Biodiversity research requires more rotors and wheels on and above ground, as well as below water

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Abstract

Human activities have caused rapid decline in biodiversity, with accelerating species extinction. Simultaneously, recent advancements in artificial intelligence and autonomous systems offer transformative potential for biodiversity research. Unmanned vehicles—such as drones, ground robots, and underwater robots—equipped with high-resolution sensors enhance our ability to monitor ecosystems with unprecedented efficiency and scale. Here, we review studies published in Web of Science (1930–2023) using unmanned vehicles for ecological monitoring and explore how it could be done more broadly to further biodiversity research. Drones are most commonly used for vegetation mapping, species monitoring, and habitat assessment in terrestrial ecosystems; ground and underwater robots focus on aquatic environments, supporting benthic surveys, water quality monitoring, and sample collection. Still, we identify key gaps: this growing body of research predominantly addresses plants (46%) and animals (44%), with minimal focus on microbes (10%). Additionally, key biodiversity hotspots—such as South Africa, Central America, and South America—are underrepresented. Our findings emphasise the need for expanded taxonomic and biogeographic efforts to maximise the impact of these technologies. We argue that, by incorporating innovative combination of unmanned vehicles, payloads, AI and in novel application scenarios, researchers could achieve cost-effective, accurate, and multi-scale ecological monitoring. Strengthening collaborations between ecologists and roboticists will advance biodiversity conservation and address 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, ~80% of living species remain unknown to science, and their extinction rate is estimated 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].

Against global change[1,8,9] and biodiversity loss[3,6], significant technological advancements have emerged in computer science[10] and autonomous navigation[11] in the past decades, which offer unique opportunities for biodiversity research. For instance, progress in deep learning has revolutionised ecology in species identification, animal behaviour, and biodiversity estimation[12]. Concurrently, advancements in autonomous navigation systems[13,14], sensors[15,16], and intelligent robotics[17] have facilitated the use of unmanned aerial[21], ground, and underwater vehicles[21] in biodiversity monitoring and ecological conservation. These technologies are greatly expanding the spatial range accessible to ecologists cost-effectively, and significantly enhancing our ability to monitor diverse ecosystems now that we need it the most.

<Fig. 1>

Given these unprecedented challenges and opportunities, ecologists are impelled to examine how these technological advancements can be used to monitor, understand, and protect ecosystems more effectively. Here, we review the current application of unmanned vehicles in ecological monitoring, and highlight how it could be done more broadly to further biodiversity research. Specifically, we: 1) systematically review the application of unmanned 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 unmanned aircraft systems (*i.e.*, drones) and 386 papers employing unmanned ground/underwater vehicles in biodiversity studies (details of the search in Appendix S1). 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% 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 drones and robots in biodiversity studies

Timeline and ecosystem biases in drone and 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[25], drifters[26]). However, the application of drones in biodiversity research has surged exponentially since the 2010s (Fig. 1c). This increase is driven by more affordable commercial drone models equipped with advanced sensor systems, user-friendly operation methods, and highly efficient data collection capabilities. Indeed, the release timeline of some of the groundbreaking built-in sensors and functions in DJI drone models (a primary maker, with 80% of the market worldwide[27]) took place right before and during the rapid increase in their usage in ecology. Importantly, said sensors range from $100s (*e.g.*, RGB cameras) to ~$10,000s (*e.g.*, multispectral, LiDAR; https://www.dronenerds.com/collections/cameras-sensors?page=1&count=24), depending on sensor type and resolution. In comparison, ground/underwater robots remain more specialised, often less commercially available to the ecological community, and are priced much higher. For instance, due to the outdoor nature of ecological monitoring deployments, these platforms may be expensive to design and implement. In particular, marine applications require specialised waterproofing[118], etc. (Fig. 1b).

