provide. It is estimated that more than 50% of the world's coastal wetlands have been lost during the past century (Davidson 2014), resulting in diminished biodiversity, increased carbon emissions, and increased vulnerability to storm surges and sea level rise (Li et al. 2018). Over the past 30–50 years, warm-water coral reefs have declined by a minimum of 50%. Ongoing losses are expected due to warming temperatures, ocean acidification, and local stressors such as pollution and overfishing (Hoegh-Guldberg et al. 2017). There are fewer data available on changes in the global extent of kelp forests, but declines have been observed in many regions (Krumhansl et al. 2016, Wernberg et al. 2019), and ocean warming presents an increasingly severe threat to these ecosystems (Smale 2020). There has not yet been a clear global increase in the frequency of harmful algal blooms (HABs) (Hallegraeff et al. 2021), but positive regional trends have been documented and linked to interactions between increased temperatures and eutrophication (Anderson et al. 2021).

To manage coastal ecosystems in the face of these challenges, scientists and managers need more information on how these ecosystems are changing, the drivers of those changes, and how ecosystems will respond to future changes in climate and other anthropogenic factors. Addressing such questions begins with improved monitoring. Long-term monitoring over large spatial scales is required to characterize the effects of global change, as separating anthropogenic effects from natural variability is challenging for highly dynamic systems. On the other end of the spectrum, short-lived episodic events, such as marine heatwaves, storms, and HABs, can have major impacts on coastal ecosystems that may be missed by periodic sampling. Studying these short-lived events requires observations at high spatial and temporal resolution. Furthermore, many physical and biological processes require monitoring in the coastal zone. The scientific community has recognized these needs and made substantial efforts to develop observing systems to monitor coastal ecosystem dynamics.

Coastal ocean observing systems are networks of instruments, platforms, and technologies designed to monitor and collect data on coastal ecosystems. A key component of these systems is coordination among government agencies, academic organizations, and the private sector to develop methods for collecting, processing, and analyzing data from disparate sources to inform a wide variety of research and operational needs (Liu et al. 2015). This coordination has helped to prioritize ocean observations, and international ocean observing systems have developed a list of essential ocean variables (Lindstrom et al. 2012, Miloslavich et al. 2018), most of which are relevant to coastal ecosystems. Further, all biology and ecosystem essential ocean variables are applicable to coastal ecosystems. Communication and collaboration across coastal ocean observing systems have helped accelerate the development of new technologies for monitoring variables, such as high-frequency radar (Thomas et al. 2015) and Imaging FlowCytobots (Kudela et al. 2021). These systems also coordinate the deployment, processing, and data management for networks of sensors, thereby expanding the spatial and temporal coverage of coastal observations. Support from coastal ocean observing systems has been instrumental in the development of new technologies that have recently made substantial advances on three major observational fronts: temporal extent and resolution, spatial extent and resolution, and measurable variables.

After describing each of these three categories of observational advancements, we synthesize the literature on new technologies for monitoring coastal ecosystems, which include salt marshes, mangrove forests, sandy beaches, rocky intertidal zones, seagrass beds, coral reefs, kelp forests, and the nearshore pelagic zone. We focus on advances that have occurred over the past two decades in six different categories of emerging technologies: satellite monitoring, aerial drones, underwater drones, networks of in situ sensors, fiber optic monitoring systems, and community science observatories. In an Appendix, we also discuss how developments in analytic methods such as machine learning (ML) and artificial intelligence (AI) are supporting each of these technological developments.

OBSERVATIONAL ADVANCEMENTS: TIME, SPACE, AND MEASURABLE VARIABLES

Technological advancements in coastal monitoring over the past two decades have resulted in expansions in both the spatial and temporal coverage of observations within coastal ecosystems (**Figure 1**). In addition, we can now leverage historical data and long-term monitoring programs to identify trends in ecosystem characteristics like habitat extent (e.g., global mangrove cover; Bunting et al. 2022) and population abundances (e.g., the sizes of penguin colonies; Jones et al. 2018). Rapid increases in the amount of data collected have necessitated advances in data processing and analytic approaches to help scientists make sense of increasingly large amounts of data (see the Appendix).

Coastal observations now have expanded temporal coverage thanks to both new technologies and legacy monitoring systems that have been in place for decades. For example, new CubeSat constellations and geostationary satellites are providing daily to hourly observations of ocean color and coastal habitats, while efforts to cross-calibrate ocean color observations across satellite platforms such as the Coastal Zone Color Scanner (CZCS), Sea-Viewing Wide Field-of-View Sensor (SeaWiFS), and Moderate Resolution Imaging Spectroradiometer (MODIS) have resulted in time series that span decades (Antoine et al. 2005). Improved connectivity and communication of in situ sensors have enabled real-time monitoring at high frequencies over long time periods (Glenn et al. 2000).

The spatial coverage of coastal observations has expanded due to increases in the density of in situ sensors and in the spatial resolution of remote sensing datasets. There has been a large increase in the availability of high-resolution satellite imagery of the coastal zone. In situ observational systems are enabling large-scale monitoring of physical and biological variables using networks of moorings, shore stations, and fiber optic cables. Advances in unoccupied aerial vehicles (UAVs) and autonomous underwater vehicles (AUVs) are enabling very-high-resolution mapping above and below the water's surface. Additionally, community science programs are helping monitor coral reef health, invasive species, sea level rise, and many other coastal processes.

At the same time, new methods enable measurements of more coastal processes with greater accuracy than ever before. For example, algorithms have the potential to identify phytoplankton functional types from hyperspectral satellite imagery (Kramer et al. 2022). Acoustic monitoring

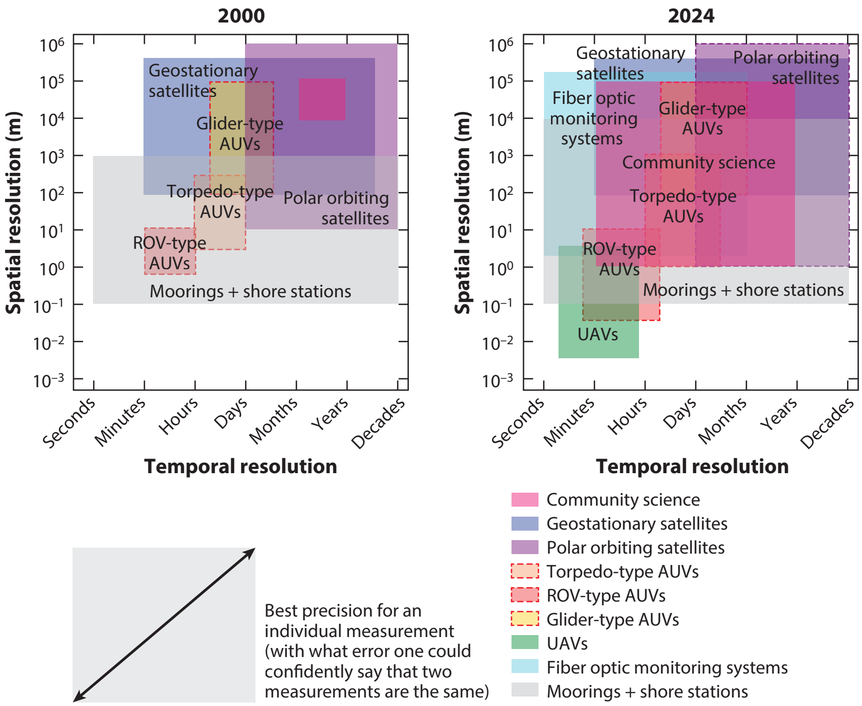

Figure 1

Conceptual diagram showing the general spatial and temporal coverage of different categories of coastal observing technologies in 2000 and 2024. Abbreviations: AUV, autonomous underwater vehicle; ROV, remotely operated vehicle; UAV, unoccupied aerial vehicle.

systems are providing new information on multiple aspects of marine ecosystem structure and function (Pieretti & Danovaro 2020). Environmental DNA (eDNA) is providing new approaches for monitoring coastal biodiversity (Miya 2022). Underpinning all of these observational technologies are new analytic approaches to process and analyze increasing data volumes (see the Appendix).

SATELLITE MONITORING

In recent years, growth in satellite monitoring programs has provided scientists with greater spatial and temporal coverage and resolution (**Figure 1**) and new ways of measuring ecosystem condition. Coastal applications of satellite-based multispectral, hyperspectral, thermal, and radar/lidar sensors have been reviewed extensively (e.g., Klemas 2011, Muller-Karger et al. 2018), and while many of these sensors no longer represent new technologies, the long-term nature of these datasets is enabling novel insight into the ecosystem impacts of processes such as low-frequency climate oscillations and climate change (Bell et al. 2020a). For example, the Landsat program has provided multispectral imagery of the coastal zone since 1972, with 30-m-resolution imagery from 1984 onward. Landsat and other global Earth observing satellites have been central in the development of regional to global data on the extent of coastal habitats such as mangroves, salt marshes, kelp forests, floating sargassum, and sandy beaches (**Table 1**). These data have been used to document extensive mangrove deforestation (Hamilton & Casey 2016) and to support conservation efforts that have resulted in a recent reduction in global mangrove loss rates (Friess et al. 2020). Ocean

Table 1 Selection of large-scale (ocean basin to global) coastal habitat datasets derived from satellite imagery

Habitat	Dataset description	Sensor(s)	Spatial extent	Temporal extent	Temporal frequency	Data access	Reference
Mangroves	Global Mangrove Watch—global mangrove change	SAR	Global	1996–2020	1996, 2007–2010, 2015–2020	**https://globalmangrovewatch.org**	Bunting et al. 2022
	Global mangrove height	Radar/lidar	Global	2000	Composite	**https://mangrovescience.earthengine.app/view/mangroveheightandbiomass**	Simard et al. 2019
Salt marshes	Global saltmarsh extent	Compilation of remote sensing data	Global	1973–2015	Composite	**https://data.unep-wcmc.org/datasets/43**	Mcowen et al. 2017
Kelp forests	Kelpwatch—regional kelp canopy changes	Landsat	West coast of North America, South America, South Africa	1984–2023	Quarterly	**https://kelpwatch.org**	Bell et al. 2023
	Global kelp extent	Sentinel-2	Global	2015–2018	Composite	**https://biogeoscienceslaboxford.users.earthengine.app/view/kelpforests**	Mora-Soto et al. 2020
Floating macroalgae	Atlantic sargassum changes	MODIS	Atlantic Ocean	2000–2018	Monthly	**https://optics.marine.usf.edu/projects/saws.html**	M. Wang et al. 2019
Coastlines	CoastSat—global shoreline position	Landsat, Sentinel-2	Global	1984–present	Biweekly	**http://coastsat.wrl.unsw.edu.au**	Vos et al. 2019
	Global sandy shoreline change	Landsat	Global	1984–present	Annual	**https://aqua-monitor.appspot.com/?datasets=shoreline**	Luijendijk et al. 2018
	Global tidal flat	Landsat	Global	1984–2016	Annual	**https://intertidal.app**	Murray et al. 2019
Coral reefs	Multiscale coral reef extent	Landsat, Sentinel-2, PlanetScope Dove, WorldView-2	Great Barrier Reef, southwest Pacific	2013–2019	Composite	**https://mitchest.users.earthengine.app/view/coral-map-explorer**	Lyons et al. 2020
	Allen Coral Atlas	PlanetScope Dove	Global	2016–present	Composite	**https://allencoralatlas.org**	Lyons et al. 2024
Seagrasses	Global distribution of seagrass meadows	Compilation of various datasets	Global	Not reported	Composite	**https://data.unep-wcmc.org/datasets/7**	McKenzie et al. 2020

Abbreviations: MODIS, Moderate Resolution Imaging Spectroradiometer; SAR, synthetic aperture radar.

color satellites such as CZCS, SeaWiFS, and MODIS have been used to monitor phytoplankton biomass and productivity since the late 1970s and characterize climate-driven trends in global ocean productivity (Behrenfeld et al. 2006), although remotely estimating phytoplankton abundance in the coastal zone continues to present a significant challenge due to colored dissolved organic matter, nutrient fertilization, and coastal sediment plumes (Dierssen 2010, Schofield et al. 2004). Satellite-based sea surface temperature time series are now of sufficient length to identify anomalous marine heatwaves, and these data have detected an 82% increase in the frequency of marine heatwaves between 1982 and 2016 (Oliver et al. 2018). Spaceborne radar altimeters have been monitoring sea level continuously over the open ocean for more than 30 years. These global datasets typically do not yet include areas within ∼20 km of the coastline due to poor sampling and inaccurate corrections; however, efforts to reprocess data from multiple sources and new satellite systems such as NASA's Surface Water and Ocean Topography mission are providing higher-resolution ocean surface topography measurements closer to shore (Srinivasan & Tsontos 2023).

