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# Ground-based robotic remote sensing for standardized biodiversity monitoring in coastal habitats

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**Keywords**
artificial intelligence, biodiversity indicators, computer-vision, conservation technology, ecological monitoring, remote sensing, robotic survey

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## Abstract

Autonomous remote-sensing technologies are increasingly contributing to biodiversity monitoring by enabling scalable, repeatable, and minimally invasive data collection. We present a ground-based robotic remote-sensing framework that integrates artificial intelligence and standardized quality assurance to support the derivation of decision-ready ecological indicators. Using European coastal dunes as a case study, we deployed an AI-enabled quadruped robot equipped with near-ground imaging sensors to monitor the host–herbivore interaction between *Pancratium maritimum* and *Brithys crini*. In this citizen-to-robot pipeline, expert-verified citizen-science imagery was used to train lightweight detection models for on-board inference and higher-capacity models for offline auditing, ensuring reproducibility and transparency across missions. Field trials demonstrated that the system achieved consistent image quality, accurate detections, and low-disturbance operation under natural conditions, capturing spatially explicit evidence of herbivory and host condition. By coupling standardized protocols with robotic autonomy, this approach implements a proximal remote-sensing layer that complements aerial and satellite observations. The workflow is designed to support transferable quantification of species interactions and habitat condition across sites and seasons, contributing to the integration of robotics and ecological remote sensing for biodiversity assessment and conservation management.

## Introduction

The efficacy of environmental management is contingent upon monitoring systems that provide biodiversity information that is comparable, repeatable, and minimally invasive, all while being cost-effective. However, increasing anthropogenic pressures, such as land and sea-use intensification, habitat fragmentation, invasive species,

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pollution, and climate change, are transforming ecosystems and the interaction networks that sustain their functions (Sala et al., 2000). Global frameworks underscore the necessity for indicators to align with management needs and to be measured consistently across programs and regions (Feld et al., 2010; Pereira et al., 2013).

These pressures act across multiple spatial and temporal scales, from local habitat degradation to landscape-level reconfiguration of ecological networks, making single-scale monitoring approaches insufficient. Effective ecosystem monitoring therefore requires multi-scaled observation frameworks that integrate local, fine-resolution measurements with broader spatial coverage to capture both mechanisms and emergent patterns of change (Sparrow et al., 2020). As anthropogenic drivers increasingly dominate ecosystem dynamics worldwide, the ability to detect, compare, and interpret biodiversity responses across scales has become a central requirement for evidence-based environmental management (Gómez-Márquez, 2025). Remote sensing has become integral to biodiversity monitoring, facilitating scalable, repeatable, and non-invasive observation of ecological patterns across extensive spatial and temporal scales. Recent advancements have enhanced the integration of satellite and airborne data with ecological and evolutionary frameworks, thereby supporting conservation planning and biodiversity indicators (Cavender-Bares et al., 2022; Kamran & Yamamoto, 2023). Nonetheless, numerous ecologically pertinent processes such as species interactions, fine-scale habitat conditions, and organism-level responses to environmental change occur at spatial and temporal scales that remain challenging to resolve using conventional satellite or drone platforms. To address this limitation, proximal remote sensing has emerged as a complementary approach, offering near-ground observations with sufficient spatial detail to bridge the gap between field surveys and landscape-scale remote sensing (Pierrat et al., 2025; Tao et al., 2022). Recent studies indicate that integrating proximal and aerial sensing can significantly enhance biodiversity assessment across diverse ecosystems (Afrasiabian et al., 2025), underscoring the necessity for standardized near-ground sensing solutions that integrate seamlessly within multi-scale monitoring frameworks.

Robotic and autonomous systems (RAS) have the potential to address persistent challenges in biodiversity monitoring by enhancing access to remote locations, facilitating consistent sampling across spatial and temporal scales, and managing substantial data volumes in near real-time (Pringle et al., 2025). Expert analyses have identified four recurrent limitations in ecological fieldwork: physical access (Rafiq et al., 2024), reliable detection and identification (Kellner & Swihart, 2014), data management (Urbano et al., 2024), and power/connectivity (Hahn et al., 2022). This suggest that RAS could standardize survey efforts and mitigate human risk, contingent upon the validation of training data and the implementation of explicit quality assurance/quality control (QA/QC) procedures (Mazzolai et al., 2025; Pringle et al., 2025). Concurrently, bioinspired legged platforms, which integrate “natural intelligence” (the interplay of morphology, control, and environment), are emerging as effective tools for navigating challenging terrains while carrying multi-sensor payloads for ecological observation (Angelini et al., 2023; Tolomei et al., 2025). Collectively, these advancements facilitate a transition from ad-hoc, expert-driven campaigns to repeatable, protocol-based surveys that can be scheduled, audited, and compared across various programs and jurisdictions. Within this context, autonomous legged robots function as ground-based remote-sensing instruments that complement UAV and satellite data by enabling fine-scale, standardized observations in otherwise inaccessible environments.

Artificial intelligence (AI) further reduces processing bottlenecks and operational costs. Automated image analysis has improved throughput and cost efficiency in conservation, allowing managers to extend spatial and temporal coverage without proportional increases in personnel (Ditria et al., 2022). Progress depends on curated, expert-verified training datasets and deployment on resource-limited hardware; recent open datasets captured with legged robots in EU Habitats Directive (Directive 92/43/EEC) Annex I habitats show how interdisciplinary teams can create suitable labels for object detection in natural environments (Di Lorenzo et al., 2025), while modern detection architectures have improved the feasibility of real-time inference on embedded devices (Edozie et al., 2025) as shown in Figure 1. These developments link robotics and remote sensing into a unified ecological workflow, transforming raw sensor data into biodiversity indicators.

