Biodiversity research requires more motors in the mud, air and water

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Word count: 3800 out of 4,000 max

Number of figures: 4 out of 6 max (Figures and Tables)

Number of tables: 1 out of 6 max (Figures and Tables)

Number of references: 95 out of 100 max

Abstract

Human activities have accelerated species extinctions, causing a rapid biodiversity decline. Simultaneously, recent advancements in artificial intelligence and autonomous systems offer transformative potential for biodiversity research. Uncrewed vehicles—such as aerial drones, ground robots, and underwater vehicles—equipped with high-resolution sensors enhance ecosystem monitoring with unprecedented efficiency and scale. Here, we review studies published in Web of Science (1930–2023) using uncrewed vehicles for ecological monitoring and explore their broader potential to further biodiversity research. Drones are predominantly used for vegetation mapping, species monitoring, and habitat assessment; underwater vehicles focus on supporting benthic surveys, and water quality monitoring; and ground robots are used mostly for sample collection. Despite this breadth of existing applications, we identify key gaps: the growing body of research predominantly addresses plants (46%) and animals (44%), with minimal focus on microbes (10%). Additionally, key biodiversity hotspots are underrepresented, including South Africa, Central America, and South America. Our findings emphasise the need to expand taxonomic and biogeographic coverage to maximise the impact of these technologies. We argue that integrating uncrewed vehicles, payloads, and AI through collaborations between ecologists and roboticists can enable cost-effective, accurate ecological monitoring, advancing biodiversity conservation and addressing pressing knowledge gaps in the Anthropocene.

Keywords: autonomous systems, biodiversity, conservation, drones, robots, ecological monitoring.

Main

The Anthropocene, a geological era characterised by the profound environmental impacts of humans, poses key challenges for biodiversity. The extent of our footprint in this new era is already staggering: in 2020, the global mass of human-made materials exceeded the mass of all living organisms on Earth[1]. Indeed, human infrastructure has encroached upon at least 80% of the 15,150 terrestrial key biodiversity areas[2]. These and other human activities have accelerated species loss, driving modern human-induced extinction rates to 100-fold above the background rates for mammals[3] and 80-fold for birds[4]. Despite this alarming reality, an estimated 80% of living species remain unknown to science, and their extinction rate is appraised to be higher than that of already known species[5]. The scale of this human footprint and global change[6] demands urgent, cost-effective biodiversity monitoring solutions, as species may have gone extinct before we even know of their existence[7].

In parallel to the on-going global change[1,8,9] and biodiversity loss[3,6], significant technological advancements have emerged in recent decades in computer science[10] and autonomous robotics[11] that offer unique opportunities for biodiversity research. For instance, progress in deep learning has revolutionised species identification, animal behaviour recognition, and biodiversity estimation[12]. Concurrently, advancements in autonomous navigation systems[13,14], sensors[15,16], and intelligent robotics[17] have facilitated the use of uncrewed vehicles for air[18], ground[19], and water[20] in biodiversity monitoring and conservation. These technologies are greatly expanding the spatial range accessible to ecologists cost-effectively, and significantly enhancing our ability to monitor biodiversity.

<**Fig. 1**>

Given these unprecedented challenges and opportunities, ecologists must examine how these technological advancements can be used to monitor, understand, and protect ecosystems more effectively. Here, we review the current usage of uncrewed vehicles in ecological monitoring, and highlight how these applications could be extended to further biodiversity research. Specifically, we: 1) systematically review the application of uncrewed vehicles in biodiversity studies; 2) identify gaps for biodiversity study for future research; and 3) point out potential future efforts in bridging these gaps. To address both goals, we conduct a literature review of publications from 1930 to 2023 in Web of Science, and identify 769 papers using uncrewed aerial systems (*i.e.*, drones) and 386 papers employing uncrewed ground/underwater vehicles in biodiversity studies (details of the search in Appendix S1). Given that drones account for the majority of existing applications, we present them separately from other uncrewed vehicles to better understand the factors driving their popularity and distinct roles in biodiversity research. These insights may also help identify key gaps—such as technological limitations, deployment constraints, and commercialisation challenges— in other robots that need to be addressed to facilitate their broader application in biodiversity studies. The country, ecosystem, taxonomy, spatial scale (*i.e.*, subdiscipline of ecology) of the applications were automatically extracted from each abstract via scraping algorithms in R (Appendix S2), which performed at a high precision (78-92% validation accuracy; Appendix S1: Table S1). From the total of 1,155 papers, 20% (232 papers) were randomly selected for a full-text review to extract the remotely operated platform, payload, and application scenarios, which we used to assess their broader applicability in biodiversity research.

Current applications of robots in biodiversity studies

Timeline and ecosystem biases in robotic applications

The first applications of drones in biodiversity research took place two decades later than that of ground and aquatic robots (*e.g.*, Remotely Operated Vehicles-ROV[21], drifters[22]). However, the application of drones in biodiversity research has surged exponentially since the 2010s (Fig. 1). This increase is driven by more affordable commercial drone models equipped with diverse sensor systems, user-friendly navigation and mission controls, and efficient data collection capabilities. Indeed, the release dates of particularly important built-in sensors and functions in DJI drone models (a primary drone maker, with 80% of the market worldwide[23]) appears to have triggered the rapid increase in their usage in ecology. Said sensors range from \$100s (*e.g.*, RGB cameras) to ~\$10,000s (*e.g.*, multispectral, LiDAR), depending on sensor type and resolution, offering a wide range of options for different project budgets.

Ground/underwater robots remain more specialised than drones. Robots currently differ in commercial availability, costs, and the challenges associated with deployment and management. The commercial and consumer applications of drones align well with the needs of field ecologists, making commercial off-the-shelf (COTS) drones readily accessible for ecological research[24]. In contrast, although ground robots are technologically more mature than drones, the lack of consumer alignment has prevented the development of COTS options, resulting in limited availability and an absence of standardized controls and infrastructure[24]. Underwater gliders and other uncrewed vehicles are specially developed for ecological surveys and are not be significantly more expensive than top-end drones[25,26]. However, the deployment and management of ground and underwater vehicles remain considerably more challenging than that of drones, primarily due to the terrain complexities of operating in terrestrial and aquatic environments rather than due to limitation of the platforms themselves[26,27](Fig. 1b).

Nevertheless, robots have found multiple ‘ecological niches’ due to their diverse applications and versatility across ecosystems. Drone applications span terrestrial and marine environments, but to date their usage has been biased towards terrestrial ecosystems (20% since the 2020s; Fig. 1c). This terrestrial bias in drone applications is likely due to the availability of drone-mountable sensors like LiDAR and hyperspectral cameras that are well-suited to the survey of terrestrial ecosystems, as well as algorithms such as structure-from-motion (SfM) that can process the outputs of these sensors to yield useful digital artefacts[28]. This combination of technologies facilitates the monitoring of vegetation structure and plant physiology in structurally complex ecosystems, like forests or savannas[28]. Ground robots are less frequently used than underwater robots in biodiversity studies (Fig. 2c). Underwater robots are often used in monitoring benthic communities, marine fauna, and physical conditions (Appendix S2: Table S1).

Typical sensors and their functions

In our review, optical sensors make up 94% of drone payloads. These optical sensors include RGB cameras (54%), multispectral (18%), hyperspectral (6%), LiDAR (8%), and thermal/near-infrared camera (8%) (Fig. 2c). RGB cameras are typically used to monitor land cover and habitat quality[29], detect environmental hazards (*e.g.*, fire[30], green tide[31]), conduct post-disaster assessments[32], and track populations of megafauna[33], and birds[34] (Appendix S3: Table S1). In aquatic systems, the usage of aerial drones includes monitoring water quality[35] and macroalga[36], surveying benthic communities in shallow waters[37], and tracking the behaviour of marine megafauna, like whales[38](Box 1). Moving beyond the visible spectrum, drones with multispectral and hyperspectral cameras enable researchers to detect subtle spectral differences, which have facilitated applications such as species classification and mapping[39], estimation of plant biomass[40] and monitoring of physiological traits[41], as well as monitoring of water and soil quality[42,43]. Thermal infrared sensors are often applied in population surveys[44] and behaviour monitoring[45] of large animals, as well as in mapping temperature distributions across landscapes[46]. LiDAR-equipped drones are particularly valuable for generating high-resolution topographical data, including forest structure mapping[47] and morphological measurements of marine animals via digital surface models[48]. Additionally, RGB sensors, combined with SfM algorithms, can generate 3D reconstructions of objects, offering a cost-effective alternative to LiDAR to estimate changes in biomass and structural attributes and, when repeated through time, ecosystem-level changes[47].