Spatial resolution has long been a major limiting factor for large-scale remote sensing studies of coastal ecosystems. Mapping many coastal ecosystems (e.g., submerged aquatic vegetation, coral reefs, and small estuaries) requires high-resolution imagery (<5 m; Klemas 2011), and almost all coastal ecosystems can benefit from higher-resolution observations. High-resolution multispectral satellite imagery has been available for more than two decades from systems such as IKONOS (4 m), QuickBird (2 m), WorldView (0.5–2 m), and GeoEye-1 (2 m). However, limited temporal coverage and the relatively high cost of acquiring images limited most studies to areas of less than hundreds of square kilometers and prohibited long-term repeated monitoring. Recently, the development of commercial small satellite constellations (CubeSats) has provided global, high-resolution, multispectral data with high repeat frequency at a relatively low cost. One of the largest of these CubeSat constellations is PlanetScope, which provides 3-m-resolution multispectral imagery with near-daily global coverage. PlanetScope data have been used to estimate the extent of the world's coral reefs (Li et al. 2020) (**Table 1**), map small remnant patches of kelp following a heatwave disturbance (Cavanaugh et al. 2023), monitor mangrove reforestation projects (Veettil 2022), and create high-resolution coastal bathymetry maps (Li et al. 2019).

Recent and planned satellite missions are also providing imagery with greater spectral resolution, i.e., the number of wavelength intervals that a sensor can measure. Increased spectral resolution enables the monitoring of a greater variety of physical and biological processes in the coastal zone. Hyperspectral imagery can help to go beyond mapping the extent of coastal habitats to provide information on species' physiology, such as giant kelp pigment concentrations (Bell & Siegel 2022), and differentiate salt marsh (Hladik et al. 2013) and mangrove (Lassalle et al. 2023) species. Increased spectral information can also be used to retrieve the optical properties of the water column and bottom reflectance, which enables improved mapping of benthic habitats such as coral reefs (Thompson et al. 2017), seagrasses (Phinn et al. 2008), and other submerged aquatic vegetation (Hestir et al. 2008). Furthermore, the ability to differentiate phytoplankton pigments allows for insight into phytoplankton community structure and may facilitate the identification of specific taxonomic groups such as those associated with HABs (Dierssen et al. 2020, Kramer et al. 2022). Over the next five years, three new NASA missions—Plankton, Aerosol, Cloud, Ocean Ecosystem (PACE; **http://pace.gsfc.nasa.gov**); Surface Biology and Geology (SBG; **http://sbg.jpl.nasa.gov**); and the Geostationary Littoral Imaging Radiometer (GLIMR; **http://eos.unh.edu/glimr**)—will provide new satellite-based hyperspectral data on global scales (Dierssen et al. 2023). Together, these programs will provide regional to global coverage with high revisit frequencies, supporting a wide range of coastal applications.

UNOCCUPIED AERIAL VEHICLES

Aerial drones, also known as UAVs, have revolutionized the observation and study of coastal ecosystems by providing very-high-resolution imagery and control over the timing of image acquisition. These systems can be equipped with a variety of sensors, including color cameras; multispectral, hyperspectral, and thermal imagers; and lidar (Olson & Anderson 2021), enabling the mapping of complex coastal features like shoreline and sand dune dynamics and biological communities like rocky intertidal systems with submeter geospatial accuracy.

UAVs can resolve centimeter-scale imagery over areas often in the tens of hectares in a single flight (**Figure 1**). One primary use of UAVs is habitat mapping of coastal ecosystems such as salt marshes, kelp forests, mangroves, and coral reefs. Salt marshes represent dynamic and heterogeneous landscapes that include multiple species of vegetation, ponds, channels, wrack, and pans (Pennings & Bertness 2000). Imagery acquired from UAVs has been used to classify these features and document fine-scale variability in wrack cover that affect vegetation density and invertebrate abundance (Lynn et al. 2024). The ability to discern and discriminate plant species using high-resolution UAV imagery has enabled the monitoring of salt marsh restoration (Haskins et al. 2021). This technology has also led to the identification of invasive plant species in salt marsh systems (Cruz et al. 2023), which shows the potential use of UAVs to target invasive species eradication efforts while minimizing the impacts of field surveys. The mapping of floating kelp forest canopies using UAVs has enabled efficient and reproducible canopy classification methods to determine the effect of tides and currents on canopy area and validation of satellite canopy biomass estimates (Bell et al. 2020b, Cavanaugh et al. 2021). After a regional collapse of bull kelp forests in California in 2014, UAV imagery was used to identify small remnant populations across thousands of hectares (Saccomanno et al. 2023). In addition to maps of vegetation, UAVs can estimate structural information by using structure-from-motion techniques or carrying a lidar instrument. Surface wave properties can be leveraged in high-frame-rate imagery collected from UAVs to estimate the three-dimensional structure of aquatic targets such as coral reefs. This technique, known as fluid lensing, utilizes refractive lensing to remove distortions and enhance the effective spatial resolution of the resulting imagery (Chirayath & Instrella 2019). This promising technique has led to accurate assessments of coral reef ecosystem health, where the heterogeneity of benthic cover types and reef morphology is evident on centimeter scales.

The ability to decide the timing of UAV operations enables the monitoring of coastal ecosystems over time and in response to events. This is especially important as many variables of interest, such as intertidal habitats, are discernible only at specific tidal heights. For example, high-resolution lidar point clouds generated from UAVs at low tide capture fine-scale ground-level changes in heavily vegetated salt marshes, producing independent maps of vegetation and ground height that can estimate vertical accretion and quantify the effect of storm disturbance (Pinton et al. 2020b). Repeat flights across a tidal cycle have also been used to track surface flow velocities in salt marsh tidal channels, where dye was released and imaged by UAVs to reduce the effects of human perturbation on the data (Pinton et al. 2020a).

Perhaps no coastal ecosystem can benefit more from the advantages of UAVs than the rocky intertidal zone. The position of the rocky intertidal zone as a narrow band along the coast, the short tidal window when the lower intertidal zone is exposed, the difficult and hard-to-access terrain, and the heterogeneous structure necessitate temporally nimble acquisitions and very-high-resolution spatial data (**Figure 2**). Low-altitude UAV surveys can obtain color imagery at <1-cm resolution and provide reliable estimates of canopy-forming algae and other dominant organisms, although understory species obscured by the algal canopies may be underestimated (Murfitt et al. 2017). Konar & Iken (2018) found that while observer visual surveys resulted in

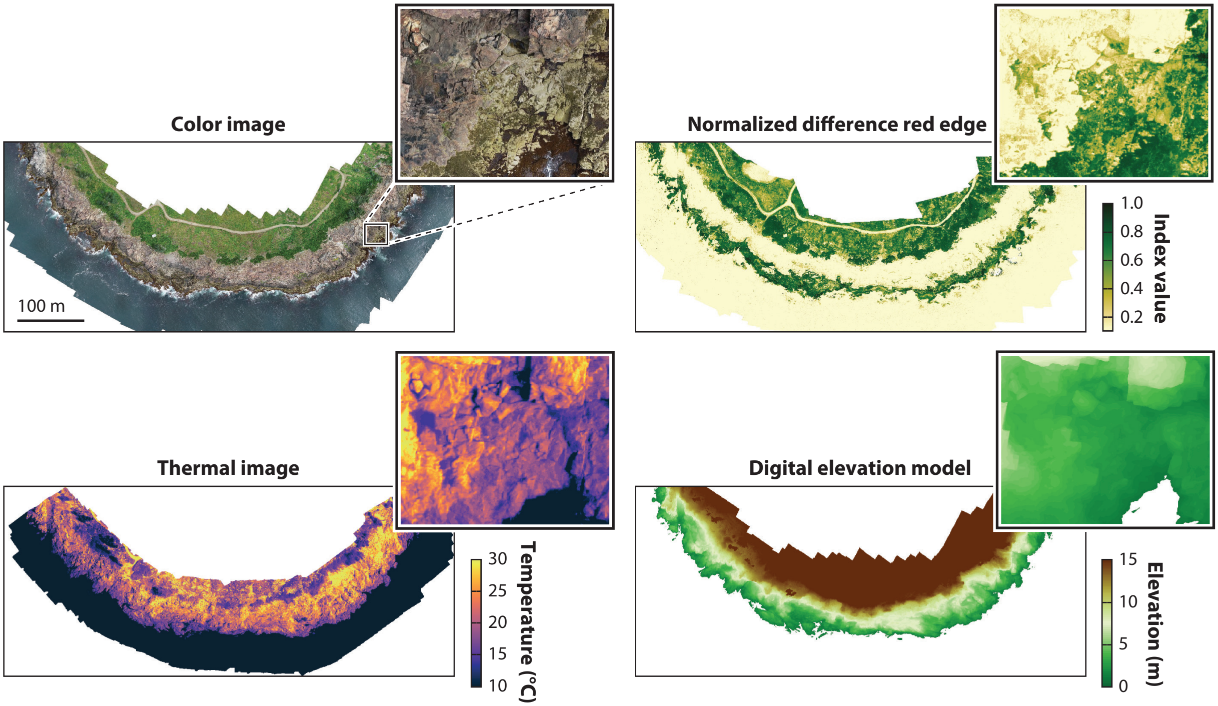

Figure 2

Data acquired with an unoccupied aerial vehicle from the southern coast of Allen Island, Maine, on July 17, 2022. The normalized difference red edge index is a measure of vegetation cover; note the macroalgae cover along the edge of the coastline within the intertidal zone. The digital elevation model was derived from the color imagery using the structure-from-motion technique.

data with the highest taxonomic richness, concurrent UAV surveys yielded similar results when data were aggregated to lower taxonomic resolution. The use of multispectral imagery acquired from UAVs can be used to distinguish macroalgae from other dominant cover types in the rocky intertidal zone, and the combination of high spatial and nonvisible spectral information can more accurately distinguish between macroalgal species compared with occupied aerial and satellite imagery (Rossiter et al. 2020).