Standardized AI-enabled data streams are most effective when integrated with management-oriented ecosystem modeling. Ecosystem models incorporate field and expert data to evaluate management strategies, quantify uncertainty, and support trigger-based interventions, with best practices including model-skill assessment against monitoring data and ensemble approaches to explicitly address uncertainty (Geary et al., 2020). This aligns with the broader concept of environmental intelligence, which combines citizen observations with ground, aerial, aquatic, and satellite sensors using advanced analytics, subsequently directing decision-relevant information to managers (Mazzolai et al., 2025). Our pipeline operationalizes these principles by translating multi-expert knowledge into models deployable on robotic platforms, resulting in low-disturbance, protocol-driven surveys

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**Figure 1.** Example of in situ robotic image acquisition and AI-based detection/segmentation of focal taxa. The quadruped platform (ANYmal C) conducts a minimally invasive survey across dune vegetation. The on-board model identifies the host plant *Pancratium maritimum* (purple box) and its specialist herbivore *Brithys crini* (blue box). This workflow enables standardized, near-ground data collection under natural light and terrain conditions.

ensuring comparable indicators that can inform management workflows. To make the management pathway explicit, we define a small, transferable set of decision-ready indicators and standardized reporting templates to harmonize future surveys across sites and years; these indicators are specified but not estimated in this study. To ensure comparability across years and programs, we present a formal QA/QC protocol covering pre-run calibration, inter-annotator agreement thresholds for labels, automated image/inference quality checks, and ISO/Darwin Core metadata. Together, these elements align the proposed framework with the goals of remote sensing in ecology and conservation: providing transparent, reproducible data streams that integrate across spatial scales and sensing modalities.

Our workflow aims to translate community observations into field autonomy. Citizen-science acquired images are annotated by volunteers using assisted tools and by experts; all annotations are then verified by domain specialists to ensure label quality. From these curated labels, we train two complementary model families: (i) lightweight detectors/segmenters for on-device, online inference on the robotic platform, and (ii) higher-capacity models for offline evaluation (re-scoring, uncertainty estimation, and detailed post-hoc analysis) applicable to the datasets acquired by the robot. This setup enables standardized, low-disturbance surveys that capture co-occurring biotic targets and their spatial context simultaneously in co-registered frames, so evidence relevant to species–habitat associations and biotic interactions is collected in a single pass without co-scheduling multiple field teams. All imagery, metadata, and model outputs are archived for remote expert audit and QA/QC, decoupling data capture from on-site expertise and reducing logistics to a single operator or to supervised autonomous robot operations where permitted. The subsequent case study illustrates how this design supports analysis of specific ecological dynamics. In doing so, it demonstrates how AI-driven robotics can serve as a ground-based component within the broader remote-sensing network, extending the spatial and ecological resolution of conservation monitoring.

Within interaction networks, plant–pollinator and plant–herbivore relationships are particularly sensitive and relevant to management. The decline of pollinators, driven by multiple stressors, is well-documented (Goulson et al., 2015; Potts et al., 2010), and climate change is altering phenologies and interaction strengths (Kumar et al., 2024; Trunschke et al., 2024). These insights highlight the necessity for monitoring approaches that capture



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not only species occurrences but also the specialized relationships that structure communities. European coastal sand-dune systems exemplify both the need and the opportunity: They provide essential ecosystem services, host high beta-diversity along sharp environmental gradients, and are recognized as habitats of community interest (Acosta et al., 2009; Berardo et al., 2015; Drius et al., 2016; Fattorini, 2021; Tordoni et al., 2018). Early and mobile dune systems, such as embryonic shifting dunes (habitat type 2110) and shifting dunes with *Ammophila arenaria* (2120), are particularly dynamic, valuable for coastal geomorphology and biodiversity, and challenging to survey consistently. They also represent an ideal testing ground for integrating proximal remote sensing with ecological field validation.

Within these habitats, Lepidoptera function as both pollinators and herbivores, linking plant reproduction, primary production, and higher trophic levels (Siemann et al., 1998; Wäckers et al., 2007). Butterflies and moths, as ectotherms that thermoregulate via physiological, behavioral, and phenotypic traits, are an especially informative model for studying the effects of climate change on species ecology (Hill et al., 2021). Moth assemblages can reflect environmental stress gradients (Uhl et al., 2016), and cross-taxon analyses reveal coherent diversity patterns between plants and butterflies across Mediterranean dunes (Rasino et al., 2024). A focal example of host specificity is the lily borer *Brithys crini* (Fabricius, 1775) on *Pancratium maritimum*, a pair characteristic of dune habitats 2110/2120 (Catania & Mifsud, 2024; Zilli & Romano, 1992). The noctuid *Brithys crini* is considered threatened in Europe because its larvae feed almost exclusively on the sea lily *Pancratium maritimum*, an imperiled bulbous plant characteristic of coastal beach and dune systems (Fattorini, 2021). *P. maritimum* is widely regarded as an indicator of well-preserved coastal dune habitats, while *B. crini* reflects the ecological continuity and functional integrity of these systems through its specialized herbivory. Together, this host–herbivore pair provides a biologically meaningful indicator of coastal dune ecosystem health. The larvae feed on alkaloid-rich tissues of *P. maritimum*, with chemical and physiological adaptations implicated in this tight association (Nair et al., 2020), making the interaction a useful indicator for targeted monitoring. This species pair thus provides a concrete example of how robotic remote sensing can resolve organismal interactions relevant to conservation and management.

