УДК 004.896:504.064

AERIAL, GROUND AND SURFACE ROBOTS IN ENVIRONMENTAL MONITORING: A COMPARATIVE ANALYSIS OF CAPABILITIES AND LIMITATIONS

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Abstract. *Detailed environmental monitoring requires frequent observations unavailable through manual sampling and fixed stations. Aerial, ground, surface, and underwater robots combine broad coverage with diverse equipment. This paper compares platforms across payloads, constraints, data processing, and system challenges, outlining heterogeneous edge architectures.*
Keywords: *environmental monitoring; multi-robot systems; remote sensing; edge computing.*

Introduction. Rapid environmental degradation, climate-induced hydrological shifts, and biodiversity loss demand frequent, spatially explicit monitoring of rivers, forests, and soils [1]. Traditional manual field campaigns are labor-intensive, hazardous in remote terrain, and temporally sparse. Conversely, stationary sensor networks provide high temporal resolution but suffer from poor spatial coverage, while satellite remote sensing is constrained by cloud cover, coarse spatial resolution, and long revisit intervals [2]. Mobile robotics bridges this observational gap by enabling targeted, repeatable, and high-resolution data acquisition across air, land, and water [1]. **The purpose** of this paper is to compare the capabilities and operational limitations of aerial, ground, and aquatic robotic platforms in environmental monitoring, systematize their sensing and data-processing workflows, and identify critical system-level challenges and future development pathways.

Platform types. Environmental monitoring relies on four primary mobile platform classes, each tailored to specific physical domains [1]:

• **Unmanned Aerial Vehicles (UAVs).** Fixed-wing and multi-rotor UAVs carry lightweight RGB, multispectral, thermal, and compact LiDAR payloads [2]. They achieve rapid, wide-area coverage over forests, wetlands, and river corridors. However, UAVs face strict payload capacity limits, short battery endurance (typically 20–45 minutes), sensitivity to wind and precipitation, and regulatory line-of-sight restrictions [2].

• **Unmanned Ground Vehicles (UGVs).** Wheeled and legged UGVs support heavy payloads, including high-density 3D LiDARs, ground-penetrating radar, soil probes, and robotic manipulators for physical sampling [1,3]. While offering multi-hour endurance, UGVs are severely constrained by rough terrain, dense vegetation, steep slopes, and unreliable Global Navigation Satellite System (GNSS) reception beneath forest canopies [3].

• **Unmanned Surface Vehicles (USVs).** Autonomous boats and catamarans carry acoustic Doppler current profilers, single- or multibeam sonar, water-quality sondes, and above-water LiDARs [1]. USVs provide high payload capacity and long endurance for riverine and coastal surveys, yet their mobility is restricted by shallow waters, submerged debris, strong currents, and shoreline vegetation [5].

• **Autonomous Underwater Vehicles (AUVs).** Torpedo-shaped and hovering AUVs employ side-scan sonar, optical cameras, and chemical sensors to map benthic habitats and water columns

[1]. Their deployment is limited by the total absence of radio-frequency communication and GNSS underwater, requiring acoustic localization and high-energy propulsion.

Sensing and data. Robotic environmental perception combines remote and contact modalities. Multispectral cameras capture narrow spectral bands critical for assessing vegetation vigor, algal blooms, and soil moisture [2]. Airborne and terrestrial LiDAR sensors reconstruct 3D canopy structure and riverbank topography [3,4], while sonar systems map submerged bathymetry [1]. Unlike aerial remote sensing, USVs, UGVs, and AUVs also perform in-situ physical measurements (e.g., pH, dissolved oxygen, turbidity, and soil compaction) essential for calibrating remote observations [1].

Processing these high-dimensional datasets relies heavily on deep learning. Semantic segmentation of 2D multispectral imagery and 3D point clouds – using architectures such as Point Transformer v2 – enables automated mapping of riverine land cover, including water, sand, gravel, and riparian vegetation [4]. Combining geometric coordinates with spectral reflectance features substantially improves classification accuracy over geometry-only baselines [4]. However, because pixel- and point-level manual annotation of complex natural scenes is prohibitively expensive, weakly supervised and semi-supervised learning approaches are increasingly used to train models from sparse or image-level labels [4].

System-level problems. Scaling robotic monitoring from single-platform trials to sustained ecosystem surveillance introduces five overarching engineering challenges:

• **Autonomy and energy.** Long-term missions require energy-aware path planning and autonomous docking or recharging, particularly for power-hungry multi-rotor UAVs and high-drag aquatic vehicles [1,2].

• **GNSS-denied navigation.** Beneath dense forest canopies or near steep riverbanks, multipath interference and signal blockage degrade GNSS accuracy, forcing reliance on LiDAR- or visual-inertial simultaneous localization and mapping (SLAM) using sparse, unstructured natural landmarks [3].