Nevertheless, drones and 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 advanced sensors like LiDAR and hyperspectral cameras as well as structure-from-motion (SfM) technology. These sensors facilitate monitoring of vegetation structure and plant physiology in structurally complex ecosystems, like forests or savannas[28,29]. There is less application of ground robots than underwater robots in biodiversity studies (Fig. 2c), which serve specialised roles 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 to 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[30-33], detect environmental hazards (*e.g.*, fire, green tide)[34,35], conduct post-disaster assessments[36-38], and track populations of megafauna, and birds[39-42] (Appendix S3: Table S1). In aquatic systems, the usage of drones includes applications such as monitoring water quality[43] and macroalga[44], surveying benthic communities in shallow waters[45], and tracking the behaviour of marine megafauna, like whales[46,47] (Box 1). Advanced sensors in drones, including multispectral and hyperspectral cameras, enable researchers to detect subtle spectral differences, which have facilitated applications such as species classification and mapping[48-51], estimation of plant biomass[52-54] and monitoring of physiological traits[55-57], as well as monitoring of water and soil quality[58-60]. Thermal infrared sensors are applied in population surveys[40,61-63] and behaviour monitoring[64] of large animals, as well as in mapping temperature distributions across landscapes[65-67]. LiDAR-equipped drones are particularly valuable for applications such as canopy structure analysis[68-70], habitat classification[47], carbon stock estimation, disturbance detection, and recovery monitoring. Additionally, RGB sensors, combined with SfM algorithms, can generate 3D models 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[70-72].

<**Box 1**>

Compared with drones, ground/underwater robots have lower diversity in optical sensor types, but a higher diversity in non-optical sensor types. Indeed, in our review, optical sensors only make up to 57% of payloads of ground/underwater robots, while these were found in 94% of drones. Physical and chemical sensors make up to 18% of the payloads of robots while only 1% for drones. Similarly, robots carry devices to sample, collect, or release materials in 17% of studies, but drones in 3% (Fig. 2, Appendix 2: Table S1). Ground/underwater robots typically rely on RGB sensors (which make up to 96% of all optical sensors) for video documentation of benthic community composition[73,74], habitat surveys[75,76], and behaviour monitoring of marine species[77,78]. 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 in monitoring ship wreck[79], air temperature, relative humidity, and leaf wetness[80]. Physical and chemical sensors monitor variables such as dissolved oxygen, salinity, temperature, chlorophyll-a, and pressure[81,82]. Specialised samplers also enable these robots to collect specimens and samples from aquatic environments, such as sediments[83], eDNA[84], or vent fluids[85]. Furthermore, autonomous gliders and drifters equipped with diverse sensors contribute to monitoring ocean currents, biogeochemical parameters, and other physical oceanographic variables[86,87].

<Fig. 2>

Applications beyond just monitoring biodiversity

Drones and robots are being used in increasingly innovative ways to support biodiversity management and conservation. In addition to carrying optical, physical, and chemical sensors, these technologies are now actively sampling gases, liquids, and sediments from the environment[88,89] and releasing biotic and abiotic materials to aid conservation efforts[90]. For example, recently, drones have been deployed to release insects in Pennsylvania (USA) as biological control agents to combat invasive plants[90]. Furthermore, new developments in bioinspired robots allow direct interaction with ecosystems[91], as in biorobots used in cognitive ecology to study species responses[92]. This new generation of robots can pave the way for conservation applications by actively interacting or interfering with wildlife to alleviate human-wildlife conflicts. Examples include bio-inspired robots to deter wild animals from artificial constructions, *e.g.* birds from airports[93].

Knowledge gaps

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

Drones have been predominantly used in China (31% as per our review), North America (17%), and Australia (6%). 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[94] and are highly vulnerable to climate change impacts[8], have to date experienced limited use of drones and robots for biodiversity monitoring, sampling, and conservation. Notably, our review 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 drone and robot deployment 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 drones and robots monitor plants and animals but neglect microbes. Indeed, 90% of studies in our review using drones and robots target plants or animals (particularly macrovertebrates, Appendix S2: Table S1), while studies targeting 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[24]. Drones and robots equipped with novel sensors like fluorescence imaging cameras[80] or samplers hold the promise to 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 application of drones and robots in plants and animals specifically, drones and robots showed great capability in bridging 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, robots have become more specialised in animal studies at the behavioural to community scale in marine ecosystems (Fig. 4b). As noted by E. O. Wilson[24], biodiversity research is often polarised towards molecular studies of a few model species or broad ecosystem-level investigations. The flexibility of drones and 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[95,96].