<Box 1>

Compared with drones, other robots used for biodiversity monitoring have lower diversity in optical sensor types, but a higher diversity in non-optical sensor types. Indeed, in our review, optical sensors only amount to 57% of payloads of ground or underwater robots, while these were found in 94% of drones. Physical and chemical sensors make up 18% of the payloads of these other robots while only 1% for drones. Similarly, ground or underwater robots carry devices to sample, collect, or release materials in 17% of studies, with drones only in 3% of the examined applications (Fig. 2, Appendix 2: Table S1). Ground/underwater robots typically rely on RGB sensors (accruing 96% of all optical sensors) for video documentation of benthic community composition[49], habitat surveys[49], and behaviour monitoring of marine species[50]. Other optical sensors used by ground and underwater robots like hyperspectral, near-infrared, and thermal infrared cameras are occasionally (4% of all optical sensors) used to monitor ship wrecks[51], air temperature, relative humidity, and leaf wetness[52]. Physical and chemical sensors monitor variables such as dissolved oxygen, salinity, temperature, chlorophyll-a, and pressure[53,54]. Specialised samplers also enable these robots to collect specimens and samples from aquatic environments, such as sediments[55], eDNA[56], or vent fluids[57]. Furthermore, autonomous gliders and drifters equipped with diverse sensors contribute to monitoring ocean currents, biogeochemical parameters, and other physical oceanographic variables[58].

<Fig. 2>

Applications beyond just monitoring biodiversity

Robots are being used in increasingly innovative ways to support biodiversity management and conservation. In addition to carrying optical, physical, and chemical sensors, robots are now being used to actively sample gases, liquids, and sediments from the environment[59,60] and to release biotic and abiotic materials to aid conservation efforts[61]. For example, recently, drones have been deployed to release insects in Pennsylvania (USA) as biological control agents to combat invasive plants[61]. Furthermore, new developments in bioinspired robots allow direct interaction with ecosystems[62], as in biorobots used in cognitive ecology to study species responses[63]. This new generation of robots can pave the way for conservation applications by actively interacting with wildlife to alleviate human-wildlife conflicts. Examples include bio-inspired robots to deter wild animals from artificial constructions, *e.g.* discouraging birds from approaching airports[64].

Knowledge gaps

Based on our review of the literature, we identify data gaps in the application of robots in biodiversity studies along four main dimensions: (1) geographic distribution, (2) taxonomic coverage, (3) spatial scale, and (4) targeted biome.

Drones to date have been predominantly used in China (31% as per our review), United States (13%), and Australia (6%). Other robots follow a similar pattern, though their applications are more frequent in the United States (Fig. 3 a, b) than China. It is worth noting that this geographic distribution does not align with the location of global biodiversity hotspots (Fig. 3c) nor with regions most at risk under climate change (Fig. 3d). Specifically, tropical regions like Central and Latin America, Africa, and Southeast Asia, which contain a high concentration of biodiversity hotspots[65] and are highly vulnerable to climate change impacts[8], have to date experienced limited use of robots for biodiversity monitoring, sampling, and conservation. Notably, we found no applications of these technologies in biodiversity hotspots across parts of Latin America and Africa such as Mesoamerica (Guatemala, Honduras, Nicaragua), West Africa (Benin, Togo, Cote d'Ivoire, Liberia, Sierra Leone, Guinea) and the Horn of Africa (Ethiopia, Somalia) (Fig. 3). The geographic mismatch between robot deployments and regions needing urgent biodiversity monitoring underscores the need for greater automation efforts in these biodiverse yet highly endangered regions of the world.

<Fig. 3>

Most studies using robots monitor plants and animals but neglect microbes. Indeed, 90% of studies in our review target plants or animals (Appendix S2: Table S1). In contrast, studies using robots to examine bacteria and protists represent only 4.7% and 3.4% of our review, respectively (Fig. 4a). This taxonomic bias likely reflects the long-standing tendency in biodiversity studies to focus on larger organisms in accessible regions, often overlooking the diversity and ecological functions of microbes[66]. Robots equipped with novel sensors like fluorescence imaging cameras[52] or samplers hold the promise to help counter-balance such a bias by detecting and monitoring microbial diversity in previously unreachable habitats. Examples of relevant studies, though few, can be found in Antarctica, glaciers, deserts, and even at deep sea (see limited studies in these extreme ecosystems in Appendix S2: Table S1).

<Fig. 4>

For applications addressing plants and animals specifically, robots bridge multiple spatial scales in various ecosystems. Drones are primarily used in plant studies at the population to landscape scale in terrestrial and coastal ecosystems. At the same time, ground/underwater robots have become more specialised in animal studies at the behavioural to community scale in marine ecosystems (Fig. 4b). As noted by the late E. O. Wilson[66], biodiversity research is often polarised towards molecular studies of a few model species or broad ecosystem-level investigations. The flexibility of robots in collecting data at multiple scales holds great potential to bridge the spatial-scale gap between the broad-scale data collected by satellite and more localised, point-based studies[52,67].

Nevertheless, the powerful combination of beyond visible spectrum optical sensors and ground robots is yet to be exploited in the study of plant physiology within challenging terrains.

The application of drones to plant surveys revealed that, despite multispectral and hyperspectral sensors making plant physiology monitoring feasible (Box 1), physiological studies of plants using them remain limited (Fig. 4b). Comparatively, drones used in animal studies span various ecosystems and biological levels of organisation/scales, except for coral reefs (Fig. 4b), where animals remain below the water surface and thus out of drones' detection range (but see [68]). While drones offer valuable data taken above the tree canopy, ground robots hold key advantages such as easier environment-proofing (*e.g.*, waterproofing), longer battery endurance, and higher payload capacity[69]. These advantages contribute to the unique niche of ground robots in studying ground flora/fauna in remote and challenging terrains—such as dense forests[70], deserts[52], rocky topography[71] *etc.*, though relevant application is still limited (Appendix S3: Table S1).

Pathways towards bridging current data gaps in biodiversity monitoring

The geographic mismatch between the location of robot applications and the biodiversity hotspots and regions most vulnerable to climate change (Fig. 3), especially in tropical regions, highlights the need for targeted research funding and technical training. Cross-country collaborations between technologically advanced nations and those with high biodiversity could help bridge this gap. Such meaningful collaboration could replace helicopter science and be stimulated by better involvement of local scientists in grants, publications, and student mentoring[72]. We urge technology-oriented research in developing countries to be prioritised by research funding programmes on biodiversity conservation, such as the Critical Ecosystem Partnership Fund (CEPF), the Darwin Initiative, the Global Biodiversity Framework Fund (GBFF), or the JRS Biodiversity Foundation.

The size bias of organisms could be reduced by expanding the capabilities of robots beyond monitoring platforms to include innovative mechanical tools like samplers, grabbers, and diggers (Fig. 2). These additions would enable sampling of smaller organisms across a wide range of environments from desserts[52] to deep sea[57], thus promoting greater exploration of microbial and smaller organism biodiversity. Currently, many commercial platforms are oriented toward monitoring (Fig. 2). However, ecologists and engineers could benefit from collaborating in the design and incorporation of specialised functions, *e.g*. deploying loggers[73] or tracking individuals[74], that could greatly benefit biodiversity studies. The potential of biosignature detection from space[75] might boost such collaboration in the most extreme environments on earth, *e.g*. volcanos, Antarctica, *etc*.

