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# Robotics for Environmental Monitoring

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Robotic systems are increasingly being utilized as fundamental data-gathering tools by scientists, allowing new perspectives and a greater understanding of the planet and its environmental processes. Today's robots are already exploring our deep oceans, tracking harmful algal blooms and pollution spread, monitoring climate variables, and even studying remote volcanoes. This article collates and discusses the significant advancements and applications of marine, terrestrial, and airborne robotic systems developed for environmental monitoring during the last two decades. Emerging research trends for achieving large-scale environmental monitoring are also reviewed, including cooperative robotic teams, robot and wireless sensor network (WSN) interaction, adaptive sampling and model-aided path planning. These trends offer efficient and precise measurement of environmental processes at unprecedented scales that will push the frontiers of robotic and natural sciences.

The need for large-scale persistent environmental monitoring has become particularly relevant in recent times after a set of serious natural disasters and environmentally harmful accidents. These include earthquakes, tsunamis, hurricanes, floods, large forest fires, volcanic eruptions, oil spills, and nuclear meltdowns.

However, understanding and quantifying environmental health, processes, responses to stressors, and trajectories require large amounts of accurate spatial and temporally disperse data. For example, meteorologists need to monitor a set of physical variables such as temperatures, airflow, and air pressure, to study the weather and to forecast its behavior. Environmental scientists study the transport and dispersion of air or water pollution. The monitoring of both physical and chemical quantities, such as airflow, and polluting gases such as $CO_2$, CO, $CO_2$, or $NO_x$, for example, is important to model and track the involved phenomena. Ecologists study the systems that may involve the monitoring of the previous physical and chemical quantities along with the detection, classification, and tracking of living organisms in their environments.

## Significant Advancements and Applications

To meet these data requirements, at a global scale, remote-sensing satellites are typically utilized, while at the regional scale, fixed monitoring stations are mainly employed. At the local scale, manual and automated sampling is typically conducted. This can be an extremely difficult task and often limits data collection, particularly, during significant events such as hurricanes and floods. Furthermore, local scale sampling is often costly and difficult to maintain persistent sampling. However, over the past few decades, sensor networks have emerged as a new tool to collect spatially dense information in real time from natural environments. Although there is a progress compared with past methodologies, traditional sensor networks only provide fixed monitoring points without the means to adapt to changes in the surrounding environment.

To increase data collection efficiencies, particularly in hostile environments, earth and life scientists see robotics as a promising tool with the capacity to improve their current means to observe and collect data about natural processes or phenomena at vast spatial and temporal scales. Oceanographers were among the first earth scientists who started using underwater robots to study the deep ocean and seafloor [1]. Geologists have also explored the use of robots to study extreme phenomena such as vulcanology [2], while some meteorologists have began using robotic aircraft in the study of microclimates and hurricane observation [3].

Robotics science has made huge progresses since the arrival of the first commercial robots on the factory floor more than 50 years ago. Principally, robots have received new and better sensors, along with algorithms that provide the means to perceive their operating environment and plan missions autonomously while reacting to various uncertainties. Nowadays, robots can be seen operating in natural or in man-made, highly unstructured environments, such as deep oceans [4], active volcanoes [5] (Figures 1 and 2), or damaged nuclear power plants [6]. Although a large range of fundamental problems still need to be solved, operating in such hostile and challenging environments has established a new frontier for robotics as well as environmental sciences.

A plethora of research literature exists relating to all aspects of robotics and sensor networks for environmental monitoring. These works relate to vehicle design, energy optimization, path planning, control, localization, and mapping. Each area by itself could be a potential article. In addition to the significant research and demonstrated advances towards robotics-based environmental monitoring, this article

**Figure 1.** Robovolc operating on Mt. Etna, Italy, Europe's largest active volcano. (Photo courtesy of University of Catania.)

identifies sensor types and technologies commonly employed to measure environmentally relevant variables and integrated sensor network systems already proved in the field. It also discusses the broad emerging research trends for achieving large-scale environmental monitoring as well as some outstanding challenges in making environmental robotics pervasive.

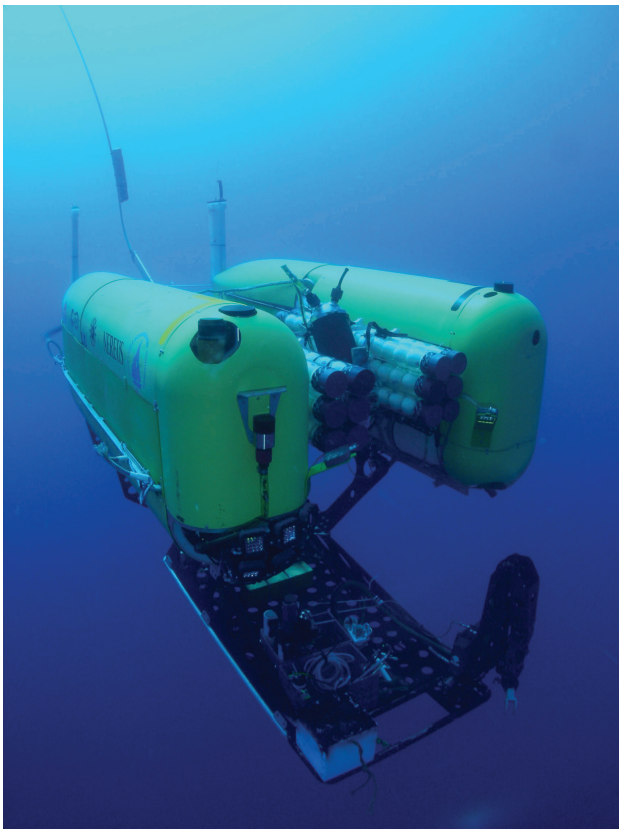

**Figure 2.** The Nereus hybrid ROV that has explored the world's deepest oceans at 10,903 m [4]. [Photo courtesy of Advanced Imaging and Visualization Laboratory, Woods Hole Oceanographic Institution (WHOI).]