Nevertheless, unique niche of advanced optical sensors and ground robots are awaiting to be applied in studying plant physiology and exploring challenging terrains respectively. Application of drones in plants revealed despite advanced optical sensors, e.g. 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 Bennett et al[97]). In contrast, robots are more commonly used in marine ecosystems, largely because most are underwater robots, other than ground robots (Fig. 2). 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, higher payload capacity, and enhanced obstacle avoidance capabilities[98]. These advantages contribute to the unique niche of ground robots in studying ground flora/fauna in remote and challenging terrains—such as dense forests[99], deserts[80], rocky topography[100] *etc.*, though relevant application is still limited (Appendix S3: Table S1).

Pathways towards bridging current data gaps in biodiversity monitoring

The geographic mismatch between drone and robot applications with 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[101]. We urge tech-oriented research in developing countries to be prioritised by research funding programmes on biodiversity conservation, such as the Critical Ecosystem Partnership Fund (CEPF), Darwin Initiative, Global Biodiversity Framework Fund (GBFF), or JRS Biodiversity Foundation.

The size bias of organisms could be reduced by expanding the capabilities of drones and robots beyond monitoring platforms to include innovative sampling tools like samplers, grabbers, and diggers (Fig. 2). These additions would enable sampling of smaller organisms across a wide range of environments from desserts[80] to deep sea[85], thus promoting greater exploration of microbial and smaller organism biodiversity. Currently, many commercial drones and robots 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[102] or tracking individuals[103], that could greatly benefit biodiversity studies. Potential technology transfer of biosignature detection from space mission[1] might boost such collaboration in the most extreme environments on earth, e.g. volcanos, Antarctica etc.

Physiological studies of plants and animals using drones and robots make up to a small portion (3%) of the current research (Fig. 5). Such bias away from physiological studies may be alleviated by wider application of advanced optical sensors, such as multi/hyperspectral sensors. Currently, there are limited application of hyperspectral sensors in physiological studies due to several factors: (1) the restricted civilian 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[57] and Aerialtronics Altura AT8[104], we expect more physiological studies to benefit from these cost-effective approaches.

Overcoming technical and cost barriers is essential to facilitate 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), and the high cost of terrestrial robots which are custom-designed to mitigate these issues but only at tiny production scales[119] will continue to limit their widespread use in these ecosystems. The successful popularization of drones, driven by advancements in technical solutions and cost reductions, offers valuable lessons for the commercialization of ground robots.

The coalition of drones and robots for effective ecological monitoring

Environmental and ecological processes occur across multiple spatial and temporal scales[105,106]. Understanding these cross-scale interactions remains a key challenge for effective biodiversity research[106,107]. Drones and 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 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. Successful cross scale studies have been implemented in hydrodynamic monitoring[96,108] and vegetation mapping[95,109].

Beyond their role as remote sensing platforms, drones and robots hold promise in conservation work. Similar to their use in agriculture for applying chemicals and planting seeds[110,111], drones and robots could also release environmental sensors into remote and hard-to-access regions for automatic ecological monitoring[112], or collect biotic or abiotic samples[85]. Of significant promise in the future are biorobots (Fig. 1b) as a conservation tool for exploration, data collection, intervention, and maintenance tasks[113]. For example, once bioethical issues are appropriately addressed[114], biorobots could be programmed to engage directly with organisms to influence their behaviour. Such interference of 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[113]. Expanding the use of drones and robots in such applications could significantly broaden their utility beyond traditional monitoring.

Finally, integrating AI technologies directly into drones and robots could enhance their adaptability and efficiency. Current AI focuses on post-processing tasks like species classification, but embedding AI onboard drones and robots could enable real-time navigation, exploration, and target tracking, improving data collection and task efficiency. For example, some drones equipped with on-board processing capabilities are already capable of using computer vision methods to recognise and detect forest fire[115] based on the still images or the video input from the drone cameras. When integrating sensor-based target detection with autonomous navigation control, drones/robots are capable of dynamically identifying and tracking the targets. Successful applications include boundary detection of hazardous aerial plumes in real time[116] and deepwater animal tracking[117]. 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.