• **Large-area communication.** Transmitting high-bandwidth point clouds and imagery across infrastructure-less corridors suffers from vegetative shadowing and non-line-of-sight (NLOS) propagation [5]. Commercial Wi-Fi mesh networks provide high throughput over localized clusters but degrade over long distances [5], whereas low-power wide-area protocols (e.g., LoRa) offer multi-kilometer range at bitrates suitable only for telemetry. Within Robot Operating System 2 (ROS 2) architectures [8], middleware selection critically impacts reliability: while CycloneDDS excels over wired links, Zenoh demonstrates superior latency and lower trajectory drift over lossy Wi-Fi and cellular links [6].

• **Multi-robot coordination.** Coordinating heterogeneous fleets requires distributed task allocation, shared spatial representations, and collision avoidance across platforms with vastly different kinematics and sensing footprints [7].

• **Digital twin integration.** Transforming raw, asynchronous sensor streams into actionable ecological models requires standardized pipelines that continuously assimilate robotic observations into environmental digital twins [4,8].

Comparison of robotic platforms. Table 1 synthesizes the primary tasks, advantages, and operational limitations of each robotic platform class.

Table 1

Comparative analysis of robotic platforms in environmental monitoring

Platform	Primary monitoring tasks	Key strengths	Key limitations	Refs
UAV (Aerial)	Canopy mapping, river corridor imaging, rapid disaster assessment	High spatial coverage; fast deployment; immune to terrain obstacles	Short flight endurance; low payload capacity; weather-sensitive	[2,4]
UGV (Ground)	Forest inventory, soil sampling, under-canopy 3D mapping	High payload & power budget; direct in-situ soil/plant contact	Slow traversal; blocked by rough terrain; GNSS-denied under canopy	[1,3]
USV (Surface)	Bathymetry, water quality profiling, riverbank inspection	Long endurance; high payload; bridges aerial and underwater domains	Constrained by shallow water, currents, and submerged obstacles	[1,5]
AUV (Underwater)	Benthic habitat mapping, deep-water chemical profiling	Access to submerged environments invisible to remote sensing	No underwater GNSS/RF; high acoustic localization complexity	[1]

Ways forward. Overcoming individual platform constraints requires transitioning from isolated, single-robot deployments toward integrated, system-level architectures across four key directions:

• **Heterogeneous multi-robot collaboration.** Future monitoring frameworks should leverage cooperative fleets where platforms dynamically compensate for each other's physical limitations [1,7]. In a hierarchical workflow, fixed-wing or multi-rotor UAVs perform rapid wide-area reconnaissance to detect environmental anomalies – such as algal blooms, riverbank erosion, or canopy gaps – and subsequently dispatch UGVs or USVs for targeted in-situ sampling [1,2,7]. Additionally, UAVs can serve as mobile aerial communication relays to bridge non-line-of-sight (NLOS) gaps between ground or surface units operating under dense forest canopies or in deep river valleys [5,7].

• **Edge intelligence and adaptive middleware.** Streaming raw 3D point clouds and high-resolution multispectral imagery over field wireless networks is unsustainable at scale [4,5]. Integrating hardware-accelerated edge computing onboard robots enables real-time local execution of semantic segmentation and SLAM pipelines, transmitting only compact semantic maps, traversability grids, or anomaly alerts [3,4,8]. Pairing edge processing with bandwidth-aware ROS 2 middlewares – such as Zenoh – ensures resilient, low-latency data synchronization across intermittent Wi-Fi mesh and cellular links [5,6,8].

• **Label-efficient and self-supervised perception.** Because pixel- and point-level manual annotation of complex natural ecosystems is prohibitively costly, future perception models must rely on weakly supervised, semi-supervised, and self-supervised learning [4]. Incorporating human-in-the-loop active learning – where robots flag uncertain or out-of-distribution terrain features for targeted expert labeling – will accelerate model adaptation across seasonal changes and diverse geographic regions [3,4].

• **Standardized digital twin assimilation.** Finally, advancing standardized ROS 2 data schemas and spatiotemporal calibration protocols will allow asynchronous observations from aerial,

terrestrial, and aquatic robots to be continuously assimilated into unified environmental digital twins, enabling predictive ecological modeling and automated decision support [4,6,8].

Conclusions. Aerial, ground, surface, and underwater robots offer complementary environmental monitoring capabilities, yet face trade-offs in coverage, endurance, payload, and accessibility. Overcoming current bottlenecks requires solving GNSS-denied navigation, non-line-of-sight networking, and multimodal semantic segmentation. Future progress lies in heterogeneous robot fleets powered by edge computing, ROS 2 middlewares, label-efficient learning, and standardized digital twin integration.

Use of AI tools. Claude (Sonnet 5.5) was used for selecting and analyzing references, as well as structuring the text according to the template. The author has reviewed and verified all content and takes full responsibility for the publication.

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