Despite their significance, conventional biodiversity monitoring remains fragmented, labor-intensive, and costly, often requiring cross-disciplinary coordination and resulting in incomplete or non-comparable datasets, particularly for specialized taxa and fragile habitats. Within the European Union, the Natura 2000 network (SAC/ZSC and SPA/ZPS) aims to maintain or restore the favorable conservation status of habitat and species of Community interest (Directive 92/43/EEC) while sustaining the ecosystem services they provide (Bastian, 2013). Meeting this mandate requires routine, standardized biodiversity evidence that is comparable across sites and years, supported by indicators and harmonized protocols (Feld et al., 2010; Pereira et al., 2013). At the same time, accelerating anthropogenic pressures on ecosystems and their interaction networks further heighten the need to improve monitoring efficiency, repeatability, and spatial coverage (Sala et al., 2000). To address these challenges, we propose a two-stage monitoring framework that (i) leverages citizen science to collect broad, cost-effective observations subsequently verified and annotated by experts and (ii) synthesizes multi-expert knowledge into on-device neural networks deployed on a legged robot to conduct standardized, minimally invasive field surveys. All raw imagery, metadata, and model outputs generated across both stages are archived for remote expert audit and quality assurance/quality control (QA/QC), enabling transparent and reproducible monitoring workflows.

Ground-based robotic sensing is designed here as a form of proximal remote sensing that complements UAV and satellite observations by providing centimeter-scale ecological information under controlled disturbance and standardized acquisition protocols. To contextualize this choice, we also conducted a limited UAV feasibility pilot to assess whether low-altitude aerial imagery could support proximal observations of small invertebrates in dune habitats. As a case study, we apply this framework to foredune systems where habitat-defining plants co-occur with specialized herbivores. Using the *Brithys–Pancratium* system (including sites within habitats 2110/2120), we compile an expert-validated instance-segmentation dataset, train recognition models suitable for on-board and offline inference, and assess field performance under natural conditions. Our objective is to establish a transferable pathway that yields comparable indicators across sites and years, facilitating trend assessment, revisit-interval planning, and trigger-based management actions in alignment with international monitoring frameworks (Pereira et al., 2013).

## Materials and Methods

This section describes the implementation of the proposed monitoring framework, including the study sites, data sources, annotation workflow, robotic platform, and quality assurance procedures used in the case study. Supplementary material can be found in Appendices A, B, and C.

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## Regional setting and protection status

Data were collected from two Mediterranean dune systems representative of Annex I coastal habitats. The primary study area is the coastal strip of Circeo National Park (ZPS IT6040015; SAC Dune del Circeo IT6040018), characterized by a narrow beach–dune belt with a pronounced sea–land gradient and fine-scale mosaics of psammophilous communities referable to habitats 2110 and 2120. Recurrent pressures—winter storm surges, episodic erosion channels, and recreational trampling—impact pioneer vegetation crucial for sand accretion and ridge maintenance. A second site is Parco Regionale Migliarino–San Rossore–Massaciuccoli (SAC Selva Pisana IT5170002), which hosts an extensive littoral dune complex with psammophilous communities referable to habitats 2110 and 2120, providing consistent targets for standardized visual surveys. This site offered controlled access and broad transect corridors suitable for repeatable, low-disturbance missions and was therefore used for the robotic pilot. The locations are shown in Figure 2.

For completeness, we reference prior image collections from two North Sardinian SACs: Dune e Ginepreto di Platamona (ITB010003; a 17 km beach with longitudinal/parabolic dunes aligned NW–SE) and La Maddalena National Park (SAC Arcipelago di La Maddalena ITB010008) (Di Lorenzo et al., 2025). Data from these Sardinian experiments contribute to variability in illumination, substrate, and plant architecture for *Pancratium maritimum*, which was used to enrich training/validation, with fieldwork windows aligned to optimal dune-vegetation sampling periods (Ercole et al., 2016).

## Habitats and management context

Habitats 2110 and 2120 are dynamic and management-sensitive. Embryonic shifting dunes (2110) represent initial dune construction at the upper beach–foredune interface and are characterized by salt- and burial-tolerant species such as *Thinopyrum junceum* and *Achillea maritima*, with frequent presence of *Eryngium maritimum* and *P. maritimum*. Shifting dunes along the shoreline with *Ammophila arenaria* (2120) form the mobile "white-dune" cordon, where *A. arenaria* acts as a keystone sand-binder maintaining ridge morphology; *E. maritimum* and *P. maritimum* commonly co-occur in gaps and dune slopes (Bonari et al., 2021; Ercole et al., 2016). Typical species provide operational indicators of habitat structure and functions and guide conservation assessment and monitoring. Psammophilous plants in Mediterranean dunes show traits suited to high salinity, wind exposure, and low nutrient or water availability (e.g., rigid or hairy leaves with thick cuticles, extensive branched roots), supporting persistence under mechanical stress (Acosta & Ercole, 2015). Patches of the invasive succulent *Carpobrotus acinaciformis* occur locally (Bagella et al., 2025; Tordoni et al., 2021; Viciani et al., 2020); it is known to alter dune vegetation and degrade conservation status but was not a labelling or modeling target here.