## Environmental Sensing

One of the key goals in environmental science and ecology is to gain baselines, detect changes, and correlate these to various driving factors. The issues in detecting the changes in ecosystems are considered by Carpenter and Brock [7]. They show that increased variability should occur prior to threshold transitions in many ecosystems. However, they identify that the challenge of deriving the true variability of ecosystems is the essential long-term, high-frequency observations.

Furthermore, ecology is one of the most statistically orientated sciences, requiring elaborate experimental design and sampling protocols. Gaines and Denny [8] evaluate the issues associated with misrepresentation and use of statistics, highlighting the importance of not only data capture but also the sampling regime.

Traditionally, data were obtained manually, limiting the spatial and temporal coverage of the study sites as well as being dictated by weather and cost. Ballesterös-Gomez et al. [9] provide an overview of the traditional methods of environmental monitoring, including sensors, calibration, and field applicability. They recognize that environmental sensor networks (ESNs) (i.e., a wireless network of sensors distributed throughout the environment) are revolutionizing the observation of various processes and identify the importance of these networks and robotic systems in obtaining high-fidelity time-series data. However, problems with interoperability, calibration, communication, and longevity are limiting their uptake in ecosystem sciences. Solutions to these issues are also a key requirement to realize pervasive environmental robots.

## Sensors

A key attribute of environmental monitoring is the measurement of relevant environmental variables, being physical, chemical or biological. Most physical variables, such as temperature, pressure, and light intensity, can be easily measured with portable off-the-shelf sensors. On the other hand, standard measurements of environmental chemical variables are mostly performed using bulky and heavy analytical instrumentation installed in fixed stations.

The development of inexpensive, low-power consumption and small sensing devices, based in reasonably stable electrochemical cells, metal oxide gas sensors (MOX), or chemiluminescent devices is seen as a major step to the development of chemical sensing systems able to be integrated in robots for environmental monitoring. However, a large set of contaminants of interest (e.g., metals, radioisotopes, and biological contaminants) are present in small concentrations in natural environments that no sensor with enough sensitivity, selectivity, and long-term stability currently exist.

For a deeper treatment about environmental sensors, we direct the reader toward a multitude of articles dealing only with this subject. For example, overviews of sensors and requirements for general environmental monitoring

are investigated by [16] and [30]. A recent survey on sensors for aquatic environments is provided in [31], with marine chemical sensors summarized in [20] and [32]. Zielinski et al. [29] investigates sensors and systems to detect hazardous substances and microorganisms in marine environments. Sensor technologies for soil monitoring are addressed by Allen et al. [33], with current advances in sensors for ecology discussed in Porter et al. [34]. Table 1 summarizes the most relevant variables measured in environmental monitoring, their ranges of interest, and the technologies regularly employed.

## Sensor Networks

Sensor networks were the first major shift in distributed monitoring and real-time observation. There has been extensive research summarized in many articles relating to

**Table 1. Sensors for common physical and chemical environmental variables.**

| Type | Range of Interest | Technology | Comments and References Using the Sensor |
|---|---|---|---|
| Physical quantities | | | |
| Temperature | –60–+80 °C | RTD, thermistors, semiconductor | Used in most environmental studies [3] |
| Radiation | 0–1,367 $W.m^{-2}$ | Thermopiles, photodiodes | Global solar radiation in a $0.3-2.8\mu m$ band or band-specific measurements [e.g., ultraviolet (UV) or infrared (IR)] [10] |
| Pressure | 800–1,060 mbar for ground measurements | Microelectromechanical systems capacitive | 0.5 bar at 5,500 m height; 1 bar/10 m depth [11], [12] |
| Airflow | 0–70 $m.s^{-1}$ | Mechanical, ultrasound, thermal | Ultrasound arrays provide intensity and direction |
| PM10, PM2.5 | 0–400 $mg/m^3$ | Light scattering | DustTrak was used in [13] |
| Turbidity | 1–4,000 NTU | Nephelometers | Nephelometric turbidity units |
| Distance | 0–11,000 m | Sound navigation and ranging (SONAR), light detection and ranging | 3-D mapping, bathymetry, ice thickness [14], [15] |
| Chemical substances | | | |
| pH | 0–14 pH | Glass pH electrode (−59.16mVpH) | Molar concentrations of hydrogen and hydroxyl ions |
| SO | 5 ppb–0.5 ppm | UV fluorescence; electrochemical cell | eCell 0 − 200 ppm [5] |
| NO*x* | 5 ppb–0.5 ppm | Chemiluminescent | Relevant pollutants, but not monitored in the surveyed robotics literature [16] |
| $O_3$ | 5 ppb–0.5 ppm | Chemiluminescent, UV photometer | |
| CO | 0.5 ppb–50 ppm | Nondispersive IR (NDIR), MOX sensors | |
| Hydrocarbons | ppb–ppm | Flame ionization detection, photoionization detection, MOX, IR | Methane sensor [17], [18], MOX [19] |
| $CO_2$ | 0.1 ppm–$10^4$ ppm | NDIR | Sometimes combined with other measurements [5], [20] |
| $O_2$ | 0.01 mg/l–2,000 mg/l | Chemiluminescent | Dissolved oxygen [18] |
| Biological sensing | | | |
| Image | ≈ 20 Mpixel visible | Charge-coupled device (CCD) and CMOS cameras | UV, visible [21], [22], and IR [23], [24] bands are frequently sensed; centimeter-scale resolution with UAVs [25] |
| Sound | 10 Hz–1 MHz | Microphones and sonars | Krill density estimation by echolocation [26] |
| Plankton | | Spectrometers and cytometers | Density estimation [27], [28] |
| Blue-green algae | | Fluorometers | Density estimation by chlorophyll fluorescence [29] |

The references provided refer to works using that given sensor.

communication aspects [35], deployments [36], [37], data gathering and processing [38], and energy efficiency [39]. Several articles about ESNs have recently been published. Corke et al. [40] reported the progresses in WSNs for environmental and agricultural applications and analyzed the weaknesses that still need to be solved to have systems deployable directly by the end users. A similar article [41] gives emphasis to future trends and [42] includes a table with the main ESN projects done until 2005. Rundel et al. [43] provide an extensive and complete survey from an ecological perspective.