While aerial drones have significantly advanced coastal ecosystem research in recent years, they come with notable limitations. Their usage remains constrained by limited battery life and flight time, and regulations restrict airspace and flight distance. Weather conditions such as high winds, rain, and fog present operational challenges, especially in the dynamic coastal environment. The processing and analysis of the large volumes of data collected by drones demand substantial time and specialized expertise, and there are significant gaps in data management and accessibility best practices (Wyngaard et al. 2019).

AUTONOMOUS UNDERWATER VEHICLES

A new generation of AUVs is exploiting recent advances in low-cost edge computing hardware and underwater sensing and communications technologies to serve as effective mobile sensing platforms observing spatiotemporally evolving processes in the coastal ocean. For these in situ data collection tasks, autonomous platforms bridge the gap between spatially dense but temporally sparse manual surveys (e.g., by divers or research vessels) and temporally dense but spatially sparse passive monitoring systems (e.g., moorings, buoys, and fixed seafloor sensors).

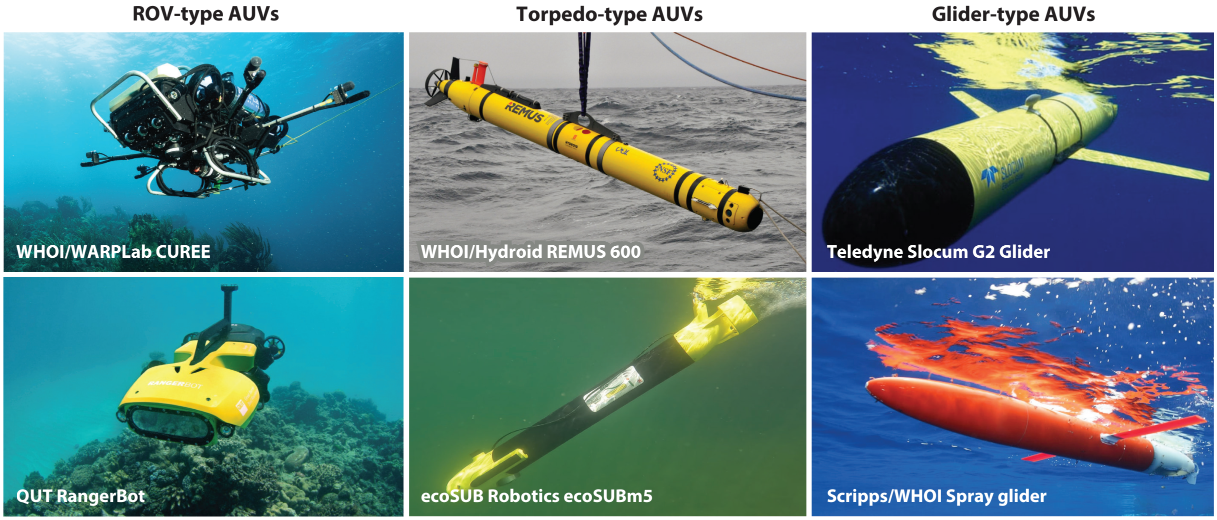

Figure 3

Example platforms for each of the three types of AUV systems. Photos by Austin Greene, WHOI (CUREE); Sheri White, WHOI, Ocean Observatories Initiative (REMUS 600); Ben Allsup, Teledyne Webb Research (Slocum G2 Glider); QUT (RangerBot); ecoSUB Robotics (ecoSUBm5); and Robert Todd, WHOI (Spray glider), adapted with permission. Abbreviations: AUV, autonomous underwater vehicle; CUREE, Curious Underwater Robot for Ecosystem Exploration; QUT, Queensland University of Technology; REMUS, Remote Environmental Measuring Units; WHOI, Woods Hole Oceanographic Institution.

AUV systems exist on a spectrum that trades off vehicle controllability versus vehicle endurance (**Figure 3**; **Table 2**). At one end of the spectrum are remotely operated vehicle (ROV)–type AUVs [e.g., the Curious Underwater Robot for Ecosystem Exploration (CUREE) (Girdhar et al. 2023) and the RangerBot ROV] that have many thrusters and five or more degrees of freedom and are ideal for missions in regions with high clutter, where precise positioning of the AUV and the ability to avoid obstacles is crucial. ROV-type AUVs carry high-resolution sensors that allow them to achieve centimeter-scale localization to enable high-precision maneuverability. Imaging sonars, cameras, and underwater lidar are all common in these vehicles. At the other end of the spectrum are glider-type AUVs (e.g., the Slocum Glider; Schofield et al. 2014), which use buoyancy engines as a power-efficient way to propel the AUV through the water column, allowing gliders to be deployed for weeks to months at a time. To remain energy efficient, gliders typically have a very limited sensor suite that measures basic parameters such as conductivity, temperature, and pressure or use intermittent sampling with more power-intensive sensors such as active acoustics. In

Table 2 Approximate AUV capabilities by type of system

AUV type	Mission duration	Mission area	Underwater localization
ROV	0.5–4 hours	Hundreds of square meters	GPS + visual odometry + USBL (centimeter-scale accuracy)
Torpedo	1–5 days	Tens of square kilometers	USBL + DVL + GPS (meter-scale accuracy)
Glider	2–8 weeks	Hundreds of square kilometers	GPS + dead reckoning (100-m-scale accuracy)

Abbreviations: AUV, autonomous underwater vehicle; DVL, Doppler velocity log; GPS, Global Positioning System; ROV, remotely operated vehicle; USBL, ultrashort baseline.

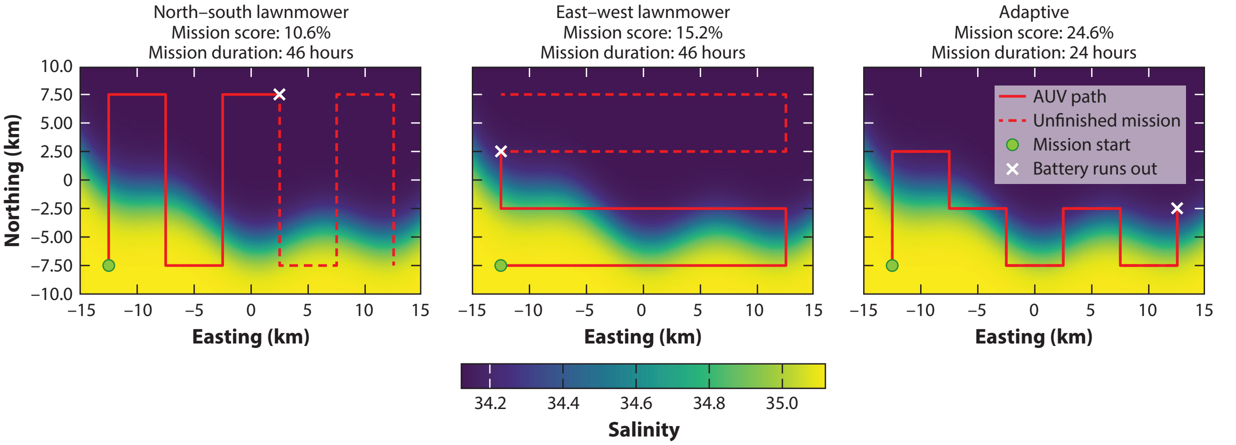

Figure 4

Comparison of 24-hour sampling missions along a simulated salinity front for an AUV. Missions are planned using a 5-km grid. The mission score is the percentage of mission total time spent along the front, defined as the 20% of the mission region with the highest salinity gradient. Lawnmower patterns cannot fully sample the mission region before the battery is depleted. Adaptive sampling produces a path that spends 61% more time along the front than the best-performing lawnmower. Abbreviation: AUV, autonomous underwater vehicle.

between these two extremes lie torpedo-type AUVs such as Iver (Crowell 2013), ecoSUB (Phillips et al. 2017), and the Remote Environmental Measuring Units (REMUS) family of AUVs (Allen et al. 1997), which retain the energy-efficient hydrodynamic shape of glider-type AUVs while using a single thruster and control fins instead of the buoyancy engine of the glider. This allows torpedo-type AUVs to move efficiently while maintaining level motion, which is ideal for large-scale bathymetric surveys using sidescan or imaging sonars. Within each of these broad categories there is considerable variation in capabilities, as individual AUVs make trade-offs among depth rating, endurance, sensor payload, and many other factors.

What sets modern AUVs apart from their predecessors is the integration of real-time data processing from the vehicle's scientific and sensing payload into the autonomous control loop. This allows an AUV to reason about its mission objective while the mission is underway and adapt its behavior based on what it is observing to optimize its behavior for a scientific mission objective, rather than simply following a preplanned mission such as one-dimensional transects or boustrophedon (or lawnmower) area coverage. This adaptive behavior can result in significant improvements in data quality and mission completion time, since compared with nonadaptive methods, the AUV is not wasting valuable mission time sampling in low-value areas (Hollinger & Sukhatme 2014) (**Figure 4**). While lawnmower-style AUV surveys already offered significant cost and scalability improvements over occupied vessels, the efficiency of adaptive techniques can compound these benefits, greatly expanding our ability to conduct science in the coastal ocean.

The effectiveness of adaptive autonomy for AUVs has been demonstrated across a wide range of applications. Many physical variables, such as temperature and salinity, and some biological variables, such as chlorophyll fluorescence, can be easily measured in real time by an AUV. By mapping these variables over the study area, the AUV can then choose the trajectory that best observes the variable of interest (Hwang et al. 2019). However, AUVs are not limited to using only information collected by the vehicle during its mission. Predictive model output (Ford et al. 2022), remote sensing products (Dos Santos et al. 2019), datasets from prior missions (Das et al. 2015), and real-time updates from research vessels or other AUVs (McCammon et al. 2021) can all be used as inputs to improve the adaptive AUV behavior by expanding the information available to the decision-making algorithms beyond the limited view of the world provided by an AUV's own sensors. In shallower water, many AUV platforms use visual imagery as the input for adaptive behaviors, a data stream that carries complex categorical data. These data can be used to classify benthic habitat types with (Shields et al. 2020) or without (Jamieson et al. 2021) a priori knowledge of the different habitat classes. Visual data also allow AUVs to track large marine organisms such as fish, rays, squid, or jellyfish without relying on acoustic tags (Cai et al. 2023). Sonar is another common data source used by AUVs and is often used in underwater object identification and mapping tasks (Palomeras et al. 2018) where the AUV must use a partial model of an underwater object to select the next viewpoint that maximizes the amount of the scene that will be revealed by the sonar. Finally, adaptive behavior also includes not only selecting which observations to make but also how to make those observations. Dynamic trajectory generation allows AUVs to choose energy-efficient paths, maximizing mission duration given onboard battery limitations (Kuhlman et al. 2021).

IN SITU SENSOR NETWORKS

In situ observations from platforms such as anchored moorings, shore stations, coastal high-frequency radar arrays, and ship-based sampling have historically been central to our understanding of coastal ecosystems and are excellent sources of long-term data at high temporal frequency. In the 1990s and 2000s, improvements in communications enabled widespread dissemination of near-real-time observations, further improving the temporal coverage of these observations (Glenn et al. 2000). However, a fundamental challenge with in situ observations is capturing the high spatial variability in coastal physical and biological processes. One approach for addressing this challenge has been the development and expansion of observational networks such as coastal moorings (Bailey et al. 2019) and high-frequency radar arrays (Roarty et al. 2019), which has led to expanded spatial coverage of in situ observations (**Figure 1**).