Operationally, standardized surveys were implemented along transects perpendicular to the shoreline, documenting vegetation in contiguous $1 \times 1\,m^2$ plots to capture compositional change across the environmental gradient. Prior robotic monitoring advanced in 1 m steps to acquire co-registered imagery and context for each adjoining plot, enabling comparable, low-disturbance observations across sites and years (Angelini et al., 2024). Combined, these habitat-defining species provide practical targets for standardized, image-based indicators of dune condition and associated biotic interactions, aligning local surveys with Natura 2000 reporting needs.

## Focal taxa

*Pancratium maritimum* (Amaryllidaceae) is a perennial bulbous plant of ecological and medicinal importance, well known for its ability to thrive in harsh coastal environments and for its diverse secondary metabolites, including various alkaloids (Sait Ertuğrul et al., 2025). Commonly known as the "sea daffodil," it is a steno-Mediterranean species with a wide native range. *P. maritimum* primarily grows in coastal dunes and beaches, often with leaves and flowering stems partially buried in sand. The flowering stem can reach up to 40 cm in height, producing 2–14 white flowers in an umbel, each up to 14 cm long. The species flowers from June to September, following a "satiation strategy" to reduce insect predation. It is common in the perennial vegetation of coastal dunes (Habitats 2110 and 2120) but declines under high anthropogenic pressure.

*Brithys crini* is a noctuid moth found in warm Mediterranean climates, extending southward across Africa and eastward to Asia and Oceania (Annecke & Moran, 1982; Zilli & Romano, 1992). In Italy, it is largely restricted to coastal dune and retrodunal environments (Fattorini, 2021). The species is closely associated with *P. maritimum*. Several overlapping generations occur between May and October; adults, egg clusters, and larvae of multiple instars can co-occur on the same host. Females lay clusters of a few dozen eggs on host leaves. After hatching, larvae feed primarily on leaf tissue but may burrow into bulbs, sometimes defoliating plants within days (Catania & Mifsud, 2024) as per Figure 3. Larvae sequester Amaryllidaceae alkaloids, reducing predation risk (Nair et al., 2020), with known predators including the carabid



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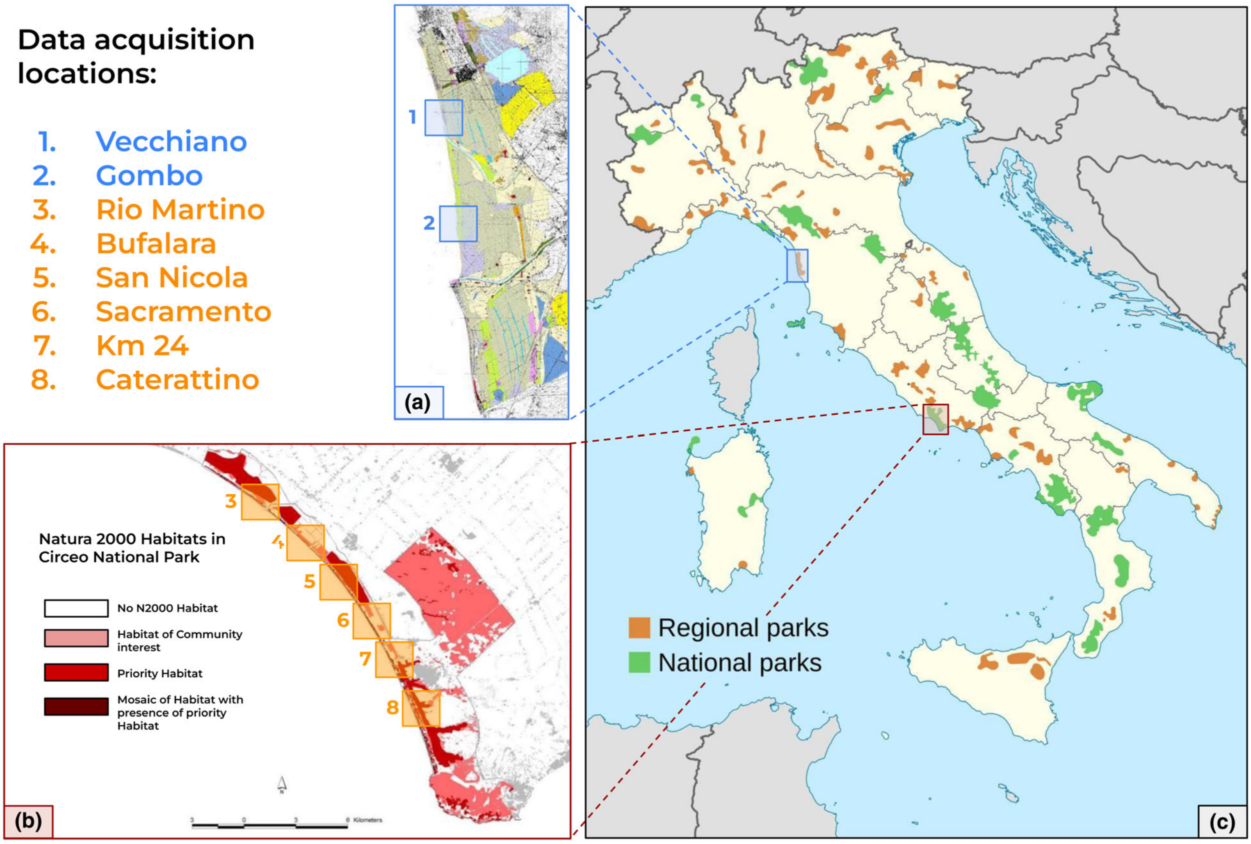