A major limitation of ESN is the generally fixed sampling locations. To improve measurement coverage, some ESNs acquire measurements under constrained mobility. For example, cable winches are used in ecological monitoring of water [44] and forest environments [45]. However, although improving spatial coverage of measurements, they are still a constrained resource. Now with the emergence of dependable robotic systems, researchers have begun adding increased mobility to sensor nodes. This is where the era of environmental robotics has come to light.

## Early Environmental Robotics

Robotics as a research field has been to develop the fundamental building blocks to allow autonomous operation, mobility, localization, mapping, and control. The advancements in each of these areas have been incredible and to address each is beyond the scope of this article. Environmental robotics is an extension and application to these fundamental robotic research areas in which the robots become mobile sensors to explore and measure aspects of the natural environment. Through these applications, a set of new robotics science has been created, including adaptive sampling, model-aided path planning, and natural habitat classification and mapping (discussed in "The Era of Environmental Robotics" and "Trends in Environmental Robotics" sections).

The heritage of environmental robotics has been to explore particularly challenging natural environments. In their simplest form, these early robotic systems were developed to follow preset mission plans and capture data that was retrieved after the experiment. The early pioneering robotic systems for environmental monitoring were predominately maritime. This is primarily due to the relative benign, uncluttered nature of the domain with low risk to humans or other activities compared with terrestrial or aerial domains. More importantly, it was a domain that researchers knew very little about, and the only way to explore this hostile environment safely and cost effectively was remotely perfect for robots.

**Figure 3.** The Aerosonde UAV following a successful 17-h autonomous sampling mission in 2009 of katabatic winds in Antarctica. (Photo courtesy of AAI Aerosonde.)

There are many examples of autonomous underwater vehicles (AUVs) for oceanographic measurements, such as the REMUS [11] and AutoSub [12]. Early version of these vehicles had limited endurance (e.g., 7 h for REMUS and 12 h AutoSub). However, they proved research into integrated system design, global positioning system (GPS)-denied navigation, mission, and path planning could allow capture of accurately localized environmental data in harsh environments over extended periods of time. With advances in battery technologies, the endurance of newer generations of these vehicles has been greatly increased, allowing autonomous missions to be conducted in highly complex environments, for example, under arctic ice sheets lasting 25 h [14]. Whitcomb [1] and Yuh [46] provide surveys of these early underwater robotic systems and their technical advancements.

Beyond the oceanographic sampling, pioneering AUV researchers teamed up with other science domain specialists to apply these systems to investigate specific science questions such as sub sea lava flow thickness [47] or to discover and study deep-sea hydrothermal vents [15].

Although the majority of early robots for environmental monitoring were maritime, there are significant examples of airborne and terrestrial systems. Elfes et al. [21] developed a semiautonomous airship to capture ground images and atmospheric measurements, highlighting the research challenges in underactuated control and navigation in dynamic environments. The Aerosonde [48] unmanned aerial vehicle (UAV) (see Figure 3) was a pioneering example demonstrating the use of airborne systems to conduct large-scale, beyond line-of-sight climate monitoring, which included a 27-h autonomous trans-Atlantic flight in 1998 traveling 3,270 km [49].

Some well-known early works of terrestrial robots operating in unstructured natural environments were produced by groups from Carnegie Mellon University and included the Dante-walking robots [50]. The advancements in legged robot locomotion, perception, and path planning allowed demonstration of autonomous mobility and exploration on the uneven terrain of a volcano. Also, long-duration autonomy experiments using wheeled rovers were conducted in the Atacama Desert [51]. The goal of this research was to improve the autonomy of remote sampling platforms and to explore how domain scientists interact with and task robotic systems, particularly during robotic planetary missions.

These early works illustrated some unique applications of robotics for environmental monitoring. They did, however, raise many research challenges, particularly around localization, perception, path planning, mapping, vehicle mobility, endurance, and safety, which are considered more broadly in the robotics literature over the past few decades.

## The Era of Environmental Robotics

Since those pioneering works presented in the "Early Environmental Robotics" section, much of the research over the following decade was directed toward solving many of the fundamental challenges to allow robots to operate more accurately and reliably in a range of natural and man-made environments. The following sections describe some key scientific and engineering achievements that are allowing robotics today address a wide range of environmental monitoring problems.

### *Energy-Efficient Sampling Platforms*

Most robotics platforms used for environmental monitoring are based on traditional electric and hydrocarbon-propelled vehicles such as AUVs, autonomous surface vehicles (ASVs), autonomous ground vehicles (AGVs), and UAVs. The endurance of these active systems is limited by the available onboard energy storage, particularly for AUV and UAVs, or the amount of solar panels they can carry in the case of electric-powered AGVs and ASVs. However, there has been significant research and developments in improving the energy efficiency, harvesting capabilities, and hence, endurance of robots, particularly for marine applications.

Arguably, the greatest contribution to date in spatially distributed long-time series robotic sampling is from the Argo profiling float program [52]. By simply changing their buoyancy, the floats rise and lower through the water column. Because of the limited actuation required, at the top and bottom of the vertical profile, they are incredibly energy efficient, with design endurance exceeding 1,500 days as they drift in the ocean currents. The simplicity of operation and reliability of these autonomous profiling floats has transformed ocean observation, and, at the time of writing this article, there were 3,308 operational floats in the world's oceans (see Web site http://www.argo.ucsd.edu).