Cost reductions for mature technologies in the form of sensor miniaturization, lower-cost platforms, and cheaper materials have been important in facilitating the expansion of in situ monitoring networks given the historically high costs (for a review of this topic, see Z.A. Wang et al. 2019). Continued cost reductions should enable more variables to be observed within these networks. For example, low-cost spectrophotometric sensors have been developed for CO_2 (Yang et al. 2014) and nutrient measurements (Beaton et al. 2012), variables that are still relatively difficult to measure in situ. Improvements in spatial coverage have also been facilitated by advances in deployment methods, such as the inclusion of multiple small sensors on a single platform (Rérolle et al. 2018), the development of animal-borne sensors (Roquet et al. 2017), and the use of existing coastal infrastructure such as piers as monitoring platforms (e.g., see the section titled Fiber Optic Monitoring Systems) and ships of opportunity, including military, merchant, fishing, and private vessels (Rosa et al. 2021).

In general, technologies for in situ monitoring of physical oceanographic and meteorological variables tend to be more mature than biological sensors. However, there have been significant recent advances in our ability to monitor biological processes. For example, new technologies for automated monitoring of phytoplankton species diversity and toxin concentrations are enabling the monitoring of HABs in coastal waters. The California Imaging FlowCytobot Network and the HAB Observing Network–New England are two examples of networks of Imaging FlowCytobots, which are automated microscopes that use ML to identify phytoplankton species diversity and abundance (Dashkova et al. 2017). Other HAB sensing systems include automated systems known as labs on a chip or labs in a can, which collect water samples and use measurements of ribosomal RNA or toxin concentrations to identify HABs (Scholin et al. 2009). For broader investigations of coastal biodiversity, eDNA metabarcoding is increasingly being used to detect multiple species from water samples (Miya 2022). One methodological challenge associated with eDNA metabarcoding is the need for reference databases, as incomplete databases can lead to false positives and negatives. However, collaborations among scientists are helping to enhance the coverage of these databases (e.g., Stoeckle et al. 2020). eDNA analysis is typically conducted via manual sampling, which limits the spatial and temporal coverage of studies, but technological advancements are reducing the cost and complexity of automated sampling systems (Hendricks et al. 2023).

FIBER OPTIC MONITORING SYSTEMS

Novel sensing methods with seafloor fiber optic cables have the potential to dramatically expand the spatial and temporal coverage of coastal observations due to the relatively high density of existing fiber optic cables near coasts for telecommunication and other purposes (**Figure 5**) and the potential for continuous measurements at meter scales (**Figure 1**). Fiber optic monitoring primarily encompasses distributed temperature sensing (DTS) and distributed acoustic sensing (DAS). Both DTS and DAS are established technologies, but their use in oceanographic settings is novel and comes with unique challenges (e.g., Lindsey et al. 2019, Sinnett et al. 2020). An interrogator connected to a fiber optic cable uses scattering of laser pulses to measure up to tens of kilometers of fiber optic cable and can be used on either existing or purpose-deployed cables; while DTS requires single-mode fiber, DAS can be used on either single- or multimode fiber. These technologies can facilitate the acquisition of precise information on physical variables that play a critical role in comprehending both short- and long-term changes in coastal systems. These variables include temperature, dynamic processes such as surface and internal waves, and upwelling. Such seafloor measurements may be especially useful in shallow, coastal environments and can provide

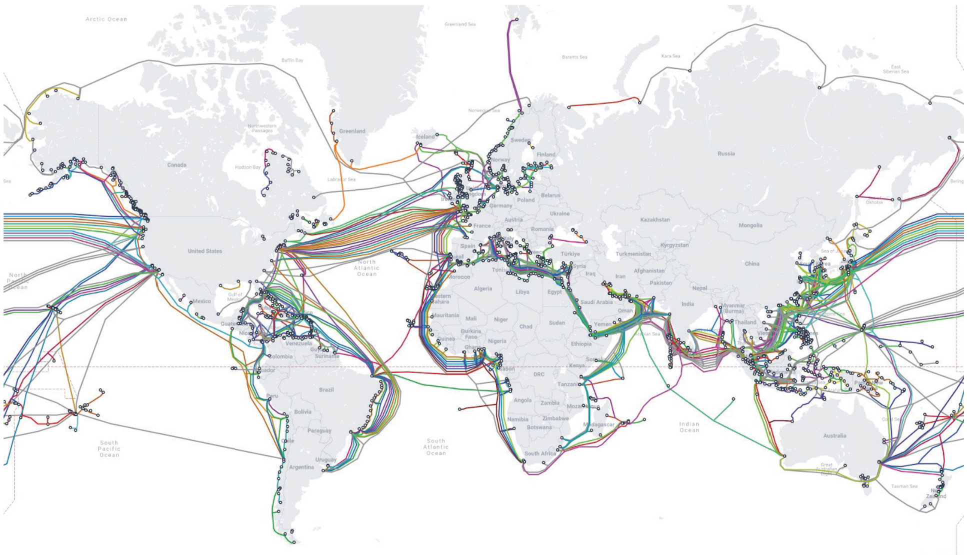

Figure 5

Map of existing global seafloor telecommunication cables. Figure adapted from TeleGeography and submarinecablemap.com (CC BY-SA 4.0). This figure is licensed under a Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) license.

a critical complement to surface observations obtained from satellite or airborne sensing methods. These methods have only recently been adopted by the ocean research community, and thus many of the potential applications are still unexplored.

DTS uses Raman scattering of coherent pulses of laser light off impurities in glass fiber to determine temperature profiles along a length of fiber optic cable (e.g., Hausner et al. 2011). Measurements on scales of meters to kilometers are possible where the Raman frequency bands in the backscattered light spectrum are influenced by the thermal state of the fiber. Calibration of the raw DTS data to retrieve absolute temperatures is necessary, and measurement schemes must balance trade-offs between spatial resolution and measurement precision, making it ideal for locations with strong thermal gradients (e.g., Reid et al. 2019). Spatially and temporally continuous measurements of water temperature allow resolution of rapid and isolated changes in temperature in the nearshore, such as those from tidal fronts (Connolly & Kirincich 2019). DTS was also previously used with a 4-km-long cable on a coral reef atoll to observe significant changes in temperature associated with internal waves (Reid et al. 2019). Calculation of a spatially resolved heat budget showed that internal waves have the potential to reduce thermal stresses on reef systems but may also drive fluxes of nutrients onshore, resulting in calcification (Reid et al. 2019). These types of observations allow for the connection between offshore physical processes and properties in nearshore benthic ecosystems.

DAS uses the Rayleigh scattering of laser light off glass fiber impurities to quantify changes in optical path length, which responds to strain on the fiber caused by acoustic and other perturbations. While the most common oceanographic application of seafloor DAS to date is seismology and earthquake monitoring, the frequency and spatial resolution have also been used to quantify many physical oceanographic processes, including upwelling (Pelaez Quiñones et al. 2023), surface wave attenuation and transformation (Glover et al. 2024, Smith et al. 2023), and internal waves (Williams et al. 2023). Temperature anomalies resulting from internal waves and upwelling events compare well with estimates from more traditional sensing methods at lower resolution (Pelaez Quiñones et al. 2023). Using DAS for thermometry raises unique challenges, especially for calibration methods and separation from other signals, but increases the possible coverage for high-resolution temperature sensing in coastal environments. There is also potential to use DAS for biodiversity monitoring, as these methods have been used to observe and monitor marine mammals (namely, whales; Bouffaut et al. 2022), and acoustic monitoring seems to be a promising application based on the utility of acoustic indices from other instrumentation.

Passive acoustic monitoring (e.g., from hydrophones) has increasingly been used to identify abundances and habitat use in marine environments (Luczkovich et al. 2008). Marine mammals are commonly observed as their calls propagate long distances, but soundscapes from other marine species, including fish, crustaceans, and other invertebrates, can also be monitored (Lindseth & Lobel 2018). Acoustic indices, specifically, provide a tool for understanding marine biodiversity trends and ecosystem health [see review by Pieretti & Danovaro (2020)]. Acoustic remote sensing methods may also be able to monitor the health and variability in the coastal ecosystem vegetation, such as measuring the gas bubbles associated with seagrass (Ballard et al. 2020). Even underwater action cameras (e.g., GoPros) can be utilized as soundscape recordings, providing opportunities for community science over widespread habitats (Chapuis et al. 2021) (see the section titled Community Science Observatories). The ability to monitor over large distances and long spatial scales is a strength of ecoacoustics that will further benefit from applying the same methods to long stretches of fiber enabled by DAS. In the future, monitoring acoustic indices with DAS should be a priority for testing and exploration. However, data management and processing of acoustic data are key challenges for scaling up that will only increase with the larger data volume and spatial resolution. ML approaches will likely be critical to this transition (see the Appendix).

COMMUNITY SCIENCE OBSERVATORIES

While science has long been the domain of experts, the world is full of people interested in the ocean. This interest and the internet's ability to connect large numbers of disparate people sharing common interests have led to the rise of community science in a wide variety of coastal scientific endeavors (Garcia-Soto et al. 2021). Interested individuals can now connect to a wide variety of ocean science projects [e.g., on SciStarter (**https://scistarter.org**), which currently features more than 150 ocean science projects]. These projects include direct in situ biodiversity observations recorded as part of coordinated projects, opportunistic data collection from smartphone app-based projects (often with data processed by AI back ends), and efforts where scientists use online platforms to offer data to participants for classification or annotation.

Biodiversity observing may represent the most visible form of community science. Recreational biodiversity observing activities, such as birdwatching, have long traditions in human society. More recently, community science projects have sought to co-opt the passion of nature enthusiasts into projects like eBird (Sullivan et al. 2009). In marine habitats, biodiversity observation is more difficult. Ocean biodiversity observing projects range in complexity, accommodating a wide variety of expertise in participants. At one end are organizations like the Reef Environmental Educational Foundation (REEF; **https://reef.org**), which focuses on opportunistic sampling by roving divers who make qualitative observations of target species. Such organizations are easily accessible to interested observers and are often accompanied by a great deal of outreach and promotion. They can bring in large quantities of data, although the nature of the data can be biased toward certain taxa and spatial areas. These efforts can have enormous value for heavily sampled taxa or regions as well as connecting participants to conservation. At the other end are programs like Reef Check (Hodgson 1999), which uses detailed survey design protocols and hence focuses a great deal of effort on the training of participating community scientists. Often, scientists work alongside community members in such programs, providing highly detailed data, but with a potential trade-off in extent of reach in terms of people and areas. Many of these efforts have incredible value regionally, connecting members of the community or student groups with local museum, conservation, or academic institutions while providing high-quality data for use in management and conservation, such as the intertidal Long-Term Monitoring Program and Experiential Training for Students (LiMPETS) program in Northern California (Osborn 2003; **https://limpets.org**). Other efforts fall somewhere in between, with scientists training or working with participants but using simpler protocols where participants collect data directly on some organisms but for others collect imagery or other forms of samples for scientists to process later, such as the Reef Live Survey (Edgar & Stuart-Smith 2014; **https://reeflifesurvey.com**).