**Figure 2.** Geographic context of the study sites and in situ data acquisition locations. (a) Coastal sector of Parco Regionale Migliarino–San Rossore–Massaciuccoli (SAC Selva Pisana IT517000) showing the distribution of sampling sites along the shoreline. (b) Detailed map of Circeo National Park (ZPS IT6040015; SAC Dune del Circeo IT6040018) illustrating the spatial distribution of Natura 2000 habitats, including priority habitats and habitat mosaics, in relation to the monitored sites. (c) Regional overview of Italy highlighting the position of the study areas within the national and regional parks. Numbered locations indicate robotic and citizen-science data acquisition points (1–8).


**Figure 3.** Larvae of the moth *Brithys crini* feeding on the leaves of the sea lily *Pancratium maritimum* (a–c). Its larvae, with their aposematic coloration, are occasionally predated by the tenebrionid beetle *Erodius siculus* (d). All images show AI-based detection and instance segmentation and are representative samples from the annotated dataset used in this study, which is publicly available via the Zenodo repository reported in the Data Availability section.


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*Scarites buparius* and tenebrionids *Erodius siculus* (Solier, 1834) and *Pimelia bipunctata* (Fabricius, 1781) (Fattorini et al., 2017).

## Citizen observations: ingestion and governance

Over a period of three years, approximately twenty citizen contributors participated, ranging in age from 18 to 66 and spanning both non-specialists and professional naturalists. This diversity resulted in images that varied in framing, resolution, and metadata completeness, while simultaneously expanding spatial and temporal coverage. Contributors were engaged through local networks, with participation voluntary and unstructured. Participants received only basic guidance on photographing focal taxa and recording minimal metadata, ensuring that observations reflected natural variability in contributor skill, equipment, and effort.

The focal moth species (*Brithys crini*) was intentionally selected for citizen-based data collection because of its high visual distinctiveness (a conspicuous black-and-white, barcode-like larva) and its strict association with a widely known host plant (*Pancratium maritimum*). These characteristics allowed instructions to contributors to remain simple and robust, reducing the risk of misidentification. Participants were asked to photograph suspected larvae on Pancratium leaves, with minimal guidance on framing, distance, or equipment, in order to preserve natural variability in image quality, viewpoint, and background conditions. Citizen-science imagery was collected specifically to build the *Brithys crini* dataset presented in "Dataset and baseline models summary" section, whereas host–plant detection relied on an independent, previously published *Pancratium maritimum* dataset. Those images were contributed via ad-hoc campaigns and personal devices, with basic metadata (date/time, device, approximate location). All submissions were curated under open licenses compatible with dataset release, anonymized, checksum-verified, de-duplicated via perceptual hashing, assigned unique IDs, and normalized to a tabular schema. A human-readable filename convention was applied in releases.

## Annotation workflow and label verification

Annotations were produced by trained volunteers and domain experts. Volunteers first generated coarse boxes and masks using assisted tools (semi-automatic pre-segmentation with SAM2) (Ravi et al., 2024) within a hosted annotation environment (Roboflow). Experts refined and verified labels; disagreements were resolved by consensus. Labels are released in COCO-style JSON and YOLO-txt formats with tool/version metadata. Test splits were frozen before model development, and verification was performed on raw imagery without model overlays.

To discourage over-generalization to "any caterpillar," we included images containing non-target Lepidoptera larvae from the same habitats. When *B. crini* was absent, frames were left unlabeled, functioning as hard negatives. The curated corpus combines (i) multi-season observations from Circeo and San Rossore, (ii) robot imagery from San Rossore, and (iii) previously collected images from North Sardinia. In this release, we annotate a single biological class—the focal herbivore *B. crini* (larvae/eggs)—to meet edge-compute constraints. Consistent with host specificity, detections of *B. crini* larvae were assumed to occur on or immediately adjacent to *P. maritimum* leaves/rosettes. Host context was recovered offline by applying a *P. maritimum* detector trained on an independent dataset (Di Lorenzo et al., 2025) to the same imagery.

The annotations were output as YOLO-txt format, as all AI-based recognition in this study is implemented using models from the YOLO family, specifically YOLOv11 (Hussain, 2024; Khanam & Hussain, 2024), trained for instance segmentation. We adopted a dual-model configuration comprising lightweight YOLOv11 segmentation models for on-device (edge) inference on the robotic platform, and higher-capacity YOLOv11 segmentation models for offline evaluation, rescoring, and scientific analysis. A more detailed description can be found in Appendix A.

## Robotic platform for monitoring missions on sand

Locomotion on loose, deformable substrates such as sand is challenging. UAVs are often used for remote sensing rather than truly proximal measurements and have endurance limits (Kelaher et al., 2023; Piccioli-Resta et al., 2020); low-altitude flights can also elicit wildlife responses (Afridi et al., 2025). Wheeled or tracked ground robots support persistent, proximal sensing, but mobility degrades in unstructured terrain. Legged systems—particularly quadrupeds—offer a workable compromise, enabling reliable traversal of dune habitats with near-ground sensors while minimizing disturbance.