Physiological studies of plants and animals make up a small portion (3%) of the current research that uses robots (Fig. 4b). Such a bias away from physiological studies may be alleviated by the wider application of sensors with high spectral resolution, like multi/hyperspectral sensors. Currently, there are limited application of hyperspectral sensors in physiological studies due to several factors: (1) the restricted commercial adoption of these sensors has impeded their miniaturisation and cost reduction, preventing them from achieving the widespread use in ecological research that RGB cameras have attained (Fig. 1); (2) their lower stability and precision in material detection compared to contact-based methods, such as physical and chemical analyses (Fig. 2); and (3) insufficient exploration of the potential and feasibility of multispectral and hyperspectral sensors in physiological studies. However, with the availability of lightweight hyperspectral sensors that are compatible with commercial platforms like the DJI M600[41] and Aerialtronics Altura AT8[76] we expect more physiological studies to benefit from these cost-effective approaches.

Overcoming technical and cost barriers is essential to the widespread adoption of ground robots. Though drones have been widely applied in terrestrial ecosystems with complex vertical structures, such as forests, drones may struggle to capture data from beneath the canopy or within dense vegetation. Terrestrial robots could complement aerial monitoring by gathering ground-level data, enabling a multi-layered approach to biodiversity monitoring. However, challenges with navigation, stability on rugged terrain (but see quadruped robots[77]), and the high cost of terrestrial robots which are custom-designed to mitigate these issues but only at tiny production scales[78] will continue to limit their widespread use in these ecosystems. The successful popularisation of drones, driven by advancements in technical solutions and cost reductions, offers valuable lessons for the commercialisation of ground robots.

The coalition of robotics, computer vision and ecology for effective biodiversity monitoring

Environmental and ecological processes occur across multiple spatial and temporal scales[79]. Understanding these cross-scale interactions remains a key challenge for effective biodiversity research[80]. Drones and ground robots (Fig. 1b), combined with satellite and aerial remote sensing as well as traditional monitoring methods like ground-based surveys (Fig. 1a), offer invaluable, cross-validated, and complementary data across a wide range of spatial resolutions, from kilometers to millimeters. This integrative capability facilitates a deeper understanding of how processes at one scale relate to those at another, contributing to a comprehensive, multi-scale perspective on ecosystem dynamics. Indeed, successful cross scale studies have been implemented in hydrodynamic monitoring[67,81] and vegetation mapping[82,83].

Beyond their role as remote sensing platforms, robots hold promise in conservation. Similar to their use in agriculture for applying chemicals[84] and planting seeds[85], robots could also release environmental sensors into remote and hard-to-access regions for automatic ecological monitoring[86], or collect biotic or abiotic samples[57]. Of significant promise in the future are biorobots (Fig. 1b) as a conservation tool for exploration, data collection, intervention, and maintenance tasks[87]. For example, once bioethical issues are appropriately addressed[88], biorobots could be programmed to engage directly with organisms to influence their behaviour. Such interference in population behaviour can aid the decision-making of wild populations for conservation purposes, thus avoiding the hazards from artificial structures, *e.g.* dams or airports[87]. Expanding the use of robots in such applications could significantly broaden their utility beyond traditional monitoring.

Finally, integrating AI technologies directly into robots could greaetly enhance their adaptability and efficiency in monitoring. Current AI approaches focus on post-processing tasks like species classification[12]. Embedding AI modules on robots could enable dynamic exploration, monitoring, and target tracking, improving data collection and task efficiency. For example, drones equipped with on-board processing capabilities are already capable of using computer vision methods to recognise and detect forest fire[30] based on the still images or the video input from the drone cameras. When integrating sensor-based target detection with autonomous navigation control, robots are capable of dynamically identifying and tracking the targets. Successful applications in this regard include boundary detection of hazardous aerial plumes in real time[89] and deepwater animal tracking[90]. By integrating robust robotic platforms with cutting-edge payloads, AI, and autonomous navigation, these technologies have the potential to extend human capabilities, enabling unprecedented exploration and monitoring in otherwise inaccessible regions. Realising this potential requires a solid collaborative alliance among ecologists, biologists, conservationists, roboticists, and computer scientists, to develop purpose-built robotic systems that address the challenges of biodiversity conservation, safeguarding Earth's biological heritage amid the uncertainties of global change.

Box 1. Robots offer a wide range of applications in biodiversity monitoring. Some applications include: habitat structure analysis, species classification, biomass estimation (RGB, LiDAR), plant physiological and water quality monitoring (multi- and hyperspectral), water physical/chemical monitoring (physical/chemical sensor), and organism sampling (sampler/releaser). Word clouds were created by manually extracting application scenarios from 209 randomly selected publications from a total of 1,154 publications examined in our review. Word size represents usage frequency in these publications (source data: Appendix S2: Table S1). Word colour has no further meaning than to distinguish adjacent words.