The primary disadvantage of the Argo floats is its lack of horizontal actuation capability, with their trajectory dictated by the local ocean current profile. The next significant advancement in ocean observation platforms was by extending the profiling float concept and adding wings to create the autonomous underwater glider [53]. Again, by simply changing their buoyancy, the underwater glider undergoes a saw-tooth profile as it rises and lowers through the water column. This provides the vehicle with horizontal velocities up to 0.5 $ms^{-1}$, which can be used to alter its direction to allow limited trajectory control (dependent on the prevailing water current speeds). These gliders are now commonplace among the oceanography community.

In terms of increasing the endurance of robotic boats, Rynne and von Ellenrieder [54] developed a sailing ASV for sustained ocean operations. This was later extended to a hybrid solar and sailing vehicle in [55]. The vastly improved endurance of sailing ASVs has prompted unique applications for their use, such as tracking marine mammals across vast oceans [56].

A recent development in ASV propulsion is the Wave Glider [57]. This uniquely designed vehicle has a set of passively compliant wings suspended below the hull (see Figure 4). As the vehicle moves up and down by surface wave action, the wing moves vertically through the water producing thrust. The vehicle is capable of average forward speeds of 1.5 kn and, to date, has conducted missions exceeding one year.

In contrast, there are significant challenges associated with improving the energy efficiency of UAVs. Unlike water- or land-based robots, which can remain idle to conserve power or recharge, UAVs (fixed wing, in particular) require forward motion to remain airborne, therefore expending energy.

Solar-powered UAVs have been pursued since the 1970s with some successes, particularly in high altitude and large wing area designs. Recently, motivated by using UAVs on Mars to extend the observational range in planetary exploration, some small, lightweight UAVs with the potential to fly for extended periods powered purely by solar have been developed and demonstrated [58]. There is, however, an inherent limit to the amount of solar panels and batteries an UAV can carry for energy capture and storage. To improve endurance, Klesh and Kadamba [59] address this problem by analyzing methods for optimizing the flight path based on the interaction of the plane kinetics with the position of the sun to extract the most energy for sustained flight.

Although all these developments in energy-efficient platforms are still restricted in their maximum operating regimes, their simplicity and reliability have demonstrated

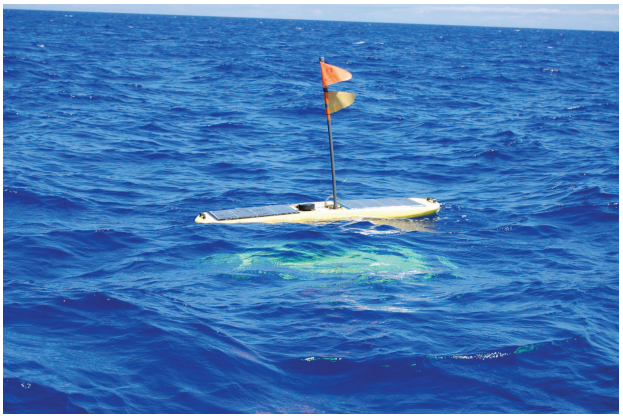

**Figure 4.** The Wave Glider ASV during trials in the Pacific Ocean off Hawaii in 2010. (Photo courtesy of Liquid Robotics.)

**Figure 5.** A UAV undertaking autonomous aquatic weed classification and mapping experiments in 2009 [60]. (Photo courtesy of ACFR.)

persistent environmental monitoring, and their application is transforming our understanding of ocean and atmospheric processes.

### *Natural Habitat Mapping*

The ability to accurately map habitats and detect changes in natural environments is an important aspect of ecology. The utility of environmental robotics is to generate a range of these data products for domain scientists, with the most common being high-resolution, georeferenced maps [two-dimensional (2-D), three-dimensional (3-D), and four-dimensional (4-D)] of natural habitats and objects of interest.

The recent availability of commercial UAV systems to domain scientists has seen significant utilization of these platforms as high-resolution imaging tools for a range of interesting habitat-mapping applications such as image-based mapping of Antarctic moss beds [25] and aquatic weed surveillance and management [60], multispectral imaging for landscape vegetation mapping and classification [61], as well as crop health assessment [62] and rangeland monitoring [63], and for performing wildlife surveys [64], [65] and tracking pests such as locusts [66].

Additionally, commercial AUVs are operated with a range of sensors to create 3-D maps of the benthos and water column processes, for example, eelgrass mapping in shallow water environments [67] and quantifying plankton abundances under ice [26]. However, as domain scientists have realized the potential of these systems, there has been a drive within the robotics community to extend the mapping and information extraction capabilities of environmental robotic systems. These include creating maps of the seafloor using multispectral imagery to classify and map the boundaries of seagrass [67].

Another significant research thread is the ability to develop high-resolution 3-D maps without the need for GPS and high-end inertial navigation hardware. Based on preliminary work from Pizarro et al. [68] researchers from the Woods Hole Oceanographic Institute (WHOI) and the Australian Centre for Field Robotics (ACFR) have developed techniques for generating habitat maps based on visual and sonar sensors attached to an AUV and simultaneous localization and mapping (SLAM) techniques [69]. The techniques have been applied to create habitat maps for detecting changes between repeated AUV-based surveys [70], illustrating the ability to accurately remap large areas over significant periods of time. Further application of these maps has been to accurately map and quantify marine biota such as cuttlefish [71].

One downside to environmental robotics is the enormous amounts of data they can produce. Hence, a particular challenge has been to streamline image processing and habitat classification. Machine learning techniques have been applied to large-scale underwater image sets to determine habitat boundaries [72] as well as detect changes in habitat composition between repeat surveys [73]. In a similar effort, real-time habitat classification and mapping using UAVs equipped with high-resolution imagery sensors has demonstrated the ability to monitor and map invasive weeds on land [22] and ponds [60] (see Figure 5).