As an extension of biodiversity observations, many community science programs have begun collecting data using smartphone applications (Land-Zandstra et al. 2016). Using smartphones allows community scientists to collect data quickly as part of an organized effort with a detailed sampling design or independently and opportunistically. Most app-based community science projects center on imagery collected by participants. This has the advantage of making data collection very easy and linking imagery to algorithms to process images into quality data. Imagery can be used as is with a reference, such as apps from the SandSnap beach grain size inventory (McFall et al. 2023) and CoastSnap sea level rise monitoring program (Harley & Kinsela 2022), or judged against a reference suggested to end users, such as apps to monitor water quality (Malthus et al. 2020).

Not all community science projects involve community scientists in the field. Online platforms enable scientists to bring data to interested community scientists for analysis. These platforms also create opportunities for education and capacity building. Perhaps the most prominent of these sites is Zooniverse (**https://zooniverse.org**), a clearinghouse of projects designed using a common web interface that can serve many kinds of data to community scientists. Projects at

Zooniverse are typically designed around vast datasets comprising different media that require some form of classifications by participants. The site started as Galaxy Zoo (**https://galaxyzoo.org**), which works with community scientists to classify galaxies from the Sloan Digital Sky Survey (Lintott et al. 2008). The success of Galaxy Zoo brought many other projects to the site over time. In terms of ocean sciences, online citizen science has been an enormous boon with a wide variety of projects. Multiple projects focus on biodiversity observation for a variety of taxa, such as Plankton Explorer (Robinson et al. 2017) and Penguin Watch (Jones et al. 2018). At larger scales, online platforms also create opportunities for community science projects that interact with remote sensing data, such as the Floating Forests project, which serves Landsat imagery of areas with giant kelp forests (Rosenthal et al. 2018; **http://floatingforests.org**).

Online citizen science projects also extend our ability to get data from the ocean by peering into the past. Many oceanographic records and biological specimens have become digitally archived over the past few decades but often lack transcription of information. The Old Weather project (Blaser 2014; **https://oldweather.org**) asks community scientists to transcribe meteorological records from captains' logs in vessels from the 1700s to the present and has filled in a wide variety of gaps in historical records of ocean conditions, enabling better climate modeling and ocean forecasting. Beyond both scientific and community benefits, online community science projects are easy to use to provide an authentic science experience for students and can improve student outcomes (Rosenthal et al. 2024). Overall, community science is expanding the spatial and temporal coverage of coastal observations by providing a flexible and cost-effective means of collecting and analyzing a wide variety of data.

CONCLUSIONS

Over the past several decades, our capacity for observing coastal ecosystems has increased significantly. Coordination of observations by coastal ocean observing systems has facilitated many of these advances by helping standardize observational methods across monitoring networks, develop data management systems, support the implementation of new observing technologies, and prioritize observational variables. New imaging, acoustic, and genomic technologies are enabling the monitoring of ecological and biological processes that were previously difficult to observe, while new sensor platforms are expanding deployment capabilities. Advances in satellite monitoring have further increased the spatial and temporal coverage of remote observations, which are being supplemented by new UAV remote sensing tools. However, there are still gaps in our observational capabilities that need to be addressed. Here are five recommendations for future research directions to continue advancing coastal ecosystem monitoring:

1. Improve connections between coastal monitoring and open ocean and terrestrial monitoring. Significant advances have been made in the spatial and temporal coverage of open ocean observations (Claustre et al. 2020, McClain 2009); however, integrating data collected from coastal and open ocean monitoring programs can be challenging due to differences in methodologies, data formats, and quality control protocols. For example, the resolution of most ocean color satellites has been too coarse to resolve important coastal processes. Meanwhile, many higher-resolution, terrestrial-focused satellites do not provide the spectral or temporal coverage necessary for ocean color measurements. NASA's PACE mission is addressing this challenge (Dierssen et al. 2023), but more work is needed to harmonize and synthesize data between open ocean and coastal ecosystems. Similarly, there is a need to better coordinate data collection and modeling between terrestrial and coastal ecosystems. For example, increased exports of organic matter from terrestrial ecosystems to the

coast have been linked to coastal water darkening, which has large implications for coastal ecosystems (Opdal et al. 2023).

2. Maintain and expand long-term monitoring programs. Long-term data collection in the coastal ocean is difficult and expensive, but the value of long-term data is increasing as the need to monitor the impacts of climate change becomes more urgent. Continued funding is needed to maintain coastal sensor networks and in situ surveys. Similarly, overlap between satellite missions is critical to facilitate the necessary cross-calibration across multiple satellite systems.
3. Develop new observation platforms using existing infrastructure. Novel uses of existing infrastructure such as fiber optic cables, oil and offshore wind platforms, piers, and ships of opportunity provide cost-effective ways to expand the spatial coverage of in situ measurements. Another underutilized platform for coastal observations is cell phone mobile apps, which can allow community-based reporting of coastal hazards, pollution incidents, and wildlife sightings.
4. Improve monitoring of coastal biodiversity. We have made advances in monitoring biological and ecological processes, but there remain significant gaps in our ability to monitor certain aspects of coastal ecosystems. Cryptic or rare species are still difficult to detect using most in situ methods, many coastal regions are remote or difficult to access, and satellite imagery can only directly observe a relatively limited number of species. Promising directions for addressing these data gaps include genomic methods (Miya 2022), community monitoring programs (Otero et al. 2024), new satellites with improved spatial and spectral resolution and radiometric quality (Muller-Karger et al. 2018), and models to link observable variables to biodiversity (Kavanaugh et al. 2021).
5. Improve the latency and accessibility of data products. The last few decades have seen technological advances in communications that have dramatically increased data transmission speeds for both in situ and satellite-based measurements (Glenn et al. 2000). Now, there is a need to increase the speed at which data are processed, analyzed, and synthesized for coastal managers, policymakers, and other stakeholders. For example, while significant progress has been made in developing global maps of coastal habitat extent from satellite imagery (**Table 1**), there is often a lag time of months to years before these datasets are updated. Because insights derived from coastal observations also need to be delivered in formats that are widely accessible, more effort should be devoted to creating user-friendly visualization and analysis tools (e.g., Bell et al. 2023, Kudela et al. 2021).

APPENDIX: THE ROLE OF ARTIFICIAL INTELLIGENCE IN MONITORING COASTAL ECOSYSTEM DYNAMICS

The proliferation of new coastal monitoring methods has led to a deluge of data. With individual sensing platforms capable of generating terabytes of data across dozens of parameters daily, new methods are necessary to help scientists interpret and draw conclusions from these large and high-dimensional datasets. Many recent calls within various environmental disciplines have stressed big data as a key strategy for addressing future challenges and furthering scientific understanding of ecosystems (e.g., Edgar et al. 2016). Alongside each of those calls, researchers have identified AI as a critical approach for wrangling big data and overcoming challenges stemming from four of the five Vs that define big data: volume, variety, velocity, and veracity (Peters et al. 2014, Wüest et al. 2020). Furthermore, as the threats facing coastal ecosystems become more pressing and complex, AI's ability to rapidly process large volumes of data and integrate data across multiple sources and disciplines will facilitate the adaptive management and real-time response to episodic events that complex systems require to ensure their continued conservation while balancing multiple uses and ecosystem services (Edgar et al. 2016, Varadharajan et al. 2022).

Although ML has immense potential, several challenges need to be addressed to ensure its proper implementation, including the risk of overfitting, difficulties in evaluating opaque black box learning models, and the need to combine principled ecological theory with data-driven learning (Zhu et al. 2023). Here, we highlight recent applications of ML in coastal monitoring and guide researchers toward potential AI approaches to address data challenges.

First, to clarify some terminology that is frequently used interchangeably: AI is a broad umbrella term referring to programming computers to mimic human intelligence and perform tasks; ML is a subfield within the study of AI and refers specifically to the training of models with a large number of parameters using statistical methods applied to approximate arbitrary functions on large and high-dimensional datasets (Murphy 2012). Once trained, ML models can be applied to rapidly analyze large quantities of ecological data, such as detecting animal species in an image (Liu et al. 2019) or categorizing water quality (Nasir et al. 2022). Training methods fall into three classes: supervised learning, unsupervised learning, and semisupervised learning. Supervised and unsupervised learning are ML frameworks that use labeled and unlabeled data, respectively. Supervised approaches require labeled data, which can be expensive and labor-intensive to produce, limiting their usefulness in specialized scientific applications (Liu et al. 2019). Unsupervised approaches do not have this label bottleneck and instead attempt to reduce the dimensionality of large datasets to a minimal set of variables that preserve key information (Doherty et al. 2018). Semisupervised learning draws on strengths of both approaches when it is not possible to have a lot of labeled data and, instead, uses a smaller amount of labeled data bolstered with abundant and more readily obtainable unlabeled data (Doherty et al. 2018). Notably, reinforcement learning, also known as self-supervised learning, is a type of unsupervised learning commonly used in robotics and agent-based learning applications. In reinforcement learning, instead of relying on labeled data, an agent learns from the feedback it receives while interacting with the environment (Anderlini et al. 2019).

To promote the adoption of ML in coastal ecosystem dynamics, here we highlight studies that exemplify potential tasks that address monitoring needs and provide a guide (**Figure 6**) that enumerates additional tasks and potential ML solutions. A primary application of ML in coastal ecosystems is processing remotely sensed imagery, which has been successfully applied across the spectrum of coastal ecosystems, including salt marshes, kelp forests, and seagrass meadows (Bell et al. 2023, Ha et al. 2020, Li et al. 2020, Marquez et al. 2022). Image processing (whether of still images from satellites/drones/cameras or video imagery) includes two common tasks: classification and segmentation. With classification, a machine determines whether an evaluated image contains the subject of interest (e.g., species or habitat type), while segmentation is when a machine also determines where the subject is in the image, thereby allowing for measurements to be derived. As sensor capabilities have increased, high-resolution multispectral drone imagery has increased our knowledge and mapping of ecosystems globally. Yet achieving very-fine-scale (centimeter) imagery of ocean environments remains challenging due to distortion from waves and attenuation of light in water. NASA recently developed an algorithm (which itself is ML) to correct for this refraction in imagery, allowing researchers to then employ supervised learning to classify coral reefs into living versus nonliving maps (at centimeter-scale resolution) and segment those coral reefs into reef types: mounding coral, branching coral, rock, or sand (Chirayath & Instrella 2019).