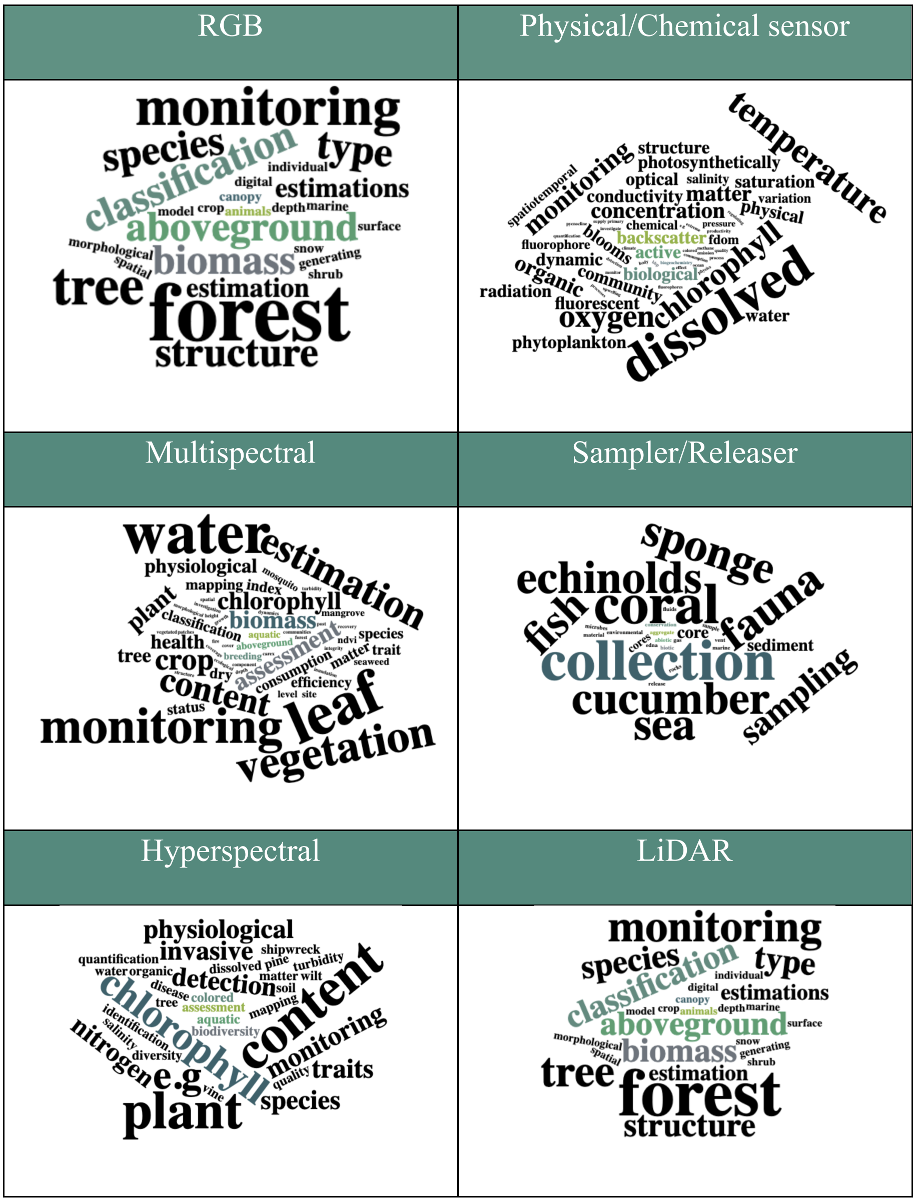


Figure captions

Figure 1. Robots are revolutionising traditional ecological monitoring methods. (**a**) Traditional ecological monitoring methods. From left to right: quadrat survey of grassland biodiversity at Wytham Woods, UK (photo credit: E. Fenollosa); field survey of understory invasive reed at Black Water Refuge, MD, USA (credit: M. Qi); Body mass of pinnipeds weighed by hand using anaesthetic and a sling[91]; benthic survey by divers (data source: https://www.benthicecology.org/prospective-students). **(b)** Novel ecological monitoring methods based on robots. Front left to right: grassland biodiversity monitoring with autonomous robots[92]; invasive reed detection (red) under forest canopy (green) by airborne LiDAR[93]; body size measurement of pinniped from point cloud of drone images[94]; automatic classification of benthic species from video/image taken by underwater robots[95].(**c**) Timeline of application and development of key innovations in drones and ground/underwater robots across different ecosystems suggest a fast uptake of payloads on drones contributing to increasing popularity of drones across various ecosystems. The stacked area chart shows the number of publications applying drones and ground/underwater robots in different ecosystems over time. Dots and vertical dashed line represent the timeline when built-in groundbreaking functionalities became available in commercial drones from DJI, a leading manufacturer of drones that holds 80% of the global market share[27]. Below is a list of DJI drones with the year they were released with built-in functionality: DJI Phantom 1 (2013) GPS, DJI Phantom 2 Vision (2013) Real time live-view, DJI Zenmuse XT (2015) Thermal, DJI P4 (2019) Multispectral, DJI Zenmuse L1 (2020)-LiDAR. Shrub_Grassland - Shrubland/Grassland/Savanna/Woodlands.

Figure 2. The payloads utilised on different robotic platforms across various ecosystems indicate that optical remote sensing is popular for drones, while robots are more specialised in

sampling and environmental physical/chemical monitoring. Results are based on a 20% random sample of the total of 1,154 examined publications where robots were explicitly used to monitor biodiversity (See Appendix S3). ROVs - Remotely Operated Vehicles, AOVs - Autonomous Underwater Vehicles.

Figure 3. Geographic mismatch between distribution of drone and robot applications and biodiversity rich but vulnerable regions. Geographic distribution of case studies using (**a**) drones and (**b**) robots in biodiversity research, showing a clear geographic mismatch with respect to (**c**) biodiversity hotspots and (**d**) climate-vulnerable ecological areas. (**c**) Biodiversity hotspots map made by Critical Ecosystem Partnership Fund [65]. The highlighted 36 biodiversity hotspots comprise 2% of the land surface of the Earth, but together contain 50% of the world's vascular plants and 42% of land vertebrates found nowhere else on Earth. The colours assigned to the hotspots are only used to distinguish adjacent hotspots and have no further meaning. (**d**) Climate-vulnerable ecological areas are indicated by the percentage of species in 100-km^2 resolution grid cells exposed to temperature beyond the realised niche of each species by 2100 under RCP 8.5[8]. Studies spanning multiple countries credit each nation involved. Marine studies that are difficult to geolocate from abstracts are excluded, including 16 cases from the Atlantic Ocean (4 from the North, 1 from the Northeast, 1 from the South-central), Mediterranean Sea (3 from the Northwest), Pacific Ocean (2 from the North, 1 from the East), Indian Ocean (1 from the Southwest), North Sea (1 from central), and Philippine Sea (1 from central).

Figure 4. Taxonomic bias of drone- and robot-based biodiversity studies towards plants and animals at spatial scales, ranging from behaviour, population, to landscape level. (**a**) Proportion of examined 1,154 publications using robots to study species from different taxonomic

kingdoms, with plants and animals representing the majority. (**b**) Percentage of the 1,154 drone and robot applications in plant and animal studies, categorised by scale and ecosystem type.

Figure 1

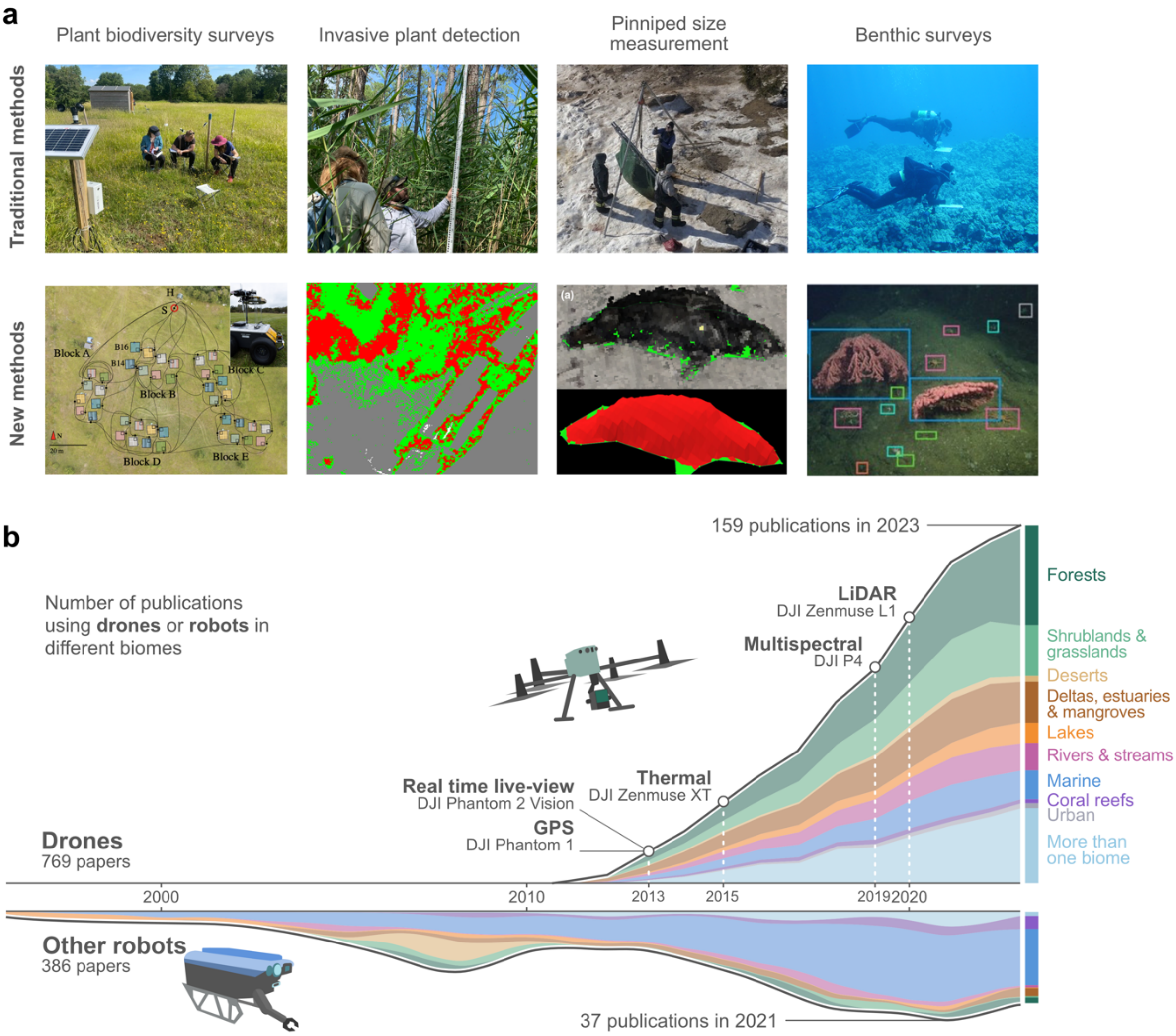

a
Plant biodiversity surveys
Invasive plant detection
Pinniped size measurement
Benthic surveys
Traditional methods
New methods
b
Number of publications using **drones** or **robots** in different biomes
159 publications in 2023
LiDAR
DJI Zenmuse L1
Multispectral
DJI P4
Thermal
DJI Zenmuse XT
Real time live-view
DJI Phantom 2 Vision
GPS
DJI Phantom 1
Drones
769 papers
2000
2010
2013
2015
2019
2020
Other robots
386 papers
37 publications in 2021
Forests
Shrublands & grasslands
Deserts
Deltas, estuaries & mangroves
Lakes
Rivers & streams
Marine
Coral reefs
Urban
More than one biome