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Box 1. Drones and robots offer a wide range of applications in biodiversity monitoring. Some application areas 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.

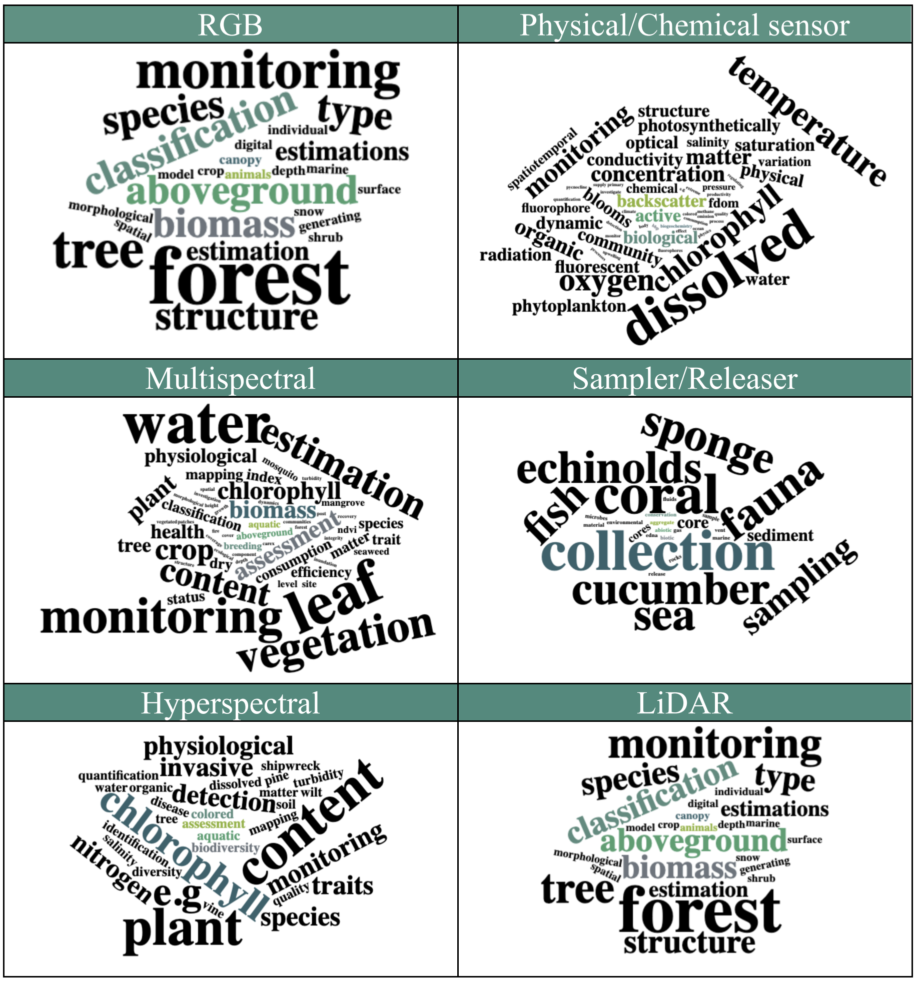


Figure captions

Figure 1. Drones and 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: Erola Fenollosa); field survey of understory invasive reed at Black Water Refuge, MD, USA (photo credit: Man Qi); Body mass of pinnipeds weighed by hand using anaesthetic and a sling; benthic survey by divers (data source: https://www.benthicecology.org/prospective-students). **(b)** Novel ecological monitoring methods based on drones and robots. Front left to right: grassland biodiversity monitoring with a autonomous navigated robots; invasive reed detection (red) under forest canopy (green) by airborne LiDAR; body size measurement of pinniped from point cloud of drone images; automatic classification of benthic species from video/image taken by underwater robots.(**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 drones and 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 [94]. 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 drones and 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