We used the ANYmal C quadruped (Hutter et al., 2017), a medium-scale robot (footprint $\approx$1.05 $\times$ 0.52 m; mass $\approx$50 kg) with three actuated joints per limb. It supports teleoperation and fully autonomous execution of preplanned paths in unstructured terrain. Sensors include a 360° multi-beam LiDAR (Velodyne VLP-16), four depth cameras, and two wide-angle RGB cameras. LiDAR supports mapping and localization; cameras

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provide synchronized color/depth imagery. Imagery and metadata (timestamps, pose) are logged continuously; still frames are captured at fixed intervals for co-registered coverage.

More generally, executing AI models on the robotic platform enables embedded and spatial AI procedures, as commonly discussed in the context of embodied artificial intelligence (Duan et al., 2022) and learning-enhanced spatial perception (Pollefeys et al., 2026). In this framework, on-device inference is not intended to replace high-precision offline analysis but to support autonomous operation during data acquisition. Potential uses include immediate, on-site quality control (e.g., detection of severe blur, exposure failures, or gross framing errors), triggering re-acquisition when QC thresholds are not met, and logging provisional metadata to support run-time monitoring and post-hoc auditing. In this study, we demonstrate a pilot dual-model configuration, where lightweight models enable embedded inference on the robot, while higher-capacity models with expert oversight are used offline for calibrated, auditable scientific interpretation.

In addition to the ground-based robotic surveys, we conducted a small UAV feasibility pilot to evaluate whether low-altitude multirotor platforms could substitute ground-based sensing for proximal detection of *Brithys crini* larvae on *Pancratium maritimum*. This pilot was designed as a qualitative comparison to assess resolution–disturbance trade-offs rather than as a primary data acquisition method. While near-ground sensing provides organism-level spatial resolution, it necessarily entails a reduced instantaneous field of view compared with UAV or satellite platforms. Accordingly, the proposed robotic surveys are not designed to guarantee exhaustive detection of all potential targets within a site. Instead, coverage is ensured procedurally through standardized transect-based sampling, with fixed station spacing, controlled standoff distances, and consistent sensor geometry. By repeating the same acquisition protocol across sites and years, the framework prioritizes comparability, repeatability, and trend detection over single-pass completeness, in line with established ecological sampling approaches.

# Results

Image validation confirmed the identity of *Brithys crini* larvae on *Pancratium maritimum* and revealed clear patterns of herbivory. Feeding was predominantly observed on green leaves during their seasonal availability (Fig. 3a–c), whereas bulb feeding was less frequent and involved fewer larvae. Distinct types of damage were documented across plant organs, and frass deposition was consistently associated with larval activity. Photographs also captured a potential natural predator, the tenebrionid beetle *Erodius siculus* (Fig. 3d), providing evidence of additional trophic interactions within the habitat. These proximal remote-sensing images demonstrate the capacity of the ground-based system to detect both direct and indirect biotic interactions at centimeter resolution.

## Data provenance, temporal coverage, and device/site balance

A label audit scanned $N = 2610$ image files; 2208 label files parsed successfully and 402 were skipped as unmatched. The corpus spans 33 acquisition dates (2023–05–12 to 2025–06–05), with peaks on 2023–05–12/13, 2024–09–24, and 2025–05–22, ensuring multi-season coverage. Five camera/device models contributed imagery: *motog84* (49.1%), *motog42* (26.4%), *motog22* (14.2%), *xiaomi22101316g* (9.9%), and *canoneos80d* (0.5%). Data were logged across eight site codes, led by *sacramento* (35.6%), *bufalara* (20.0%), *snicola* (18.8%), and *riomartino* (10.1%), followed by *caterattino*, *km24*, *vecchiano*, and *gombo*. Those locations are recapped in Figure 2. This mix supports robustness to illumination, sensor, and background shifts. All imagery, annotations, and metadata will be archived in Zenodo as reported in the Data Availability section.

## Dataset and baseline models summary

This subsection summarizes the structure of the annotated dataset and the baseline performance of the recognition models, with the aim of demonstrating the feasibility and robustness of the proposed monitoring pipeline rather than optimizing algorithmic performance. We first describe the composition of the citizen- and robot-derived image dataset, including its size, variability, and use of negative examples, to clarify the ecological and observational context in which models were trained. We then report baseline detection performance for both offline and on-device models to show that the system achieves reliable identification of focal larvae under realistic field conditions. Technical metrics are reported for transparency, but their role is to support the methodological objective of standardized, auditable monitoring rather than to benchmark computer-vision architectures. Definitions of performance metrics and technical terms are provided in Appendix C.