Figure 2

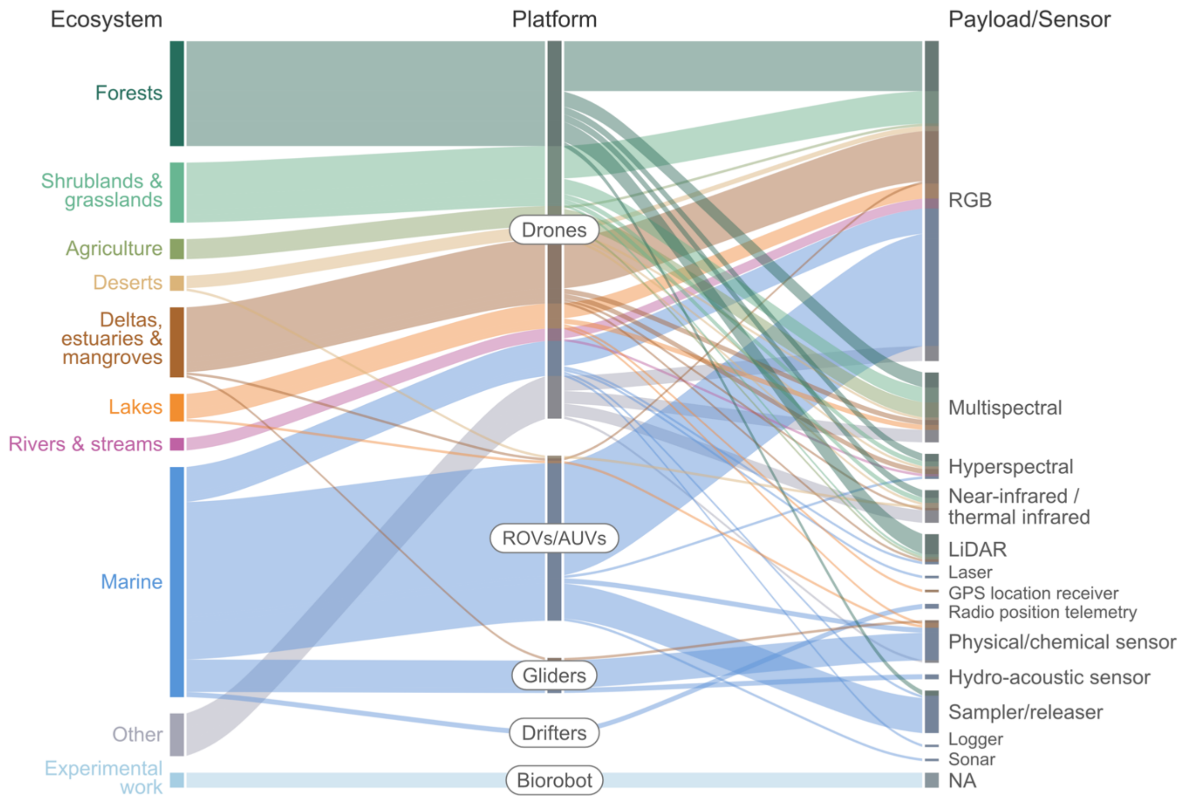
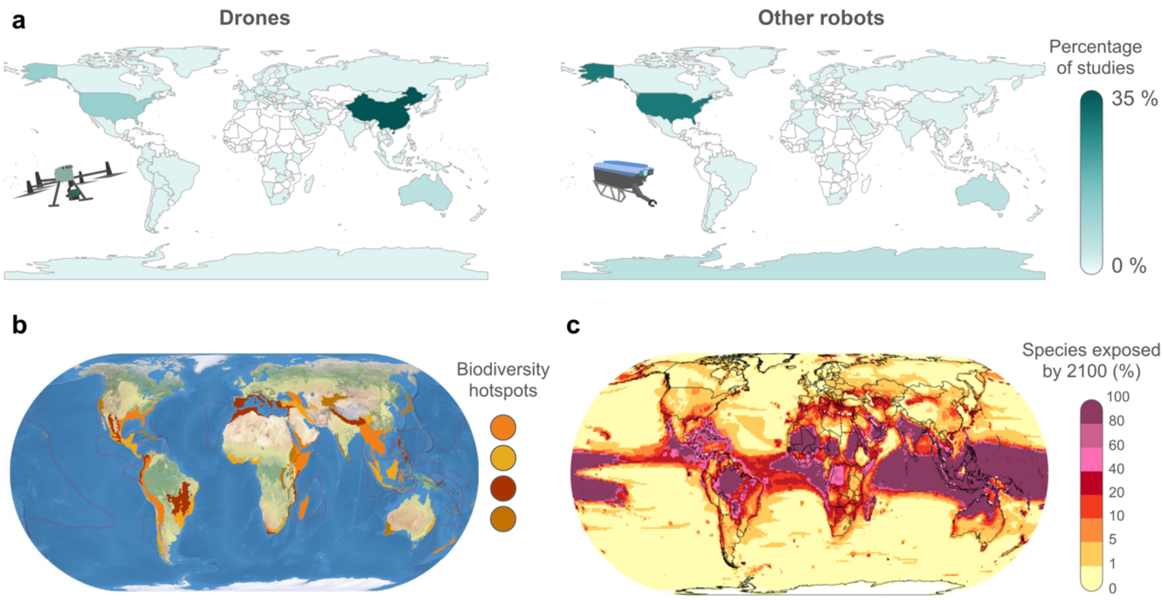
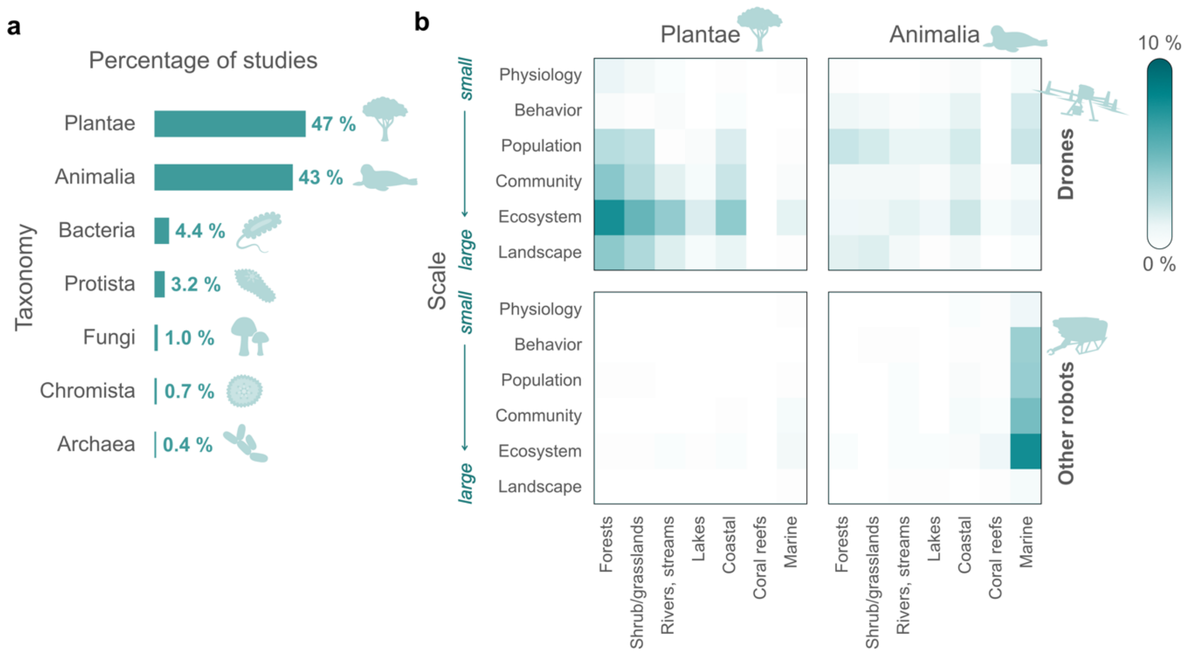