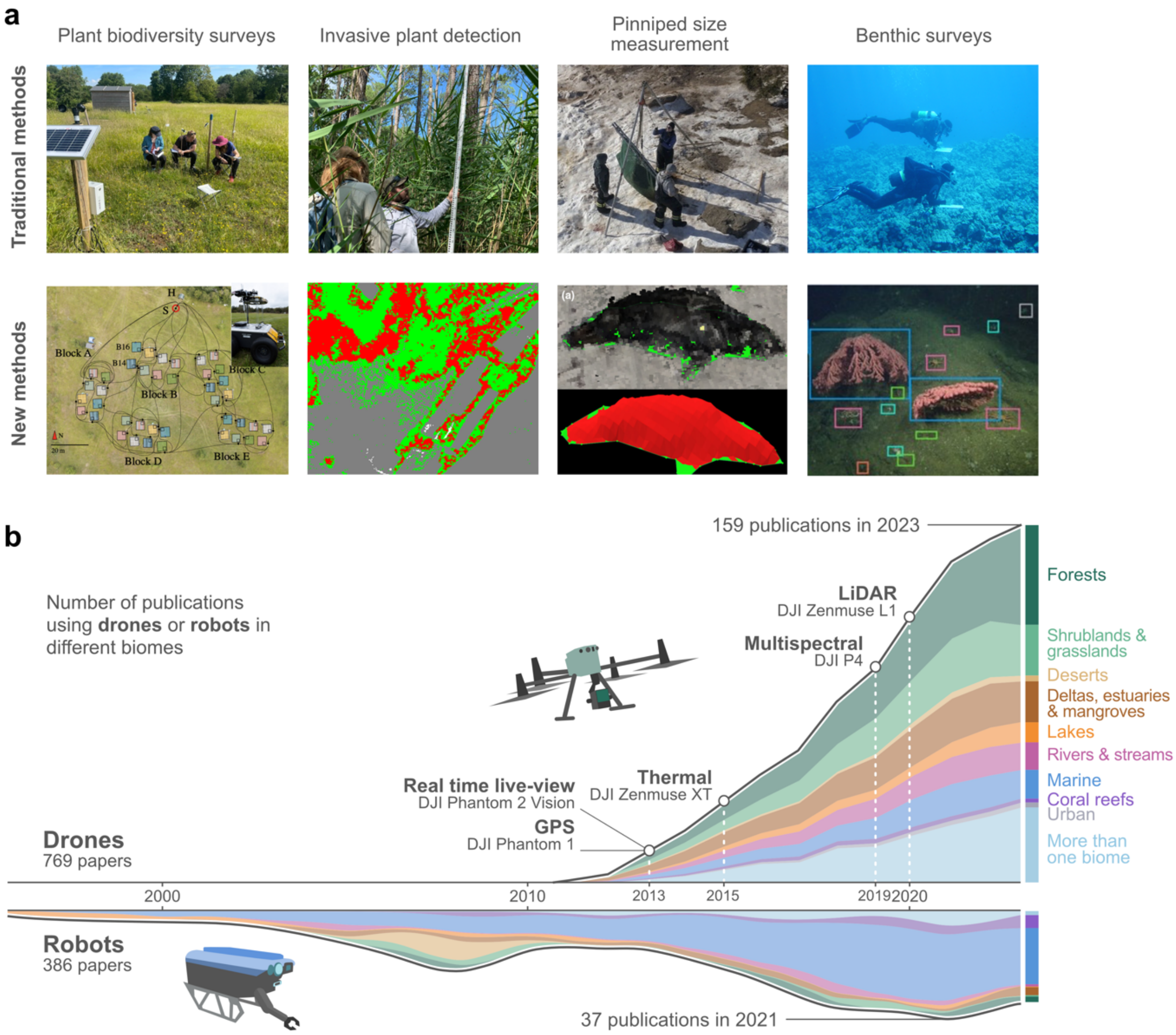