Another common task achieved through ML is interpreting the wealth of data available from various long-term monitoring projects. Although expert models can simulate many dynamics and processes, they are limited by the number of rules and parameters that scientists are aware of and can implement (Jain et al. 2020). In contrast, ML approaches use large numbers of parameters

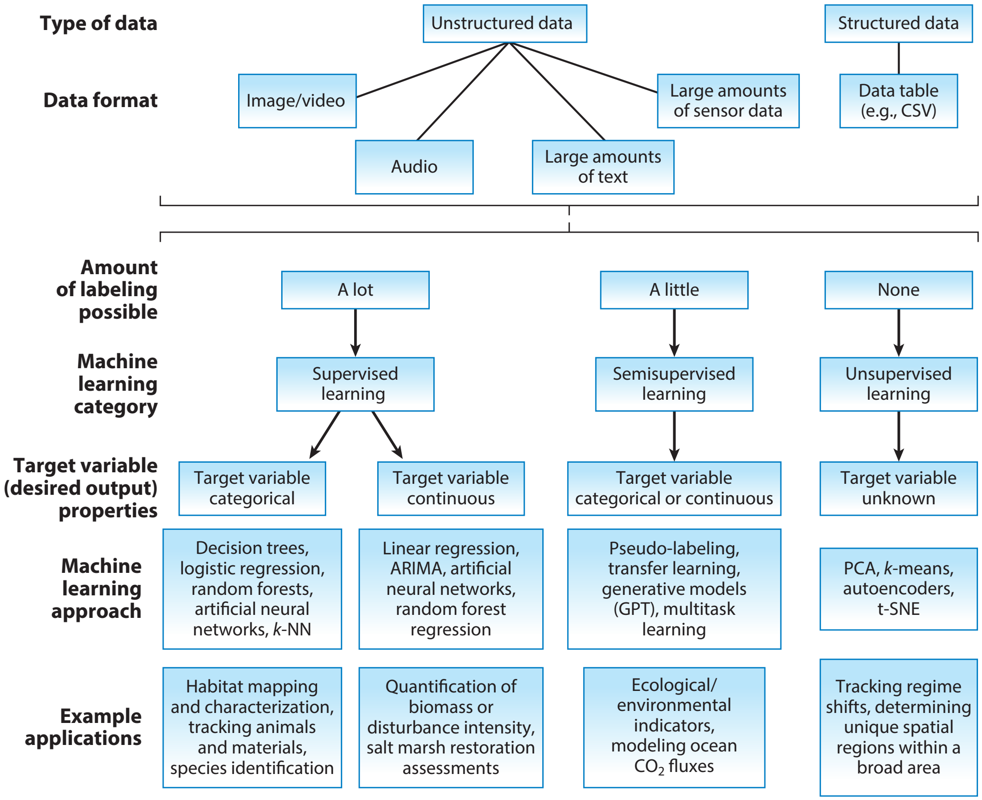

Figure 6

Conceptual diagram of different deep learning analytic approaches. Abbreviations: ARIMA, autoregressive integrated moving average; CSV, comma-separated values; GPT, generative pretrained transformer; *k*-NN, *k* nearest neighbors; PCA, principal component analysis; t-SNE, t-distributed stochastic neighbor embedding.

(in the hundreds of millions) to construct a model based on the trends exhibited in their training datasets and thus do not rely on explicit physical models. These methods are often able to achieve higher accuracies in complex systems (Jain et al. 2020, Willard et al. 2022). For example, one study achieved more accurate estimates of ocean–atmosphere CO_2 fluxes over a 26-year time period, thereby improving our estimate of the global carbon budget, using a two-step process of clustering the data (unsupervised learning) followed by regression (supervised learning) (Watson et al. 2020). Data-driven models can be challenging to train as they require a substantial amount of computation and fine-tuning of the hyperparameters of the ML model to minimize the error rates. Furthermore, there are limitations on the ability to transfer a model across similar domains (Lumini & Nanni 2019). Blended approaches that combine principled theoretical models with data-driven ML models can help address some of these issues in interpretability and achieve faster and more robust training while maintaining the benefits of data-driven ML (Boukabara et al. 2019).

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LITERATURE CITED

Allen B, Stokey R, Austin T, Forrester N, Goldsborough R, et al. 1997. REMUS: a small, low cost AUV; system description, field trials and performance results. In *Oceans '97: MTS/IEEE Conference Proceedings*, Vol. 2, pp. 994–1000. Piscataway, NJ: IEEE

Anderlini E, Parker GG, Thomas G. 2019. Docking control of an autonomous underwater vehicle using reinforcement learning. *Appl. Sci.* 9(17):3456

Anderson DM, Fensin E, Gobler CJ, Hoeglund AE, Hubbard KA, et al. 2021. Marine harmful algal blooms (HABs) in the United States: history, current status and future trends. *Harmful Algae* 102:101975

Antoine D, Morel A, Gordon HR, Banzon VF, Evans RH. 2005. Bridging ocean color observations of the 1980s and 2000s in search of long-term trends. *J. Geophys. Res. Oceans* 110(6):C06009

Bailey K, Steinberg C, Davies C, Galibert G, Hidas M, et al. 2019. Coastal mooring observing networks and their data products: recommendations for the next decade. *Front. Mar. Sci.* 6:180

Ballard MS, Lee KM, Sagers JD, Venegas GR, McNeese AR, et al. 2020. Application of acoustical remote sensing techniques for ecosystem monitoring of a seagrass meadow. *J. Acoust. Soc. Am.* 147(3):2002–19

Beaton AD, Cardwell CL, Thomas RS, Sieben VJ, Legiret FE, et al. 2012. Lab-on-chip measurement of nitrate and nitrite for in situ analysis of natural waters. *Environ. Sci. Technol.* 46(17):9548–56

Behrenfeld MJ, O'Malley RT, Siegel DA, McClain CR, Sarmiento JL, et al. 2006. Climate-driven trends in contemporary ocean productivity. *Nature* 444(7120):752–55

Bell TW, Allen JG, Cavanaugh KC, Siegel DA. 2020a. Three decades of variability in California's giant kelp forests from the Landsat satellites. *Remote Sens. Environ.* 238:110811

Bell TW, Cavanaugh KC, Saccomanno VR, Cavanaugh KC, Houskeeper HF, et al. 2023. Kelpwatch: a new visualization and analysis tool to explore kelp canopy dynamics reveals variable response to and recovery from marine heatwaves. *PLOS ONE* 18(3):e0271477

Bell TW, Nidzieko NJ, Siegel DA, Miller RJ, Cavanaugh KC, et al. 2020b. The utility of satellites and autonomous remote sensing platforms for monitoring offshore aquaculture farms: a case study for canopy forming kelps. *Front. Mar. Sci.* 7:1083

Bell TW, Siegel DA. 2022. Nutrient availability and senescence spatially structure the dynamics of a foundation species. *PNAS* 119(1):e2105135118

Blaser L. 2014. Old weather: approaching collections from a different angle. In *Crowdsourcing Our Cultural Heritage*, ed. M Ridge, pp. 45–56. London: Routledge

Bouffaut L, Taweesintananon K, Kriesell HJ, Rørstadbotnen RA, Potter JR, et al. 2022. Eavesdropping at the speed of light: distributed acoustic sensing of baleen whales in the Arctic. *Front. Mar. Sci*. 9:901348

Boukabara SA, Krasnopolsky V, Stewart JQ, Maddy ES, Shahroudi N, Hoffman RN. 2019. Leveraging modern artificial intelligence for remote sensing and NWP benefits and challenges. *Bull. Am. Meteorol. Soc.* 100(12):ES473–91

Bunting P, Rosenqvist A, Hilarides L, Lucas RM, Thomas N, et al. 2022. Global mangrove extent change 1996–2020: Global Mangrove Watch Version 3.0. *Remote Sens.* 14(15):3657

Cai L, McGuire NE, Hanlon R, Mooney TA, Girdhar Y. 2023. Semi-supervised visual tracking of marine animals using autonomous underwater vehicles. *Int. J. Comput. Vis.* 131(6):1406–27

Cavanaugh KC, Cavanaugh KC, Bell TW, Hockridge EG. 2021. An automated method for mapping giant kelp canopy dynamics from UAV. *Front. Environ. Sci.* 8:587354

Cavanaugh KC, Cavanaugh KC, Pawlak CC, Bell TW, Saccomanno VR. 2023. CubeSats show persistence of bull kelp refugia amidst a regional collapse in California. *Remote Sens. Environ.* 290:113521

Chapuis L, Williams B, Gordon TAC, Simpson SD. 2021. Low-cost action cameras offer potential for widespread acoustic monitoring of marine ecosystems. *Ecol. Indic.* 129:107957

Chirayath V, Instrella R. 2019. Fluid lensing and machine learning for centimeter-resolution airborne assessment of coral reefs in American Samoa. *Remote Sens. Environ.* 235:111475

Claustre H, Johnson KS, Takeshita Y. 2020. Observing the global ocean with Biogeochemical-Argo. *Annu. Rev. Mar. Sci.* 12:23–48

Connolly TP, Kirincich AR. 2019. High-resolution observations of subsurface fronts and alongshore bottom temperature variability over the inner shelf. *J. Geophys. Res. Ocean.* 124(1):593–614

Crowell J. 2013. Design challenges of a next generation small AUV. In *2013 OCEANS—San Diego*. Piscataway, NJ: IEEE. **https://ieeexplore.ieee.org/abstract/document/6740945**

Cruz C, McGuinness K, Perrin PM, O'Connell J, Martin JR, Connolly J. 2023. Improving the mapping of coastal invasive species using UAV imagery and deep learning. *Int. J. Remote Sens.* 44(18):5713–35

Das J, Py F, Harvey JBJ, Ryan JP, Gellene A, et al. 2015. Data-driven robotic sampling for marine ecosystem monitoring. *Int. J. Robot. Res.* 34(12):1435–52

Dashkova V, Malashenkov D, Poulton N, Vorobjev I, Barteneva NS. 2017. Imaging flow cytometry for phytoplankton analysis. *Methods* 1122017:188–200

Davidson NC. 2014. How much wetland has the world lost? Long-term and recent trends in global wetland area. *Mar. Freshw. Res.* 65(10):934–41

Dierssen HM. 2010. Perspectives on empirical approaches for ocean color remote sensing of chlorophyll in a changing climate. *PNAS* 107(40):17073–78

Dierssen HM, Bracher A, Brando V, Loisel H, Ruddick K. 2020. Data needs for hyperspectral detection of algal diversity across the globe. *Oceanography* 33(1):74–79

Dierssen HM, Gierach M, Guild LS, Mannino A, Salisbury J, et al. 2023. Synergies between NASA's hyperspectral aquatic missions PACE, GLIMR, and SBG: opportunities for new science and applications. *J. Geophys. Res. Biogeosci.* 128(10):e2023JG007574

Doherty K, Flaspohler G, Roy N, Girdhar Y. 2018. Approximate distributed spatiotemporal topic models for multi-robot terrain characterization. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3730–37. Piscataway, NJ: IEEE

Doney SC, Ruckelshaus M, Duffy JE, Barry JP, Chan F, et al. 2012. Climate change impacts on marine ecosystems. *Annu. Rev. Mar. Sci.* 4:11–37

Dos Santos MM, De Giacomo GG, Drews PLJ, Botelho SSC. 2019. Underwater sonar and aerial images data fusion for robot localization. In *2019 19th International Conference on Advanced Robotics*, pp. 578–83. Piscataway, NJ: IEEE

Edgar GJ, Bates AE, Bird TJ, Jones AH, Kininmonth S, et al. 2016. New approaches to marine conservation through the scaling up of ecological data. *Annu. Rev. Mar. Sci.* 8:435–61

Edgar GJ, Stuart-Smith RD. 2014. Systematic global assessment of reef fish communities by the Reef Life Survey program. *Sci. Data* 1:140007

Ford DA, Grossberg S, Rinaldi G, Menon PP, Palmer MR, et al. 2022. A solution for autonomous, adaptive monitoring of coastal ocean ecosystems: integrating ocean robots and operational forecasts. *Front. Mar. Sci.* 9:1067174

Friess DA, Yando ES, Abuchahla GMO, Adams JB, Cannicci S, et al. 2020. Mangroves give cause for conservation optimism, for now. *Curr. Biol.* 30(4):R153–54

Garcia-Soto C, Seys JJC, Zielinski O, Busch JA, Luna SI, et al. 2021. Marine citizen science: current state in Europe and new technological developments. *Front. Mar. Sci.* 8:621472

Girdhar Y, McGuire N, Cai L, Jamieson S, McCammon S, et al. 2023. CUREE: a Curious Underwater Robot for Ecosystem Exploration. In *2023 IEEE International Conference on Robotics and Automation*, pp. 11411–17. Piscataway, NJ: IEEE