The *B. crini* instance-segmentation dataset totals 2610 images and 5537 annotated larval instances (one class), that is, 2.12 instances (larvae) per image overall and 2.71 per annotated image, as shown in Figure 4. We include 567 null images (21.7%) as hard negatives. The negative set also includes habitat images with non-target

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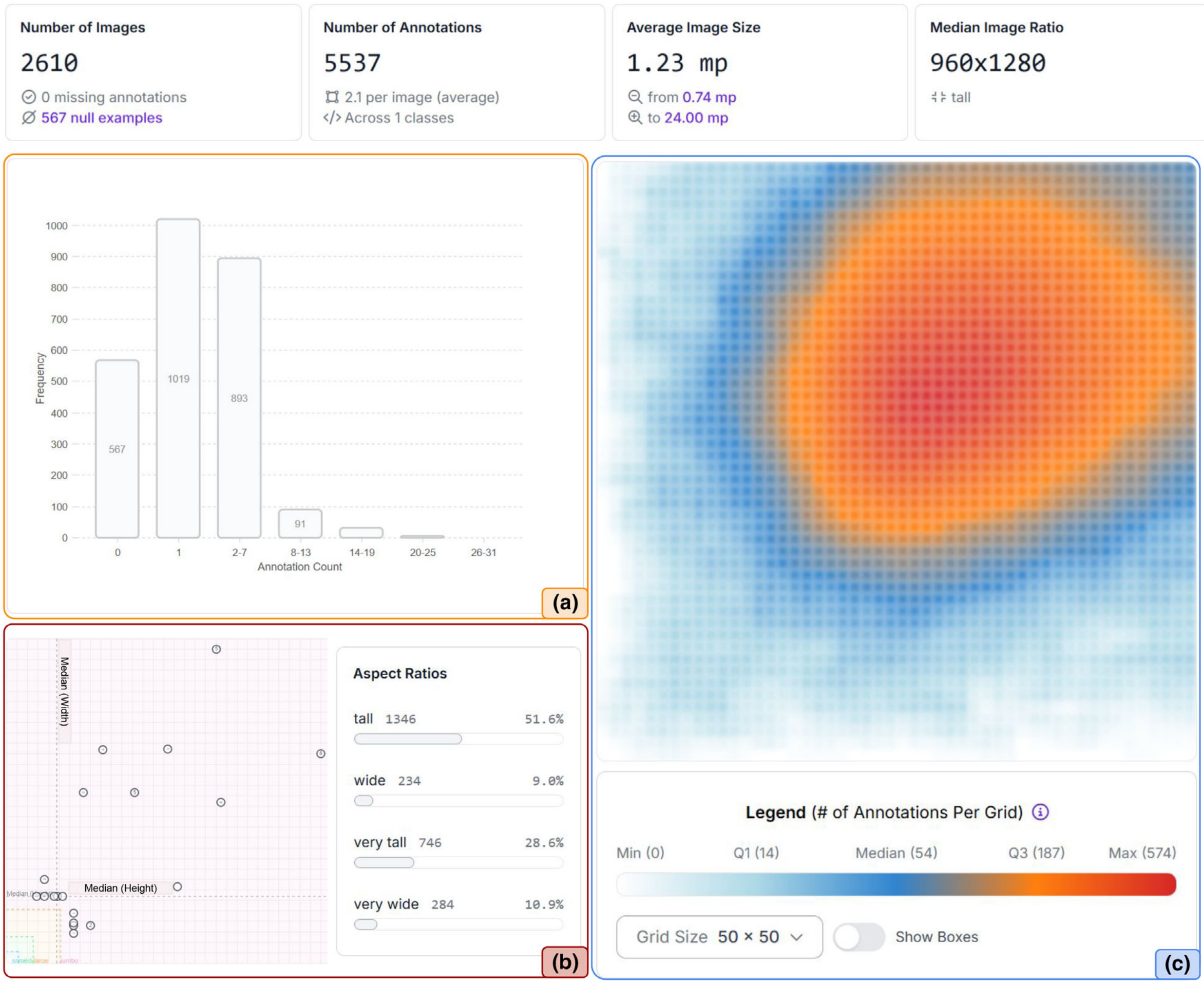


**Figure 4.** Summary statistics of the annotated instance-segmentation dataset. (a) Distribution of annotation counts per image. (b) Aspect ratio and framing distribution of the image dataset. The scatter plot shows image width versus height, while the accompanying summary indicates the proportion of frames belonging to different aspect-ratio categories (tall, very tall, wide, very wide), reflecting the variability in framing produced by different acquisition devices. (c) Spatial heatmap of annotation density in image coordinates. The heatmap aggregates the positions of all annotated instances within the image frame and highlights a center bias, where annotated objects tend to appear closer to the middle of the image. The dataset includes 2,610 images and 5,537 annotations collected from multiple devices and observation sites, combining expert-verified and citizen-derived imagery.

Lepidoptera larvae to penalize spurious detections on look-alike caterpillars and enforce species-level discrimination. A multi-class extension is planned to quantify cross-taxon confusions explicitly. The dataset includes larval occurrences across multiple plant organs, reducing the risk of organ-specific detection bias and allowing seasonal patterns of plant-part use to emerge from the deployment data.

Image resolution averages 1.23 MP (range 0.74–24 MP); the median frame is 960 $\times$1280 (portrait). Aspect ratios skew toward portrait (tall 51.6%, very tall 28.6%) with fewer landscape frames (wide 9.0%, very wide 10.9%), as shown in Figure 4b. An annotation-density heatmap as per Figure 4c indicates a center bias, reflecting the tendency for annotated instances to occur near the center of the image frame; the heatmap represents annotation positions in image coordinates aggregated across the dataset. Most images contain a single instance (39.1%) or 2–7 (34.2%); a small tail has 8–13 ($\sim$3.5%) or $\geq$14 ($<$2%) instances. These traits informed training design (maintaining null proportion, multi-scale/letterbox augmentation, random crop/translation).