As robotic systems collect even larger data sets, the processing and data product generation become a significant bottleneck. Hence, many domains (e.g., robotics, remote sensing, and computer vision) are currently looking at the problem of robust automated information extraction to expatiate scientific discovery.

### *Marine and Atmospheric Plume Detection and Localization*

The ability of robotic platforms to perform large-scale coverage missions in natural environments is now almost routine. However, there are instances, such as detection and location of chemical plumes, when complete coverage missions are inefficient either in time or energy. Therefore, a branch of environmental robotics research has focused on the detection and localization of static atmospheric or underwater pollution sources, or hydrothermal vents.

Localizing the source of substances released to a fluidic medium, be it water or air, with mobile robots can be either achieved after a mapping process, or in real time by implementing a search process to track its chemical plume until the source. Different types of searching algorithms have been proposed to address this task: some following an estimated gradient [74], others biologically inspired [75], and others adapting methods of stochastic search, such as particle swarm optimization [76]. Most of these studies were done in reduced scale environments, but the results suggest that the best searching strategy depends on the stability degree of the atmosphere and, both airflow and chemical concentration information should be used by the searching algorithm.

The use of multiple robots to track and map chemical plumes has also been noticeably studied. Multiple sampling points provide wider information about the

environment and better ability to estimate gradients in turbulent atmospheres. With a target application of detecting hazardous gas leaks, an architecture for estimating indoor environmental odor maps using multiple robots through centralized data assimilation is provided by Marques et al. [19]. A statistical method to build 2-D gas distribution maps, including the wind influence on gas dispersion, was proposed by Reggente et al. and later employed in a project to monitor pollution with garbage-collecting robots operating in urban areas [13].

There has also been a number of research activities focused around mapping various marine and aquatic dispersion processes. Carmell and Stilwell [77] compare parametric and nonparametric techniques using information theoretics for adaptive sampling of a simulated plume boundary using an AUV. A preliminary study into biologically inspired sampling behaviors [75] experimentally evaluated an adapting sampling strategy to detect and localize a single point-source chemical plume. Jakuba and Yoerger [78] propose an alternate technique and employ an occupancy grid and plume buoyancy model to estimate the location of multiple hydrothermal plumes simultaneously using sensors onboard an AUV. The resulting maps provide likely vent locations that proved accurate during field experiments.

In terms of aquatic-based atmospheric plume detection, the quantification and mapping of greenhouse gas emissions from water storages using an ASV has been demonstrated [18]. The technique uses an atmospheric gas sensor and a dispersion model to estimate the size and location of methane gas bubbles emanating from the water, which can be mapped, and the spatiotemporal variability correlated to other environmental and hydrodynamic factors [79].

These studies have demonstrated the ability of robotic systems to detect, track, and localize chemical plumes in a range of small to extremely large-scale natural environments. However, the general degree of autonomy offered to the robot in altering its sampling regime and trajectory is limited. Therefore, newer research is focused on allowing greater flexibility in sampling to improve process tracking (see the "Trends in Environmental Robotics" section).

### *Data Muling WSNs*

There are many practical challenges and compromises required in the creation and maintaining of an effective ESN [40]. Often for reasons of energy efficiency and sensor network longevity, it may be desired to reduce the communication range considerably to save power (issues with communication performance are not considered in this article). Additionally, over time, some of the sensor nodes may fail and become inoperable. These in effect may cause the network to become disconnected, resulting in the inability of the sensors to relay their data back to a central location.

Data muling refers to the process of collecting data from fixed sensor nodes using mobile robots passing in the range of communication. An early article by Shah et al. [80] considers the theoretical aspects of data muling, with a 2-D simulation study focusing on the issues of information latency, energy, and network scaling.

Examples of data muling experiments for environmental monitoring have been considered with a range of robotic systems. Data muling underwater sensor nodes have been considered by Dunbabin et al. [81]. A small-scale experiment demonstrated an AUV capable of optically and acoustically localizing and retrieving data from a set of seafloor sensor nodes using a robot and communication hardware and software solution [82]. An early example evaluating the ability of fast-moving UAVs to data mule WSNs was conducted by Teh et al. [83]. The concept of using data muling to increase the energy lifetime using a mobile robot in an indoor environment was also explored by Tekdas et al. [84].

Besides the ability to collect data from sensor nodes, the other key aspect of robotic data muling is the planning of paths to visit the nodes. Most research has focused on trajectory planning based around variants of the traveling salesman problem (TSP). This problem was extended by Bhadauria et al. [85] in an outdoor-based environment with multiple robots, whose path was chosen to collect the data from a set of sparse sensors in minimal time.

Other notable examples of path planning to improve data collection rates of disconnected sensor nodes consider limitations of vehicle mobility or communication capabilities in natural environments. Cobano et al. [86] consider the case of data muling sensor nodes using UAVs subject to maneuverability constraints and atmospheric disturbances. They address the problem of data retrieval by modifying the vehicle's path through a set of waypoints located in the active region of a number of sensing nodes to meet a set of sampling objectives. Hollinger et al. [87] consider the case of uncertain communication channel characteristics in underwater sensor networks. Their approach modifies the TSP by including the probability of data being collected from a particular node, depending on the quality of the communication.

Typically, the robotic platform being used as the data mule is only an agent to retrieve disconnected sensor data and does not value add information to the underlying environmental process being monitored. However, an emerging trend is to integrate the robotic system and the sensor network as a complete distributed sensing system (see the "Robot and Sensor Network Interaction" section).

## Trends in Environmental Robotics

Some broad trends have been identified in current environmental robotics works. These are related to the complementarities offered by mobile robots and fixed sensor networks, allowing improved spatiotemporal sampling coverage of a range of environmental observation applications.