Glenn SM, Dickey TD, Parker B, Boicourt W. 2000. Long-term real-time coastal ocean observation networks. *Oceanography* 13(1):24–34

Glover HE, Wengrove ME, Holman R. 2024. Measuring hydrodynamics and exploring nearshore processes using distributed sensing of fiber-optic cable strain. *Coast. Eng.* 190:104487

Ha NT, Manley-Harris M, Pham TD, Hawes I. 2020. A comparative assessment of ensemble-based machine learning and maximum likelihood methods for mapping seagrass using sentinel-2 imagery in Tauranga Harbor, New Zealand. *Remote Sens.* 12(3):355

Hallegraeff GM, Anderson DM, Belin C, Bottein MYD, Bresnan E, et al. 2021. Perceived global increase in algal blooms is attributable to intensified monitoring and emerging bloom impacts. *Commun. Earth Environ.* 2:117

Hamilton SE, Casey D. 2016. Creation of a high spatio-temporal resolution global database of continuous mangrove forest cover for the 21st century (CGMFC-21). *Glob. Ecol. Biogeogr.* 25(6):729–38

Harley MD, Kinsela MA. 2022. CoastSnap: a global citizen science program to monitor changing coastlines. *Cont. Shelf Res.* 245:104796

Haskins J, Endris C, Thomsen AS, Gerbl F, Fountain MC, Wasson K. 2021. UAV to inform restoration: a case study from a California tidal marsh. *Front. Environ. Sci.* 9:642906

Hausner MB, Suárez F, Glander KE, de Giesen N, Selker JS, Tyler SW. 2011. Calibrating single-ended fiber-optic Raman spectra distributed temperature sensing data. *Sensors* 11(11):10859–79

He Q, Silliman BR. 2019. Climate change, human impacts, and coastal ecosystems in the Anthropocene. *Curr. Biol.* 29(19):R1021–35

Hendricks A, Mackie CM, Luy E, Sonnichsen C, Smith J, et al. 2023. Compact and automated eDNA sampler for in situ monitoring of marine environments. *Sci. Rep.* 13:5210

Hestir EL, Khanna S, Andrew ME, Santos MJ, Viers JH, et al. 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sens. Environ.* 112(11):4034–47

Hladik C, Schalles J, Alber M. 2013. Salt marsh elevation and habitat mapping using hyperspectral and LIDAR data. *Remote Sens. Environ.* 139:318–30

Hodgson G. 1999. A global assessment of human effects on coral reefs. *Mar. Pollut. Bull.* 38(5):345–55

Hoegh-Guldberg O, Poloczanska ES, Skirving W, Dove S. 2017. Coral reef ecosystems under climate change and ocean acidification. *Front. Mar. Sci.* 4:158

Hollinger GA, Sukhatme GS. 2014. Sampling-based robotic information gathering algorithms. *Int. J. Robot. Res.* 33(9):1271–87

Hwang J, Bose N, Fan S. 2019. AUV adaptive sampling methods: a review. *Appl. Sci.* 9(15):3145

Jain P, Coogan SCP, Subramanian SG, Crowley M, Taylor S, Flannigan MD. 2020. A review of machine learning applications in wildfire science and management. *Environ. Rev.* 28(4):478–505

Jamieson S, Fathian K, Khosoussi K, How JP, Girdhar Y. 2021. Multi-robot distributed semantic mapping in unfamiliar environments through online matching of learned representations. In *2021 IEEE International Conference on Robotics and Automation*, pp. 8587–93. Piscataway, NJ: IEEE

Jones FM, Allen C, Arteta C, Arthur J, Black C, et al. 2018. Time-lapse imagery and volunteer classifications from the Zooniverse Penguin Watch project. *Sci. Data* 5:180124

Kavanaugh MT, Bell T, Catlett D, Cimino MA, Doney SC, et al. 2021. Satellite remote sensing and the marine biodiversity observation network: current science and future steps. *Oceanography* 34(2):62–79

Klemas V. 2011. Remote sensing techniques for studying coastal ecosystems: an overview. *J. Coast. Res.* 27(1):2–17

Konar B, Iken K. 2018. The use of unmanned aerial vehicle imagery in intertidal monitoring. *Deep-Sea Res. II* 147:79–86

Kramer SJ, Siegel DA, Maritorena S, Catlett D. 2022. Modeling surface ocean phytoplankton pigments from hyperspectral remote sensing reflectance on global scales. *Remote Sens. Environ.* 270:112879

Krumhansl KA, Okamoto DK, Rassweiler A, Novak M, Bolton JJ, et al. 2016. Global patterns of kelp forest change over the past half-century. *PNAS* 113(48):13785–90

Kudela RM, Anderson C, Ruhl H. 2021. The California Harmful Algal Bloom Monitoring and Alert Program: a success story for coordinated ocean observing. *Oceanography* 34(4):84–85

Kuhlman MJ, Jones D, Sofge DA, Hollinger GA, Gupta SK. 2021. Collaborating underwater vehicles conducting large-scale geospatial tasks. *IEEE J. Ocean. Eng.* 46(3):785–807

Land-Zandstra AM, Devilee JLA, Snik F, Buurmeijer F, van den Broek JM. 2016. Citizen science on a smartphone: participants' motivations and learning. *Public Underst. Sci.* 25(1):45–60

Lassalle G, Ferreira MP, Cué La Rosa LE, Del'Papa Moreira Scafutto R, de Souza Filho CR. 2023. Advances in multi- and hyperspectral remote sensing of mangrove species: a synthesis and study case on airborne and multisource spaceborne imagery. *ISPRS J. Photogramm. Remote Sens.* 195:298–312

Li J, Knapp DE, Fabina NS, Kennedy EV, Larsen K, et al. 2020. A global coral reef probability map generated using convolutional neural networks. *Coral Reefs* 39(6):1805–15

Li J, Knapp DE, Schill SR, Roelfsema C, Phinn S, et al. 2019. Adaptive bathymetry estimation for shallow coastal waters using Planet Dove satellites. *Remote Sens. Environ.* 232:111302

Li X, Bellerby R, Craft C, Widney SE. 2018. Coastal wetland loss, consequences, and challenges for restoration. *Anthr. Coasts* 1(1):1–15

Lindseth AV, Lobel PS. 2018. Underwater soundscape monitoring and fish bioacoustics: a review. *Fishes* 3(3):36

Lindsey NJ, Dawe TC, Ajo-Franklin JB. 2019. Illuminating seafloor faults and ocean dynamics with dark fiber distributed acoustic sensing. *Science* 366(6469):1103–7

Lindstrom E, Gunn J, Fischer A, McCurdy A, Glover L, Alverson K, et al. 2012. *A framework for ocean observing*. Rep., UN Educ. Sci. Cult. Organ., Paris

Lintott CJ, Schawinski K, Slosar A, Land K, Bamford S, et al. 2008. Galaxy Zoo: morphologies derived from visual inspection of galaxies from the Sloan Digital Sky Survey. *Mon. Not. R. Astron. Soc.* 389(3):1179–89

Liu S, Li X, Gao M, Cai Y, Nian R, et al. 2019. Embedded online fish detection and tracking system via YOLOv3 and parallel correlation filter. In *OCEANS 2018 MTS/IEEE Charleston*. Piscataway, NJ: IEEE. **https://doi.org/10.1109/OCEANS.2018.8604658**

Liu Y, Kerkering H, Weisberg RH. 2015. *Introduction to Coastal Ocean Observing Systems*. Amsterdam: Elsevier

Luczkovich JJ, Mann DA, Rountree RA. 2008. Passive acoustics as a tool in fisheries science. *Trans. Am. Fish. Soc.* 137(2):533–41

Luijendijk A, Hagenaars G, Ranasinghe R, Baart F, Donchyts G, Aarninkhof S. 2018. The state of the world's beaches. *Sci. Rep.* 8:6641

Lumini A, Nanni L. 2019. Deep learning and transfer learning features for plankton classification. *Ecol. Inform.* 51:33–43

Lynn T, Alber M, Shalack J, Mishra DR. 2024. Utilizing repeat UAV imagery to evaluate the spatiotemporal patterns and environmental drivers of wrack in a coastal Georgia salt marsh. *Estuaries Coasts* 47(1):189–200

Lyons MB, Murray NJ, Kennedy EV, Kovacs EM, Castro-Sanguino C, et al. 2024. New global area estimates for coral reefs from high-resolution mapping. *Cell Rep. Sustain.* 1(2):100015

Lyons MB, Roelfsema CM, Kennedy EV, Kovacs EM, Borrego-Acevedo R, et al. 2020. Mapping the world's coral reefs using a global multiscale earth observation framework. *Remote Sens. Ecol. Conserv.* 6(4):557–68

Malthus TJ, Ohmsen R, van der Woerd HJ. 2020. An evaluation of citizen science smartphone apps for inland water quality assessment. *Remote Sens*. 12(10):1578

Marquez L, Fragkopoulou E, Cavanaugh KC, Houskeeper HF, Assis J. 2022. Artificial intelligence convolutional neural networks map giant kelp forests from satellite imagery. *Sci. Rep.* 12:22196

McCammon S, Marcon dos Santos G, Frantz M, Welch TP, Best G, et al. 2021. Ocean front detection and tracking using a team of heterogeneous marine vehicles. *J. Field Robot.* 38(6):854–81

McClain CR. 2009. A decade of satellite ocean color observations. *Annu. Rev. Mar. Sci.* 1:19–42

McFall BC, Young DL, Whitmeyer SJ, Buscombe D, Stever SN, Walker BM. 2023. Sandsnap: creating a nationwide beach grain size database by engaging citizen scientists. In *Coastal Sediments 2023*, ed. P Wang, E Royer, JD Rosati, pp. 906–18. Singapore: World Sci.