Ecosystem
Platform
Payload/Sensor
Forests
Shrublands & grasslands
Agriculture
Deserts
Deltas, estuaries & mangroves
Lakes
Rivers & streams
Marine
Other
Experimental work
Drones
ROVs/AUVs
Gliders
Drifters
Biorobot
RGB
Multispectral
Hyperspectral
Near-infrared / thermal infrared
LiDAR
Laser
GPS location receiver
Radio position telemetry
Physical/chemical sensor
Hydro-acoustic sensor
Sampler/releaser
Logger
Sonar
NA

Figure 3



a
Drones
Other robots
Percentage of studies
35 %
0 %
b
Biodiversity hotspots
c
Species exposed by 2100 (%)
100
80
60
40
20
10
5
1
0

Figure 4



Acknowledgements

We thank Q. Sun, Z. Zhu, J. Jiao, and G. Zhao for assisting in abstract screening, as well as S. Krishna Moorthy Parvathi, Y. Huang, C. Hernandez, T. Stone, and E. Fenollosa Romani for comments to improve early drafts of this manuscript. M. Q. was supported by an EPSRC grant (EP/X525777/1) to N.H. and R.S.G. as well as a Marie Skłodowska - Curie Actions fellowship (EP/Z00232X/1) funded by EPSRC and hosted by R.S.G.. R.S.G. was supported by a NERC Pushing the Frontiers grant (NE/X013766/1).

Reference

1. Elhacham, E., Ben-Uri, L., Grozovski, J., Bar-On, Y. M. & Milo, R. Global human-made mass exceeds all living biomass. *Nature* **588**, 442-444, doi:10.1038/s41586-020-3010-5 (2020).
2. Simkins, A. T. *et al.* A global assessment of the prevalence of current and potential future infrastructure in Key Biodiversity Areas. *Biol Conserv* **281**, 109953, doi:https://doi.org/10.1016/j.biocon.2023.109953 (2023).
3. Ceballos, G. *et al.* Accelerated modern human–induced species losses: Entering the sixth mass extinction. *Science Advances* **1**, e1400253, doi:doi:10.1126/sciadv.1400253 (2015).
4. Cooke, R. *et al.* Undiscovered bird extinctions obscure the true magnitude of human-driven extinction waves. *Nature Communications* **14**, 8116, doi:10.1038/s41467-023-43445-2 (2023).
5. Liu, J., Slik, F., Zheng, S. & Lindenmayer, D. B. Undescribed species have higher extinction risk than known species. *Conservation Letters* **15**, e12876, doi:https://doi.org/10.1111/conl.12876 (2022).
6. Román-Palacios, C. & Wiens, J. J. Recent responses to climate change reveal the drivers of species extinction and survival. *Proceedings of the National Academy of Sciences* **117**, 4211-4217, doi:doi:10.1073/pnas.1913007117 (2020).
7. Lees, A. C. & Pimm, S. L. Species, extinct before we know them? *Current Biology* **25**, R177-R180, doi:https://doi.org/10.1016/j.cub.2014.12.017 (2015).
8. Trisos, C. H., Merow, C. & Pigot, A. L. The projected timing of abrupt ecological disruption from climate change. *Nature* **580**, 496-501, doi:10.1038/s41586-020-2189-9 (2020).
9. Kirwan, M. L. & Gedan, K. B. Sea-level driven land conversion and the formation of ghost forests. *Nature Climate Change* **9**, 450-457, doi:10.1038/s41558-019-0488-7 (2019).
10. Frank, M. R., Wang, D., Cebrian, M. & Rahwan, I. The evolution of citation graphs in artificial intelligence research. *Nature Machine Intelligence* **1**, 79-85, doi:10.1038/s42256-019-0024-5 (2019).
11. Loganathan, A. & Ahmad, N. S. A systematic review on recent advances in autonomous mobile robot navigation. *Engineering Science and Technology, an International Journal* **40**, 101343, doi:https://doi.org/10.1016/j.jestch.2023.101343 (2023).
12. Christin, S., Hervet, É. & Lecomte, N. Applications for deep learning in ecology. *Methods in Ecology and Evolution* **10**, 1632-1644, doi:https://doi.org/10.1111/2041-210X.13256 (2019).
13. Nonami, K. Present state and future prospect of autonomous control technology for industrial drones. *IEEJ Transactions on Electrical and Electronic Engineering* **15**, 6-11, doi:https://doi.org/10.1002/tee.23041 (2020).
14. Arafat, M. Y., Alam, M. M. & Moh, S. Vision-Based Navigation Techniques for Unmanned Aerial Vehicles: Review and Challenges. *Drones* **7**, 89 (2023).
15. Javaid, M., Haleem, A., Singh, R. P., Rab, S. & Suman, R. Significance of sensors for industry 4.0: Roles, capabilities, and applications. *Sensors International* **2**, 100110, doi:https://doi.org/10.1016/j.sintl.2021.100110 (2021).
16. Albustanji, R. N., Elmanaseer, S. & Alkhatib, A. A. A. Robotics: Five Senses plus One—An Overview. *Robotics* **12**, 68 (2023).
17. Gadd, M. G. *et al.* Watching Grass Grow: Long-term Visual Navigation and Mission Planning for Autonomous Biodiversity Monitoring. doi: arXiv:2404.10446 (2024).

18 Jiménez López, J. & Mulero-Pázmány, M. Drones for Conservation in Protected Areas: Present and Future. *Drones* **3**, 10 (2019).

19 Huamanchahua, D., Yalli-Villa, D., Bello-Merlo, A. & Macuri-Vasquez, J. in *2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON).* 0768-0774.

20 Di Ciaccio, F. & Troisi, S. Monitoring marine environments with Autonomous Underwater Vehicles: A bibliometric analysis. *Results in Engineering* **9**, 100205, doi:https://doi.org/10.1016/j.rineng.2021.100205 (2021).

21 Jones, S. G. & Ellis, D. V. Deep water STD at the Misima gold and silver mine, Papua, New Guinea. *Marine Georesources & Geotechnology* **13**, 183-200, doi:10.1080/10641199509388283 (1995).

22 Abbott, M. R. *et al.* Scales of variability of bio-optical properties as observed from near-surface drifters. *Journal of Geophysical Research: Oceans* **100**, 13345-13367, doi:https://doi.org/10.1029/94JC02457 (1995).

23 He, X., Li, J. & Zhu, R. The Study of Company Competitive Strategy under new Manufacturing Industry-Taking DJI as an Example. *2022 International Conference on Economic Administration and Information Systems* (2022).

24 Jackson, J. *et al.* Short-range multispectral imaging is an inexpensive, fast, and accurate approach to estimate biodiversity in a temperate calcareous grassland. *Ecology and Evolution* **12**, e9623, doi:https://doi.org/10.1002/ece3.9623 (2022).

25 Muzammal, H., Mehdi, S. A., Hanif, M. A. & Maurelli, F. in *2021 European Conference on Mobile Robots (ECMR).* 1-5 (IEEE).

26 Neira, J. *et al.* Review on Unmanned Underwater Robotics, Structure Designs, Materials, Sensors, Actuators, and Navigation Control. *Journal of Robotics* **2021**, 5542920, doi:https://doi.org/10.1155/2021/5542920 (2021).

27 Ullah, I. *et al.* Mobile robot localization: Current challenges and future prospective. *Computer Science Review* **53**, 100651, doi:https://doi.org/10.1016/j.cosrev.2024.100651 (2024).

28 Ecke, S. *et al.* UAV-Based Forest Health Monitoring: A Systematic Review. *Remote Sensing* **14**, 3205 (2022).

29 Olsoy, P. J. *et al.* Unmanned aerial systems measure structural habitat features for wildlife across multiple scales. *Methods in Ecology and Evolution* **9**, 594-604, doi:https://doi.org/10.1111/2041-210X.12919 (2018).