The path of a robot can also be chosen to maximize the information collected and, consequently, the knowledge

gained about the environment. This path can be optimized based on a previously known model or based on a model generated online during the robot's operation.

Multirobot systems, able to extend even further the complementarities obtained by robot–sensor network interaction, are another subject gaining increased attention. The main problem in this case is coordinating all the resources efficiently using centralized or a distributed approach. The following sections briefly describe some of the directions and applications advancing environmental robotics in these areas.

### Robot and Sensor Network Interaction

Realizing that there are limitations of both fixed and mobile sensor networks, researchers are looking at more formal ways of integrating these systems to achieve greater spatiotemporal measurement coverage. Attempts are being made to formalize integration and sharing of information between sensor networks and robotic systems beyond simple data mules. The goal is to improve data quality, measurement certainty, and allow accurate real-time modeling and mapping of large environmental processes.

An integration framework based on remote procedural calls that allows robots and static sensors to consider each other as providers and consumers of services is described in [88]. The approach allows functionality of the system to be extended in a way that is transparent to the sensor network. This system was experimentally evaluated on a large-scale water quality sensor network with ASVs and AUVs providing distributed sensing capabilities (see Figure 6).

A group at the University of Southern California has been considering the task of integrating technology, communications, and scientific exploration of aquatic ecosystems [89]. At the applied level of integrated robot and sensor networks, Zhang and Sukhatme [10] combine static and mobile sensors to reconstruct an underlying sensor field. Using a method based on local linear regression, the authors demonstrate the ability to reconstruct the temperature field of a small lake. A similar system comprising ten sensor nodes and a small ASV to track spatiotemporal patterns of chlorophyll and temperature across a small lake is detailed in Sukhatme et al. [90]. Component research of the group is summarized in [89], with details of other advances and application of environmental process tracking described further in the "Model-Aided Path Planning" section.

**Figure 6.** A robot and sensor network interaction system deployed on Lake Wivenhoe, Australia, for large-scale water quality monitoring and event detection. (Photo courtesy of CSIRO.)

Another unique application of robot and sensor network integration is described in [91]. Here, an ASV is equipped with an antenna to track radio-frequency identification tagged fish in a lake. Preliminary experiments show the ability of the system to detect, localize, and track tagged fish. This technique was later extended to include land-based robotic vehicle that could track fish under a frozen lake [92].

### Model-Aided Path Planning

Integrating the path-planning capabilities of robotic systems with forecast models of various environmental parameters allows improved operational performance (endurance and navigation) in dynamic environments as well as the ability to track evolving processes of interest.

One approach has been to develop cost functions that consider vehicle mobility, time, and energy constraints to generate a set of optimal (with respect to the cost function) long-term feasible paths within a dynamic environmental process. These have proved particularly useful when the environment is changing significantly over short periods of time, such as in tidal systems or storms. For example, 2-D and 3-D hydrodynamic models have been used to generate and experimentally evaluate energy and time-optimal paths for vehicles such as AUVs in highly dynamic coastal [93] and estuarine [94] environments where strong tidal currents and dynamic obstacles are present. Additionally, similar methods with atmospheric models have been developed to evaluate the feasibility of long-term energy-efficient position control of planetary exploration blimps subjected to strong winds on Titan [95].

There is also a body of work directed toward integrating ocean prediction models to track biological processes in the Southern Californian Bight [89]. Smith et al. [96] use a 3-D ocean model prediction to assist in the path planning of autonomous underwater gliders to maneuver through the ocean to locations with high-scientific merit. Here, the algorithms use ocean forecasts to plan the next waypoint for the robots, and the collected data are fed back in near real time for use by the predictive model. This has been evaluated in simulation and experimentally. These techniques were expanded to numerically track a dynamically evolving process, an oceanic algal bloom, using multiple autonomous underwater gliders [28]. The ocean predictions were used to predict the evolution of the bloom, and

path planning is used to determine the deployment location to track the evolving process.

In terms of atmospheric model integration, Techy et al. [97] present a method of synchronizing the motion of UAVs subjected to wind disturbances to coordinate sampling efforts for the monitoring of plant pathogen spores in the lower atmosphere. The decentralized technique using speed modulation was then experimentally evaluated in [98] using two UAVs, demonstrating the ability to provide regular sampling of spore plumes at consistent times.

Coordination of a team of UAV-sensing platforms to improve an ensemble-forecasting process has been investigated by Choi and How [99]. Taking into account various constraints, such as limited vehicle mobility and energy budget, their algorithms were validated in a simplified large-scale dynamic weather forecast.

### Adaptive Sampling

Physical phenomena often have unknown spatial distributions that also change over time. Consequently, the estimation accuracy depends on the spatial sampling distribution, which needs to be adapted accordingly with the perceived changes and other constraints that might exist.

With consideration to environmental robotics and ESNs, Hombal et al. [100] provides a comparison between different multiscale adaptive sampling algorithms for characterizing a particular feature, given mission constraints such as time, speed, and uniform sampling. Szczytowski et al. [101] also consider this problem and propose a Voronoi-based adaptive spatial sampling solution for a WSN that removes unnecessary samples from oversampled regions and generates additional new sampling locations in undersampled regions to fulfill prespecified accuracy requirements. Although assuming static sensor nodes, the approach can be extended to mobile sensors.

Another multiscale adaptive sampling technique using a combination of remote sensing data and onboard learned distinctions between different material types is provided by Thompson and Wettergreen [102]. Here, as the rover explores a previously unexplored environment, it constructs a map combining locally measured and remote sensing data using Gaussian process models. This allows the robot to adapt its path based on correlations to maximize its scientific discovery.