McKenzie LJ, Nordlund LM, Jones BL, Cullen-Unsworth LC, Roelfsema C, Unsworth RKF. 2020. The global distribution of seagrass meadows. *Environ. Res. Lett.* 15(7):074041

Mcowen CJ, Weatherdon LV, Van Bochove JW, Sullivan E, Blyth S, et al. 2017. A global map of saltmarshes. *Biodivers. Data J.* 5(1):11764

Miloslavich P, Bax NJ, Simmons SE, Klein E, Appeltans W, et al. 2018. Essential ocean variables for global sustained observations of biodiversity and ecosystem changes. *Glob. Change Biol.* 24(6):2416–33

Miya M. 2022. Environmental DNA metabarcoding: a novel method for biodiversity monitoring of marine fish communities. *Annu. Rev. Mar. Sci.* 14:161–85

Mora-Soto A, Palacios M, Macaya E, Gómez I, Huovinen P, et al. 2020. A high-resolution global map of giant kelp (*Macrocystis pyrifera*) forests and intertidal green algae (*Ulvophyceae*) with Sentinel-2 imagery. *Remote Sens.* 12(4):694

Muller-Karger FE, Hestir E, Ade C, Turpie K, Roberts DA, et al. 2018. Satellite sensor requirements for monitoring essential biodiversity variables of coastal ecosystems. *Ecol. Appl.* 28(3):749–60

Murfitt SL, Allan BM, Bellgrove A, Rattray A, Young MA, Ierodiaconou D. 2017. Applications of unmanned aerial vehicles in intertidal reef monitoring. *Sci. Rep.* 7:10259

Murphy KP. 2012. *Machine Learning: A Probabilistic Perspective*. Cambridge, MA: MIT Press

Murray NJ, Phinn SR, DeWitt M, Ferrari R, Johnston R, et al. 2019. The global distribution and trajectory of tidal flats. *Nature* 565(7738):222–25

Nasir N, Kansal A, Alshaltone O, Barneih F, Sameer M, et al. 2022. Water quality classification using machine learning algorithms. *J. Water Process Eng.* 48:102920

Oliver ECJ, Donat MG, Burrows MT, Moore PJ, Smale DA, et al. 2018. Longer and more frequent marine heatwaves over the past century. *Nat. Commun.* 9:1324

Olson D, Anderson J. 2021. Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture. *Agron. J.* 113(2):971–92

Opdal AF, Andersen T, Hessen DO, Lindemann C, Aksnes DL. 2023. Tracking freshwater browning and coastal water darkening from boreal forests to the Arctic Ocean. *Limnol. Oceanogr. Lett.* 8(4):611–19

Osborn DA. 2003. LiMPETS: long-term monitoring program and experiential training for students. In *Oceans 2003: Celebrating the Past...Teaming Toward the Future*, Vol. 4, pp. 2265–73. Piscataway, NJ: IEEE

Otero P, Velasco E, Valeiras J. 2024. Ecological informatics surveillance of coastal biodiversity through social network monitoring. *Ecol. Inform.* 80:102515

Palomeras N, Hurtos N, Carreras M, Ridao P. 2018. Autonomous mapping of underwater 3-D structures: from view planning to execution. *IEEE Robot. Autom. Lett.* 3(3):1965–71

Pelaez Quiñones JD, Sladen A, Ponte A, Lior I, Ampuero J-P, et al. 2023. High resolution seafloor thermometry for internal wave and upwelling monitoring using distributed acoustic sensing. *Sci. Rep.* 13:17459

Pennings SC, Bertness MD. 2000. Salt marsh communities. In *Marine Community Ecology*, ed. MD Bertness, SD Gaines, ME Hay, pp. 289–316. Sunderland, MA: Sinauer

Peters DPC, Havstad KM, Cushing J, Tweedie C, Fuentes O, Villanueva-Rosales N. 2014. Harnessing the power of big data: infusing the scientific method with machine learning to transform ecology. *Ecosphere* 5(6):1–15

Phillips AB, Gold N, Linton N, Harris CA, Richards E, et al. 2017. Agile design of low-cost autonomous underwater vehicles. In *OCEANS 2017—Aberdeen.* Piscataway, NJ: IEEE. **https://doi.org/10.1109/OCEANSE.2017.8084772**

Phinn S, Roelfsema C, Dekker A, Brando V, Anstee J. 2008. Mapping seagrass species, cover and biomass in shallow waters: an assessment of satellite multi-spectral and airborne hyper-spectral imaging systems in Moreton Bay (Australia). *Remote Sens. Environ.* 112(8):3413–25

Pieretti N, Danovaro R. 2020. Acoustic indexes for marine biodiversity trends and ecosystem health: acoustic indexes in marine environments. *Philos. Trans. R. Soc. B* 375(1814):20190447

Pinton D, Canestrelli A, Fantuzzi L. 2020a. A UAV-based dye-tracking technique to measure surface velocities over tidal channels and salt marshes. *J. Mar. Sci. Eng.* 8(5):364

Pinton D, Canestrelli A, Wilkinson B, Ifju P, Ortega A. 2020b. A new algorithm for estimating ground elevation and vegetation characteristics in coastal salt marshes from high-resolution UAV-based LiDAR point clouds. *Earth Surf. Process. Landf.* 45(14):3687–701

Reid EC, DeCarlo TM, Cohen AL, Wong GTF, Lentz SJ, et al. 2019. Internal waves influence the thermal and nutrient environment on a shallow coral reef. *Limnol. Oceanogr.* 64(5):1949–65

Rérolle VMC, Achterberg EP, Ribas-Ribas M, Kitidis V, Brown I, et al. 2018. High resolution pH measurements using a lab-on-chip sensor in surface waters of northwest European shelf seas. *Sensors* 18(8):2622

Roarty H, Cook T, Hazard L, Harlan J, Cosoli S, et al. 2019. The global high frequency radar network. *Front. Mar. Sci.* 6:164

Robinson KL, Luo JY, Sponaugle S, Guigand C, Cowen RK. 2017. A tale of two crowds: public engagement in plankton classification. *Front. Mar. Sci.* 4:82

Roquet BF, Boehme L, Block B, Charrassin J, Costa D, et al. 2017. Ocean observations using tagged animals. *Oceanography* 30(2):139

Rosa TL, Piecho-Santos AM, Vettor R, Soares CG. 2021. Review and prospects for autonomous observing systems in vessels of opportunity. *J. Mar. Sci. Eng.* 9(4):366

Rosenthal IS, Byrnes JEK, Cavanaugh KC, Bell TW, Harder B, et al. 2018. Floating forests: quantitative validation of citizen science data generated from consensus classifications. arXiv:1801.08522 [physics.soc-ph]

Rosenthal IS, Simon MN, Trouille L, Byrnes JEK. 2024. A citizen science approach to teaching climate change in introductory-level undergraduate general science courses. *J. Geosci. Educ.* 72(3):233–44

Rossiter T, Furey T, McCarthy T, Stengel DB. 2020. Application of multiplatform, multispectral remote sensors for mapping intertidal macroalgae: a comparative approach. *Aquat. Conserv. Mar. Freshw. Ecosyst.* 30(8):1595–612

Saccomanno VR, Bell T, Pawlak C, Stanley CK, Cavanaugh KC, et al. 2023. Using unoccupied aerial vehicles to map and monitor changes in emergent kelp canopy after an ecological regime shift. *Remote Sens. Ecol. Conserv.* 9(1):62–75

Schofield O, Arnone RA, Bissett WP, Dickey TD, Davis CO, et al. 2004. Watercolors in the coastal zone: What can we see? *Oceanography* 17(2):24–31

Schofield O, Creed L, Graver J, Haldeman C, Kerfoot J, et al. 2014. Slocum Gliders: robust and ready. *J. Field Robot.* 24(6):473–85

Scholin C, Everlove C, Harris A, Alvarado N, Birch J, et al. 2009. Remote detection of marine microbes, small invertebrates, harmful algae, and biotoxins using the Environmental Sample Processor (ESP). *Oceanography* 22(2):158–67

Shields J, Pizarro O, Williams SB. 2020. Towards adaptive benthic habitat mapping. In *2020 IEEE International Conference on Robotics and Automation*, pp. 9263–70. Piscataway, NJ: IEEE

Simard M, Fatoyinbo L, Smetanka C, Rivera-Monroy VH, Castañeda-Moya E, et al. 2019. Mangrove canopy height globally related to precipitation, temperature and cyclone frequency. *Nat. Geosci.* 12(1):40–45

Sinnett G, Davis KA, Lucas AJ, Giddings SN, Reid E, et al. 2020. Distributed temperature sensing for oceanographic applications. *J. Atmos. Ocean. Technol.* 37(11):1987–97

Smale DA. 2020. Impacts of ocean warming on kelp forest ecosystems. *New Phytol.* 225(4):1447–54

Smith MM, Thomson J, Baker MG, Abbott RE, Davis J. 2023. Observations of ocean surface wave attenuation in sea ice using seafloor cables. *Geophys. Res. Lett.* 50(20):e2023GL105243

Srinivasan M, Tsontos V. 2023. Satellite altimetry for ocean and coastal applications: a review. *Remote Sens.* 15(16):3939

Stoeckle MY, Das Mishu M, Charlop-Powers Z. 2020. Improved environmental DNA reference library detects overlooked marine fishes in New Jersey, United States. *Front. Mar. Sci.* 7:226

Sullivan BL, Wood CL, Iliff MJ, Bonney RE, Fink D, Kelling S. 2009. eBird: a citizen-based bird observation network in the biological sciences. *Biol. Conserv.* 142(10):2282–92

Thomas J, Hazard L, Jensen RE, Otero M, Terrill E, et al. 2015. How high-resolution wave observations and HF radar-derived surface currents are critical to decision-making for maritime operations. In *Coastal Ocean Observing Systems*, ed. Y Liu, H Kerkering, RH Weisberg, pp. 159–78. Amsterdam: Elsevier

Thompson DR, Hochberg EJ, Asner GP, Green RO, Knapp DE, et al. 2017. Airborne mapping of benthic reflectance spectra with Bayesian linear mixtures. *Remote Sens. Environ.* 200:18–30

Varadharajan C, Appling AP, Arora B, Christianson DS, Hendrix VC, et al. 2022. Can machine learning accelerate process understanding and decision-relevant predictions of river water quality? *Hydrol. Process.* 36(4):e14565

Veettil BK. 2022. Current status of mangrove vegetation in Batticaloa Lagoon, Sri Lanka, using high-resolution satellite imagery. *J. Coast. Conserv.* 26(6):74

Vos K, Splinter KD, Harley MD, Simmons JA, Turner IL. 2019. CoastSat: a Google Earth Engine-enabled Python toolkit to extract shorelines from publicly available satellite imagery. *Environ. Model. Softw.* 122:104528

Wang M, Hu C, Barnes BB, Mitchum G, Lapointe B, Montoya JP. 2019. The great Atlantic *Sargassum* belt. *Science* 365(6448):83–87

Wang ZA, Moustahfid H, Mueller AV, Michel APM, Mowlem M, et al. 2019. Advancing observation of ocean biogeochemistry, biology, and ecosystems with cost-effective in situ sensing technologies. *Front. Mar. Sci.* 6:519

Watson AJ, Schuster U, Shutler JD, Holding T, Ashton IGC, et al. 2020. Revised estimates of ocean-atmosphere CO_2 flux are consistent with ocean carbon inventory. *Nat. Commun.* 11:4422

Wernberg T, Krumhansl K, Filbee-Dexter K, Pedersen MF. 2019. Status and trends for the world's kelp forests. In *World Seas: An Environmental Evaluation*, Vol. 3: *Ecological Issues and Environmental Impacts*, ed. C Sheppard, pp. 57–78. Amsterdam: Elsevier. 2nd ed.

Willard J, Jia X, Xu S, Steinbach M, Kumar V. 2022. Integrating scientific knowledge with machine learning for engineering and environmental systems. *ACM Comput. Surv.* 55(4):66

Williams EF, Ugalde A, Martins HF, Becerril CE, Callies J, et al. 2023. Fiber-optic observations of internal waves and tides. *J. Geophys. Res. Ocean.* 128(9):1–13

Wüest RO, Zimmermann NE, Zurell D, Alexander JM, Fritz SA, et al. 2020. Macroecology in the age of big data—where to go from here? *J. Biogeogr.* 47(1):1–12

Wyngaard J, Barbieri L, Thomer A, Adams J, Sullivan D, et al. 2019. Emergent challenges for science sUAS data management: fairness through community engagement and best practices development. *Remote Sens.* 11(15):1797

Yang B, Patsavas MC, Byrne RH, Ma J. 2014. Seawater pH measurements in the field: a DIY photometer with 0.01 unit pH accuracy. *Mar. Chem.* 160:75–81

Zhu JJ, Yang M, Ren ZJ. 2023. Machine learning in environmental research: common pitfalls and best practices. *Environ. Sci. Technol.* 57(46):17671–89