30 Kinaneva, D., Hristov, G., Raychev, J. & Zahariev, P. in *42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO).* 1060-1065.

31 Shang, W., Gao, Z., Gao, M. & Jiang, X. Monitoring Green Tide in the Yellow Sea Using High-Resolution Imagery and Deep Learning. *Remote Sensing* **15**, 1101 (2023).

32 McKenna, P. B. *et al.* Old Man Saltbush mortality following fire challenges the resilience of post-mine rehabilitation in central Queensland, Australia. *Ecological Management & Restoration* **24**, 36-46, doi:https://doi.org/10.1111/emr.12579 (2023).

33 Gentle, M., Finch, N., Speed, J. & Pople, T. A comparison of unmanned aerial vehicles (drones) and manned helicopters for monitoring macropod populations. *Wildlife Research* **45**, doi:10.1071/WR18034 (2018).

34 Jiménez-Torres, M., Silva, C. P., Riquelme, C., Estay, S. A. & Soto-Gamboa, M. Automatic Recognition of Black-Necked Swan (Cygnus melancoryphus) from Drone Imagery. *Drones* **7**, 71 (2023).

35 Rahul, T., Jay, B. & John Wessley, D. G. J. Evaluation of surface water quality of Ukkadam lake in Coimbatore using UAV and Sentinel-2 multispectral data.

International Journal of Environmental Science and Technology **20**, doi:10.1007/s13762-022-04029-7 (2022).

36 Casas, E. *et al.* Macroalgae niche modelling: a two-step approach using remote sensing and in situ observations of a native and an invasive Asparagopsis. *Biological Invasions* **23**, 3215-3230, doi:10.1007/s10530-021-02554-z (2021).

37 Barbosa, R. V. *et al.* High-Resolution Drone Images Show That the Distribution of Mussels Depends on Microhabitat Features of Intertidal Rocky Shores. *Remote Sensing* **14**, 5441 (2022).

38 Torres, L. G., Barlow, D. R., Chandler, T. E. & Burnett, J. D. Insight into the kinematics of blue whale surface foraging through drone observations and prey data. *PeerJ* **8**, e8906, doi:10.7717/peerj.8906 (2020).

39 Shamaoma, H. *et al.* Use of Multi-Date and Multi-Spectral UAS Imagery to Classify Dominant Tree Species in the Wet Miombo Woodlands of Zambia. *Sensors (Basel)* **23**, doi:10.3390/s23042241 (2023).

40 Borges, D. *et al.* New Methodology for Intertidal Seaweed Biomass Estimation Using Multispectral Data Obtained with Unoccupied Aerial Vehicles. *Remote Sensing* **15**, 3359 (2023).

41 Zhao, Y. *et al.* Hyperspectral retrieval of leaf physiological traits and their links to ecosystem productivity in grassland monocultures. *Ecological Indicators* **122**, 107267, doi:https://doi.org/10.1016/j.ecolind.2020.107267 (2021).

42 Galešić Divić, M. *et al.* Estimation of Water Quality Parameters in Oligotrophic Coastal Waters Using Uncrewed-Aerial-Vehicle-Obtained Hyperspectral Data. *Journal of Marine Science and Engineering* **11**, 2026 (2023).

43 Hu, J. *et al.* Quantitative Estimation of Soil Salinity Using UAV-Borne Hyperspectral and Satellite Multispectral Images. *Remote Sensing* **11**, 736 (2019).

44 Bushaw, J. D. *et al.* Application of Unmanned Aerial Vehicles and Thermal Imaging Cameras to Conduct Duck Brood Surveys. *Wildlife Society Bulletin* **45**, 274-281, doi:https://doi.org/10.1002/wsb.1196 (2021).

45 Zhang, H. *et al.* Thermal infrared imaging from drones can detect individuals and nocturnal behavior of the world's rarest primate. *Global Ecology and Conservation* **23**, e01101, doi:https://doi.org/10.1016/j.gecco.2020.e01101 (2020).

46 Ren, H. *et al.* Vegetation growth status as an early warning indicator for the spontaneous combustion disaster of coal waste dump after reclamation: An unmanned aerial vehicle remote sensing approach. *Journal of Environmental Management* **317**, 115502, doi:https://doi.org/10.1016/j.jenvman.2022.115502 (2022).

47 Mao, Z., Lu, Z., Wu, Y. & Deng, L. DBH Estimation for Individual Tree: Two-Dimensional Images or Three-Dimensional Point Clouds? *Remote Sensing* **15**, 4116 (2023).

48 Dawson, S. M., Bowman, M. H., Leunissen, E. & Sirguey, P. Inexpensive Aerial Photogrammetry for Studies of Whales and Large Marine Animals. *Frontiers in Marine Science* **4**, doi:10.3389/fmars.2017.00366 (2017).

49 Johnston, M. A. *et al.* Characterizing the Biological Community before and after Partial Removal of an Offshore Gas Platform in the Northwestern Gulf of Mexico. *Environ Manage* **70**, 1078-1092, doi:10.1007/s00267-022-01714-8 (2022).

50 Patel, S. H., Dodge, K. L., Haas, H. L. & Smolowitz, R. J. Videography Reveals In-Water Behavior of Loggerhead Turtles (Caretta caretta) at a Foraging Ground. *Frontiers in Marine Science* **3**, doi:10.3389/fmars.2016.00254 (2016).

51 Mogstad, A. A. *et al.* Mapping the Historical Shipwreck Figaro in the High Arctic Using Underwater Sensor-Carrying Robots. *Remote Sensing* **12**, 997 (2020).

52 Warren-Rhodes, K. *et al.* Robotic ecological mapping: Habitats and the search for life in the Atacama Desert. *Journal of Geophysical Research: Biogeosciences* **112**, doi:https://doi.org/10.1029/2006JG000301 (2007).
53 Fossum, T. O. *et al.* Adaptive Sampling of Surface Fronts in the Arctic Using an Autonomous Underwater Vehicle. *IEEE Journal of Oceanic Engineering* **46**, 1155-1164, doi:10.1109/JOE.2021.3070912 (2021).
54 Pasculli, L. *et al.* New Cost-Effective Technologies Applied to the Study of the Glacier Melting Influence on Physical and Biological Processes in Kongsfjorden Area (Svalbard). *Journal of Marine Science and Engineering* **8**, 593 (2020).
55 Ritt, B. *et al.* Diversity and distribution of cold-seep fauna associated with different geological and environmental settings at mud volcanoes and pockmarks of the Nile Deep-Sea Fan. *Marine Biology* **158**, 1187-1210, doi:10.1007/s00227-011-1679-6 (2011).
56 Govindarajan, A. F. *et al.* Improved biodiversity detection using a large-volume environmental DNA sampler with in situ filtration and implications for marine eDNA sampling strategies. *Deep Sea Research Part I: Oceanographic Research Papers* **189**, 103871, doi:https://doi.org/10.1016/j.dsr.2022.103871 (2022).
57 Ramirez-Llodra, E. *et al.* Hot vents beneath an icy ocean
the Aurora Vent Field, Gakkel Ridge, Revealed. *Oceanography* **36**, 6-17 (2023).
58 Giddy, I. S., Nicholson, S. A., Queste, B. Y., Thomalla, S. & Swart, S. Sea-Ice Impacts Inter-Annual Variability of Phytoplankton Bloom Characteristics and Carbon Export in the Weddell Sea. *Geophysical Research Letters* **50**, e2023GL103695, doi:https://doi.org/10.1029/2023GL103695 (2023).
59 Bieber, P. *et al.* A Drone-Based Bioaerosol Sampling System to Monitor Ice Nucleation Particles in the Lower Atmosphere. *Remote Sensing* **12**, 552 (2020).
60 Bennett, A. *et al.* Autonomous vehicles for remote sample collection in difficult conditions: Enabling remote sample collection by marine biologists. *2015 IEEE International Conference on Technologies for Practical Robot Applications (TePRA)*, 1-6 (2015).
61 Kim, J., Huebner, C. D., Reardon, R. & Park, Y.-L. Spatially Targeted Biological Control of Mile-a-Minute Weed Using Rhinoncomimus latipes (Coleoptera: Curculionidae) and an Unmanned Aircraft System. *Journal of Economic Entomology* **114**, 1889-1895, doi:10.1093/jee/toab020 (2021).
62 Ilgün, A. *et al.* in *ALIFE 2021: The 2021 Conference on Artificial Life* 41 (2021).
63 Romano, D. & Stefanini, C. Individual neon tetras (Paracheirodon innesi, Myers) optimise their position in the group depending on external selective contexts: Lesson learned from a fish-robot hybrid school. *Biosystems Engineering* **204**, 170-180, doi:10.1016/j.biosystemseng.2021.01.021 (2021).
64 Patel, Y. & Rughani, P. H. in *Proceedings of the 2022 3rd International Conference on Robotics Systems and Vehicle Technology* 12–15 (Association for Computing Machinery, Singapore, Singapore, 2022).
65 Koenig, K. Biodiversity Hotspots Map (English labels) (2016.1). *Zenodo*, doi:10.5281/zenodo.4311850 (2016).
66 Wilson, E. O. Biodiversity research requires more boots on the ground. *Nature Ecology & Evolution* **1**, 1590-1591, doi:10.1038/s41559-017-0360-y (2017).
67 Johansen, K., Dunne, A. F., Tu, Y.-H., Jones, B. H. & McCabe, M. F. Monitoring coastal water flow dynamics using sub-daily high-resolution SkySat satellite and UAV-based imagery. *Water Research* **219**, 118531, doi:https://doi.org/10.1016/j.watres.2022.118531 (2022).