In the case where the process is not necessary known a priori, an active system that builds a model of a particular process as the robot acquires measurement samples is required. Krause et al. [103] present a unified approach based on Gaussian processes for not only determining the placement of senor network nodes to optimize the modeling of processes being observed but also to predict communication costs that are considered in the placement algorithm. When taking mobility into account, Rahimi et al. [104] describe an algorithm that iteratively optimizes the sampling process in space and time to build a model using a combined measure of information gain, navigation, and sampling cost. The system is experimentally evaluated on a cable-driven robot in a forest canopy for microclimate monitoring [105].

Camilli et al. [17] describe a conceptual framework based on experimental data to allow autonomous data-driven mission planning for the detection and localization of underwater chemical plumes using AUVs. They explore the general principles required for integration of biological and chemical sensors as a payload with active feedback onboard AUVs to maximize scientific discovery and validation.

### Cooperative Robotic Teams

Multirobot teams have been proposed to improve the monitoring and resource utilization when sampling large-scale environmental processes, particularly, when they are dynamic in nature. An example is the COMETS project, which designed and implemented cooperative systems for autonomous environmental perception, including fire detection and monitoring as well as terrain mapping, using multiple heterogeneous UAVs [106]. Here, a centralized approach to reducing the uncertainty in fire detection by using multiple robots and different observation perspectives is demonstrated.

In terms of large-scale environmental process tracking, formal approaches to the coordination and control of multiple robotics systems have been considered by Fiorelli et al. [107]. Here, a control scheme is presented based on artificial potentials and virtual bodies to coordinate a group of vehicles, in this case underwater gliders. A large-scale experimental evaluation in Monterey bay showed formation control of groups of AUVs and the ability to track environmental features of interest in a dynamic environment.

Bridging the gap between model-based predictions and sampling, Bhatta et al. [108] present the results of an experiment whereby the data collected by multiple autonomous sensing platforms were assimilated in real time into an advanced ocean model to help predict the next sampling location. Paley [109] then considers the formation control of multiple robots to meet a sampling objective and simulates a glider-coordinated control system that performs feedback control to automate fleet coordination.

Expanding on this work, Leonard et al. [110] describe the design of mobile sensor networks whose collective motion is optimized to sample natural fields in terms of reducing statistical uncertainty in their estimates. This methodology was evaluated during a month-long field experiment in Monterey Bay.

### Summary

Table 2 shows a high-level taxonomy of the surveyed literature that focused on environmental robotic science or applications, highlighting the distribution of the research focus, platform utilization, and the scale of experimental validation.

**Table 2. Distribution of research focus, platform utilization, and scale of experimental validation presented in the surveyed literature relating to environmental robotics.**

| | Small Scale | | |
|---|---|---|---|
| | **Marine** | **Aerial** | **Ground** |
| Remote sensing application | | [23], [62]–[64] | |
| Cooperative robotic teams | | | [13], [19] |
| Robot and sensor notwork interaction | [82], [91] | | [13] |
| Mapping and localization | [68], [91], [92] | [60] | |
| Image processing and classification | [68] | [60] | |
| Atmospheric modeling quantification | | [104], [105] | [13], [19], [74] |
| Data mulling | [81], [82] | | **[80]**, [84] |
| Adaptive sampling | **[100]** | [104], [105] | |
| Model-aided path planning and control | | | |
| Path planning | [81], [92] | | [74], [84] |
| Control and navigation | [44], [81], [91], **[100]** | | |
| Systems | [44], [81], [91] | [23] | |

| | Medium Scale | | |
|---|---|---|---|
| | **Marine** | **Aerial** | **Ground** |
| Remote sensing application | [15] | [25], [61], [98] | [102] |
| Cooperative robotic teams | | [24], **[97]**, [98], [106] | |
| Robot and sensor notwork interaction | [10], [88]–[90] | | |
| Mapping and localization | [15], [69], [71], [73], [75] | [24], [65], [106] | [102] |
| Image processing and classification | [71], [73] | [21], [24], [66] | |
| Atmospheric modeling quantification | | | |
| Data mulling | **[87]** | [83], [86] | [85] |
| Adaptive sampling | [10], [17], [75], [90] | | [102] |
| Model-aided path planning and control | **[94]** | | |
| Path planning | **[87]**, [90], **[94]** | [86] | [50], [85] |
| Control and navigation | | [21], **[97]**, [98] | [50] |
| Systems | [55] | [21], [106] | [5], [50] |

| | Large Scale | | |
|---|---|---|---|
| | **Marine** | **Aerial** | **Ground** |
| Remote sensing application | [14], [47], [52] | [3] | |
| Cooperative robotic teams | [28], [107], [108], **[109]**, [110] | **[99]** | |
| Robot and sensor notwork interaction | | **[99]** | |
| Mapping and localization | [47], [67], [70], [72], **[77]**, [78] | [22] | |
| Image processing and classification | [67], [70], [72] | [22] | [51] |
| Atmospheric modeling quantification | [18], [78] | **[95]** | |
| Data mulling | | | |
| Adaptive sampling | **[77]**, [96], [107] | | |
| Model-aided path planning and control | [28], [93], [96], [108], [110] | **[95]** | |
| Path planning | [4], [28], [93], [96], [109], [110] | **[59]** | [51] |
| Control and navigation | [4], [14], [18], [53], [107], [108], **[109]**, [110] | **[95]** | [51] |
| Systems | [11], [12], [52], [53], [56], [57], [70] | [49], [58] | |

The scale of the experimental validation is divided into small ($<$10,000 m$^2$), medium (10,000 m$^2 \leq$ 1 km$^2$), and large ($>$1 km$^2$). References listed in bold indicate simulation-only validation.

The dominance of AUVs as research platforms for environmental monitoring is evident in Table 2. Additionally, the validation of the research is performed at much larger scales than other domains. However, it is also evident that 1) the research areas are being developed and applied across all marine, aerial, and ground domains and 2) systems that are being utilized in environmental monitoring applications often combine more than one of these research areas.