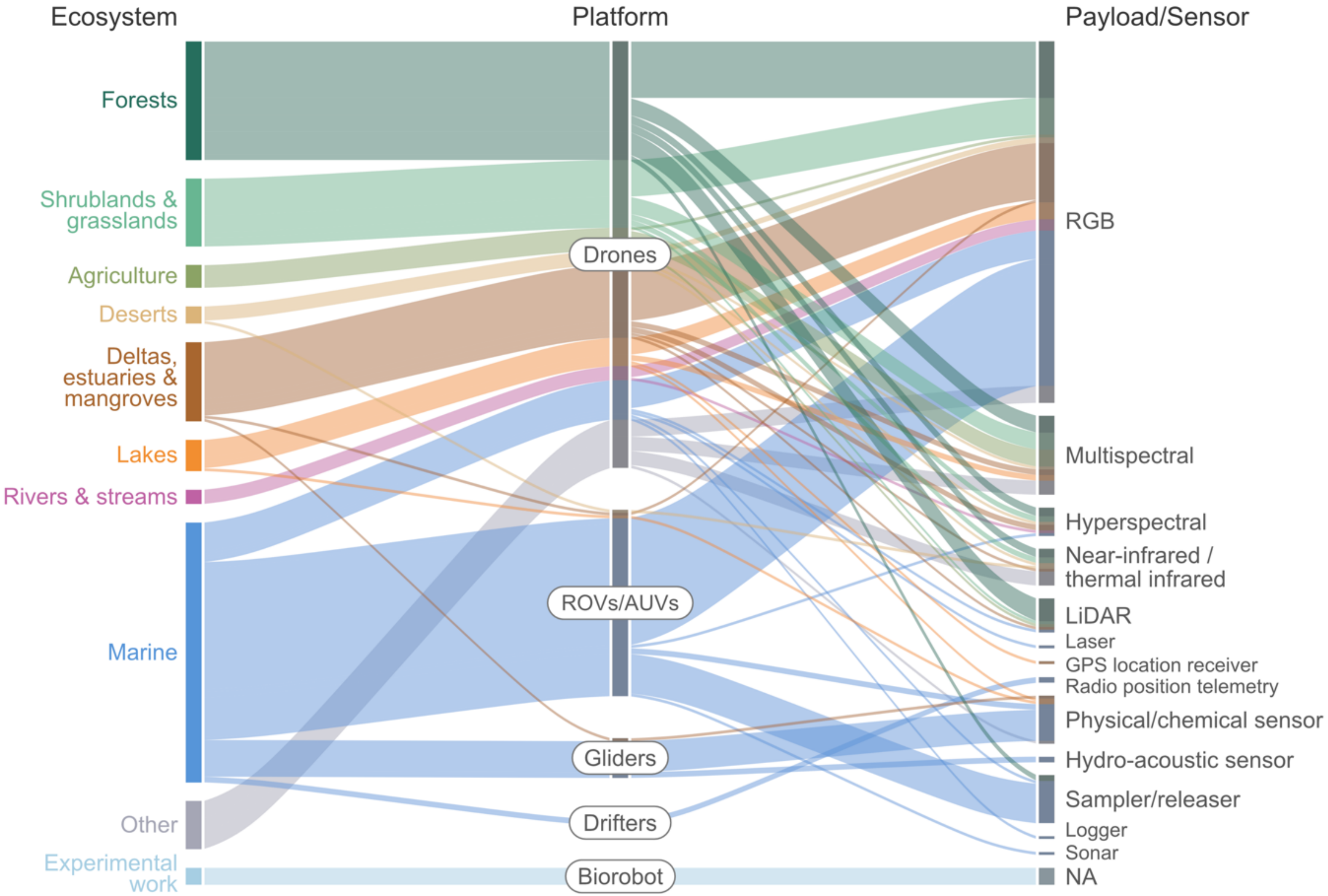