68 Bennett, M. K., Younes, N. & Joyce, K. Automating Drone Image Processing to Map Coral Reef Substrates Using Google Earth Engine. *Drones* **4** (2020).

69 Angelini, F. *et al.* Robotic Monitoring of Habitats: The Natural Intelligence Approach. *IEEE Access* **11**, 72575-72591, doi:10.1109/ACCESS.2023.3294276 (2023).

70 de Simone, L. *et al.* One small step for a robot, one giant leap for habitat monitoring: A structural survey of EU forest habitats with Robotically-mounted Mobile Laser Scanning (RMLS). *Ecological Indicators* **160**, 111882, doi:https://doi.org/10.1016/j.ecolind.2024.111882 (2024).

71 Wettergreen, D., Thorpe, C. & Whittaker, R. Exploring Mount Erebus by walking robot. *Robotics and Autonomous Systems* **11**, 171-185, doi:https://doi.org/10.1016/0921-8890(93)90022-5 (1993).

72 Adame, F. Meaningful collaborations can end 'helicopter research'. *Nature*, doi:10.1038/d41586-021-01795-1 (2021).

73 Toyoshima, T. *et al.* Logger Attaching System for Sperm Whales Using a Drone. *Journal of Robotics and Mechatronics* **33**, 8, doi:10.20965/jrm.2021.p0475 (2021).

74 Jin, T., Si, X., Liu, J. & Ding, P. An integrated animal tracking technology combining a GPS tracking system with a UAV. *Methods in Ecology and Evolution* **14**, 505-511, doi:https://doi.org/10.1111/2041-210X.14055 (2023).

75 Martins, Z. Detection of Organic Matter and Biosignatures in Space Missions. *Curr Issues Mol Biol* **38**, 53-74, doi:10.21775/cimb.038.053 (2020).

76 van der Meij, B., Kooistra, L., Suomalainen, J., Barel, J. M. & De Deyn, G. B. Remote sensing of plant trait responses to field-based plant–soil feedback using UAV-based optical sensors. *Biogeosciences* **14**, 733-749, doi:10.5194/bg-14-733-2017 (2017).

77 Mattamala, M. *et al.* Autonomous Forest Inventory with Legged Robots: System Design and Field Deployment. *arXiv preprint arXiv:2404.14157* (2024).

78 Kyberd, S. *et al.* in *Field and Service Robotics.* (eds Genya Ishigami & Kazuya Yoshida) 101-114 (Springer Singapore).

79 Chave, J. The problem of pattern and scale in ecology: what have we learned in 20 years? *Ecology Letters* **16**, 4-16, doi:10.1111/ele.12048 (2013).

80 Sutherland, W. J. *et al.* Identification of 100 fundamental ecological questions. *Journal of Ecology* **101**, 58-67, doi:10.1111/1365-2745.12025 (2013).

81 Kubryakov, A. A. *et al.* Impact of Submesoscale Eddies on the Transport of Suspended Matter in the Coastal Zone of Crimea Based on Drone, Satellite, and In Situ Measurement Data. *Oceanology* **61**, 159-172, doi:10.1134/S0001437021020107 (2021).

82 Alvarez-Vanhard, E., Houet, T., Mony, C., Lecoq, L. & Corpetti, T. Can UAVs fill the gap between in situ surveys and satellites for habitat mapping? *Remote Sensing of Environment* **243**, 111780, doi:https://doi.org/10.1016/j.rse.2020.111780 (2020).

83 Doughty, C. L., Ambrose, R. F., Okin, G. S. & Cavanaugh, K. C. Characterizing spatial variability in coastal wetland biomass across multiple scales using UAV and satellite imagery. *Remote Sensing in Ecology and Conservation* **7**, 411-429, doi:https://doi.org/10.1002/rse2.198 (2021).

84 Hafeez, A. *et al.* Implementation of drone technology for farm monitoring & pesticide spraying: A review. *Information Processing in Agriculture* **10**, 192-203, doi:https://doi.org/10.1016/j.inpa.2022.02.002 (2023).

85 Marzuki, O. F., Teo, E. Y. L. & Rafie, A. S. M. The mechanism of drone seeding technology: a review. *Malays. For* **84**, 349-358 (2021).

86 Sethi, S., Kovac, M., Wiesemüller, F., Miriyev, A. & Boutry, C. Biodegradable sensors are ready to transform autonomous ecological monitoring. *Nature Ecology & Evolution* **6**, 1-3, doi:10.1038/s41559-022-01824-w (2022).

87 Chellapurath, M., Khandelwal, P. C. & Schulz, A. K. Bioinspired robots can foster nature conservation. *Frontiers in Robotics and AI* **10**, doi:10.3389/frobt.2023.1145798 (2023).

88 Mestre, R., Astobiza, A. M., Webster-Wood, V. A., Ryan, M. & Saif, M. T. A. Ethics and responsibility in biohybrid robotics research. *Proceedings of the National Academy of Sciences* **121**, e2310458121, doi:10.1073/pnas.2310458121 (2024).

89 Seiber, C., Nowlin, D., Landowski, B. & Tolentino, M. E. in *2018 IEEE 4th World Forum on Internet of Things (WF-IoT).* 377-382.

90 Katija, K. *et al.* in *2021 IEEE Winter Conference on Applications of Computer Vision (WACV).* 859-868.

91 Shero, M. R. *et al.* Tracking wildlife energy dynamics with unoccupied aircraft systems and three-dimensional photogrammetry. *Methods in Ecology and Evolution* **12**, 2458-2472, doi:https://doi.org/10.1111/2041-210X.13719 (2021).

92 Gadd, M. *et al.* Watching Grass Grow: Long-term Visual Navigation and Mission Planning for Autonomous Biodiversity Monitoring. *arXiv preprint arXiv:2404.10446* (2024).

93 Xiong, B. *et al.* Early detection of invasive Phragmites australis at the tidal marsh-forest ecotone with airborne LiDAR. *Ecological Indicators* **167**, 112651, doi:https://doi.org/10.1016/j.ecolind.2024.112651 (2024).

94 Stone, T. C. & Davis, K. J. Using unmanned aerial vehicles to estimate body volume at scale for ecological monitoring. *Methods in Ecology and Evolution* **n/a**, doi:https://doi.org/10.1111/2041-210X.14457 (2024).

95 Katija, K. *et al.* FathomNet: A global image database for enabling artificial intelligence in the ocean. *Scientific Reports* **12**, 15914, doi:10.1038/s41598-022-19939-2 (2022).