Other more general observations from this article are that terrestrial platforms are mostly used for soil or lower atmosphere monitoring. Their missions are usually small-to-medium scale in terms of space and time and contain a human in the loop/supervision architecture.

The breadth of aerial platforms is large, ranging from small UAVs with small spatial and temporal operating ranges but with fast dynamic behavior, particularly appropriate to study fast atmospheric phenomena such as hurricanes. Slower platforms like helicopters are particularly appropriate to study habitats (e.g., capturing images of the soil, flora, and fauna). Larger vehicles capable of operating at very high altitudes and high spatial and temporal ranges, such as NASA's Global Hawk, can be used to study the global atmosphere.

## Challenges

Despite the significant advancements toward robotics-based environmental monitoring, the most mature systems remain in the marine domain focused around vehicle design, endurance, control, and mission planning. However, reviewing recent trends and potential applications for multidomain (air, land, and water) environmental robotic systems, there are more generalized unsolved research challenges identified to allow ubiquitous use of robot systems for environmental monitoring. Those dominant challenges are the following.

### *Reliability, Safety, and Endurance*

Despite the influx of commercially available AUV, AGV, and UAV systems, platform reliability and endurance still plague the widespread adoption by domain scientists as tools for environmental monitoring. Additionally, regulatory frameworks, particularly around the operation of UAVs, can severely restrict operations in regions of high scientific importance [63], [64]. Therefore, there is a need to improve the reliability and safety of these systems through new standards and formal methods of assessing dependability in robotic systems.

The "The Era of Environmental Robotics" section describes the advances in improving platform endurance, particularly in marine environments. However, consideration to hybrid vehicle design, intelligent fault-tolerant systems, and redundancy through hardware reconfigurability to improve fail safety and endurance is required to expand the operational envelop of these systems (particularly, aerial and terrestrial platforms) in collecting long-term data in harsh environments. In addition to platform reliability, as missions extend into months or years, systems that are capable of self-calibrating sensors as well as provide uncertainty bounds on their measurements over time are required.

### *Control*

The issues associated with control primarily relate to improving control authority with underactuated systems in highly dynamic environments (e.g., AUVs and lighter than air vehicles). This is where disturbance forces are much greater than the available actuation force. Also, reconfigurability through predictive, adaptive and hybrid control strategies are required to allow systems to change mobility functions for operation in different operating environments and increase longevity.

**Multirobot teams have been proposed to improve the monitoring and resource utilization when sampling large-scale environmental processes, particularly, when they are dynamic in nature.**

### *Human–Robot Interfaces*

Although large amounts of literature exists for human–robot interfaces, within the environmental robotics community systems are less intuitive and lack standards that allow nonrobot users to seamlessly operate, program, and understand behavior in the field. Research is required here to bridge the gap and make robotic systems usable and effective tools for environmental scientists.

### *Task Execution and Adaptive Mission Planning*

An underexplored area is that of task specification, including science-driven objectives, as opposed to preplanned mission paths. The goal is to provide greater onboard flexibility to the robot for decision making and automated mission planning/replanning from high-level tasks. This will allow more optimal resource utilization (particularly within coordinated heterogeneous systems) and adaptive path planning for process tracking. This higher level of task abstraction is required to allow domain scientists the ability to discover new phenomena when using these robotic systems.

### *Real-Time Dynamic Process Tracking*

Most examples presented in this article are considered the low-hanging fruit in terms of large-scale process tracking. However, little research exists for adaptive tracking and sampling of dynamic processes that are changing much

faster than the maximum robot motion capabilities, as well as tracking processes with splitting boundaries (e.g., [111]). These processes are of particular interest to atmospheric and oceanographic scientists. Other deficient areas include methods of adaptive sampling to minimize uncertainty in data-assimilated models, as well as real-time, onboard image processing strategies to classify and track various items of interest.

### *Cooperative Systems*

To address many of the proposed larger environmental monitoring problems, frameworks for integration of disparate sensing platforms, as well as for robot and sensor network interaction and information sharing are necessary. Methods are required for resource allocation to solve various observation objectives, as well as decentralized cooperative control of large groups of mobile sensing systems, particularly with low-communication bandwidth and significant asynchronicities and latencies in data transmission and information processing, and GPS-denied environments.

### *Classification and Information Extraction*

As discussed in the "Natural Habitat Mapping" section, robotic systems are now capable of generating enormous volumes of data. This data can be relatively easily transformed into spatial maps. However, the extraction of information for generation of data products to be used by managers and scientists is still predominantly performed manually. There will become a point where complete manual processing is unsustainable. Therefore, automated techniques, such as those employing machine learning (see the "Natural Habitat Mapping" section), are required to preclassify data. However, reliable segmentation and classification in naturally lit and varying scale scenes, as well as the ability to resurvey and detect and quantify change in dynamic environments remain significant challenges.

## Conclusions

This article summarizes two decades of literature relating to robotics for environmental monitoring focusing on key research activities and applications, their operating domains, and their real-world validation. A significant proportion of research focus has been on marine-based robotic systems. Hence, these are the most mature in terms of vehicle design, endurance, and scientific application base. However, in recent years, as the reliability of research and commercially available systems has improved (e.g., UAVs), other application domains have emerged, particularly atmospheric observation. This has encouraged new trends in environmental robotics science relating to robot and sensor network interaction, model-aided path planning, adaptive sampling, and cooperative robotic teams. However, some significant research challenges remain to be solved before these systems become ubiquitous scientific tools. These include vehicle control, reliability and safety, real-time dynamic process tracking, mission and task planning, and managing large cooperative robot teams. Addressing these research challenges over the coming years will see robotic systems play an increasing role in scientific data collection, advancing our fundamental knowledge of the environment and its processes.

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