a
Plant biodiversity surveys
Invasive plant detection
Pinniped size measurement
Benthic surveys
Traditional methods
New methods
b
Number of publications using drones or robots in different biomes
159 publications in 2023
LiDAR
DJI Zenmuse L1
Multispectral
DJI P4
Thermal
DJI Zenmuse XT
Real time live-view
DJI Phantom 2 Vision
GPS
DJI Phantom 1
Drones
769 papers
2000
2010
2013
2015
2019
2020
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

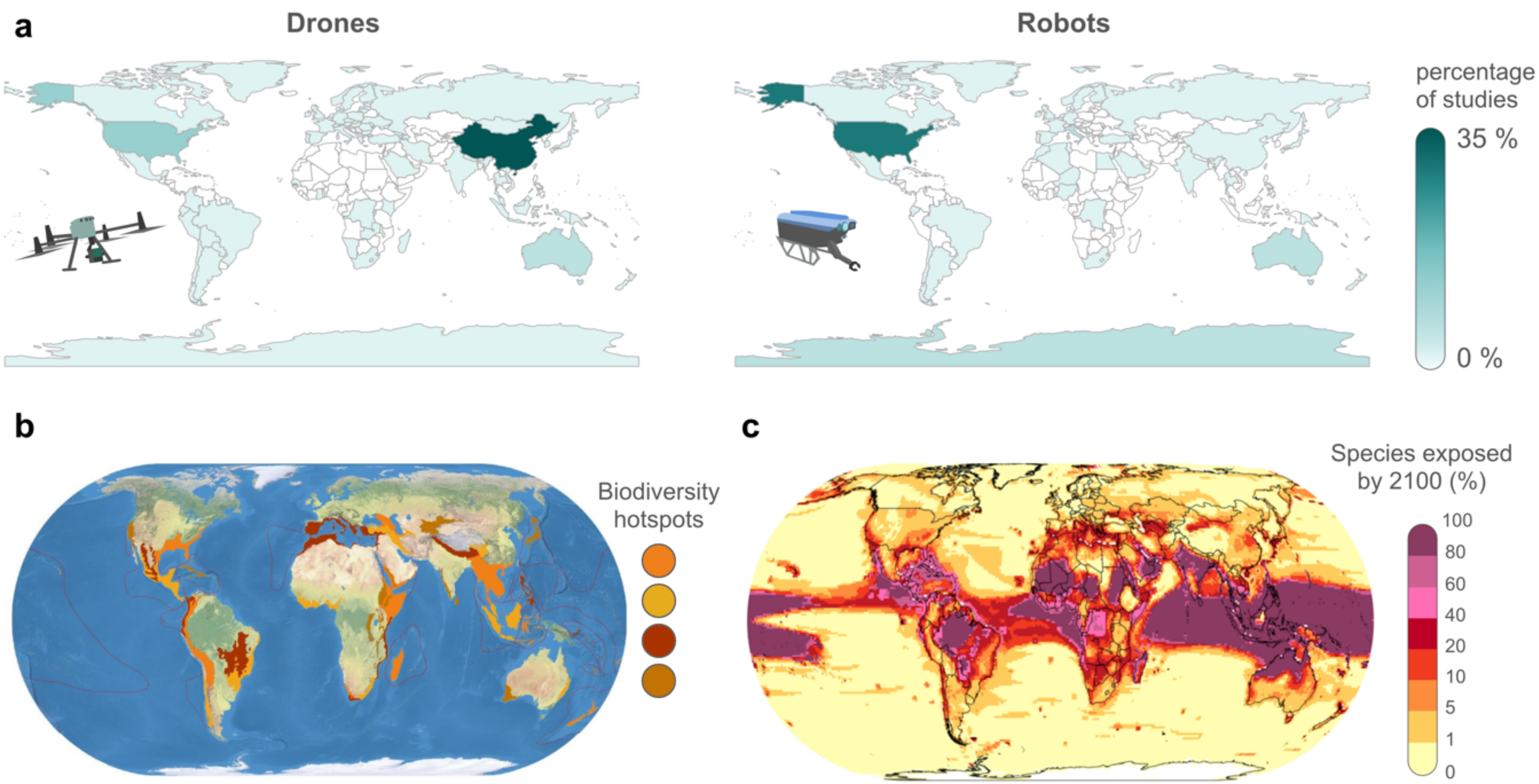
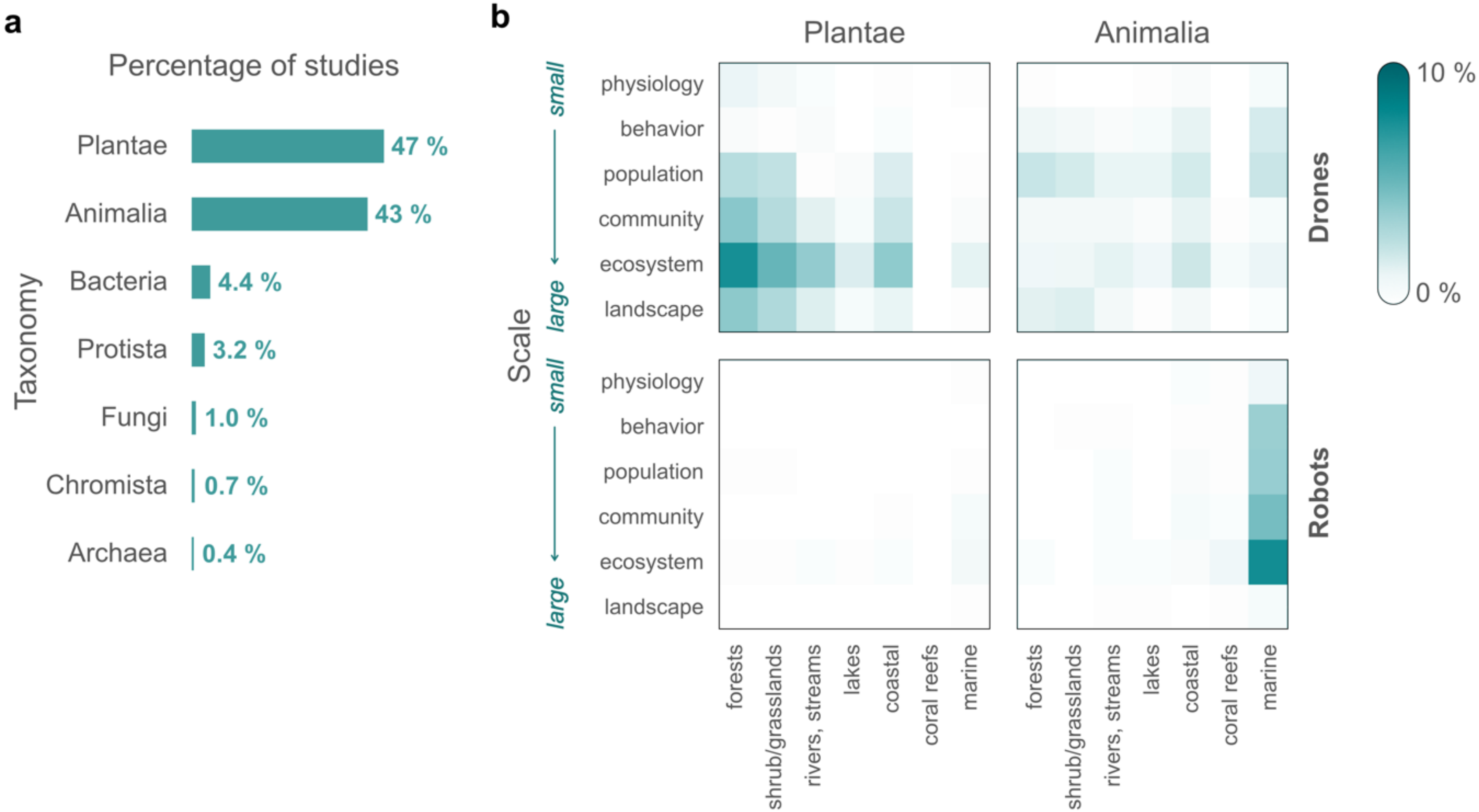

a
Drones
Robots
percentage of studies
35 %
0 %
b
Biodiversity hotspots
c
Species exposed by 2100 (%)
100
80
60
40
20
10
5
1
0

Figure 4



a
Percentage of studies
Taxonomy
Plantae 47 %
Animalia 43 %
Bacteria 4.4 %
Protista 3.2 %
Fungi 1.0 %
Chromista 0.7 %
Archaea 0.4 %
b
Plantae
Animalia
Scale
small
large
physiology
behavior
population
community
ecosystem
landscape
Drones
Robots
10 %
0 %
forests
shrub/grasslands
rivers, streams
lakes
coastal
coral reefs
marine