On the held-out test set, the offline model (YOLOv11x-seg, 62.0 M parameters) achieved $mAP_{50}$



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$= 0.871$ ($mAP_{50-95} = 0.677$; $P/R = 0.902/0.813$) and mask $mAP_{50} = 0.850$ ($mAP_{50-95} = 0.584$; $P/R = 0.897/0.792$). The edge model (YOLOv11n-seg, 2.83 M parameters) obtained $mAP_{50} = 0.794$ (0.581; $P/R = 0.854/0.749$) and mask $mAP_{50} = 0.797$ (0.525; $P/R = 0.852/0.748$). On an A100 GPU, YOLOv11x-seg ran at $\sim$5–8 ms per image (post-processing 2.5–2.8 ms), while YOLOv11n-seg ran at $\sim$0.5–1.9 ms (post-processing 1.4–2.6 ms).

To compute moth–host co-occurrence, we also trained a YOLOv11x box detector (640 input) for *P. maritimum*. Early stopping selected the best model at epoch 119 (183 total; 2.03 h; 56.8 M parameters). Validation: $P = 0.725$, $R = 0.654$, $mAP_{50} = 0.701$, $mAP_{50-95} = 0.381$. Test: $P = 0.782$, $R = 0.739$, $mAP_{50} = 0.814$, $mAP_{50-95} = 0.547$. Profiling on an A100 yielded $\sim$7.6 ms end-to-end ($\sim$ 130 FPS).

We note that accuracy-based measures and mAP capture different aspects of model behavior, while mAP reflects both localization and classification performance and is therefore retained as the primary metric, accuracy-based values may appear higher because they do not penalize localization errors and are reported only as complementary context. These detection accuracies are consistent with benchmarks reported in other ecological remote-sensing pipelines (Afsar et al., 2024; Zhang et al., 2023), and demonstrate feasibility for in-field inference.

## UAV pilot: feasibility and disturbance trade-offs

We ran a small feasibility pilot with two multirotor platforms—DJI Mini 4 K DJI (DJI mini 4K user manual v1.0, 2024) and DJI Mavic 3 Enterprise (M3E) DJI (Dji mavic 3 enterprise series: Specifications, 2022)—to assess whether low-altitude hovering imagery could substitute the ground robot for proximal larval detection. At the very low heights needed to resolve caterpillars on *Pancratium* leaves (single-digit meters above ground level), both platforms induced visible leaf/stem motion from rotor wash, increasing occlusions and motion blur; flying higher reduced downwash but lost spatial detail for reliable larval detections. Given this disturbance–resolution trade-off, we did not use UAVs for primary larval acquisition, limiting their role to site-overview and contextual imaging. This pilot underscores that proximal ground-based sensing remains superior for high-resolution organismal detection in fragile habitats.

## Robotic pilot at San Rossore: field performance and QC outcomes

This subsection reports a field pilot aimed at assessing the practical feasibility of the proposed monitoring framework under real conservation conditions. Rather than addressing ecological trends, the pilot evaluates whether a ground-based robotic platform can reliably execute standardized transects, acquire auditable imagery, and operate within conservative disturbance and quality constraints in a protected dune habitat. We conducted a pilot with the ANYmal C quadruped in IT5170002—Selva Pisana (June 12, 2025), executing autonomous shoreline-perpendicular transects under the proposed SOP (one-pass policy, standoff $\geq$0.5 m, speed cap 0.25–0.35 m $s^{-1}$), as shown in Figure 5.

Missions used 1 m station spacing; at each station, the robot paused $\leq$3 s to capture stills (2 $\times$2 m mosaics where required). Station spacing and traversal speed were selected to ensure consistent sampling effort and overlap between adjacent observation units, rather than to maximize instantaneous spatial coverage. Median dwell per station was 2.2 s; battery draw was 3%–7% per 5 min of dune walking. Automated in-run checks flagged 7%–10% of frames; immediate re-takes resolved 70%–75% of flags, leaving 2%–3% marked qc = fail. Post-run audits (100% of flagged; 10% of unflagged) met acceptance thresholds in all transects (usable frames $\geq$90%; combined blur/exposure failure $\leq$5%; LiDAR–camera time drift $\leq$100 ms). Dominant failure modes matched dataset QC (fine leaf-boundary leakage; occasional class confusions in high backlight). Spot checks detected no crushed focal plants; these serve as qualitative baselines pending a full-season assessment.

Per 1 m station, median timings were: approach/settle 0.9 s, capture+QC 0.3 s, edge inference+log 0.7 s (IQR 1.6–2.4 s), leaving margin for re-takes. Offline re-scoring processed 20–30 FPS on an A100 and 4–6 FPS on an i7 workstation, enabling same-day QC. For archived frames, we applied *Pancratium* and *Brithys* detectors offline to compute moth–host co-occurrence and populate indicator templates. We refrain from ecological rate reporting; the pilot establishes end-to-end feasibility and QC acceptance.

Qualitative review of false positives/negatives identified three dominant modes: (i) occlusion/clutter (overlapping leaves) leading to missed small larvae; (ii) shadow patches on sand mimicking larval patterns; and (iii) look-alike larvae from non-target Lepidoptera in hard-negative scenes. These mirror label-QC findings and motivate targeted augmentations and future multi-class expansion.

Citizen-science logs include verified occurrences in November, late relative to the usual May–October window, highlighting an out-of-season signal. We interpret these cautiously as possible microclimate refugia or phenological extension consistent with climate-driven shifts and recommend targeted follow-up with weather covariates and multi-year replication. Importantly, citizen

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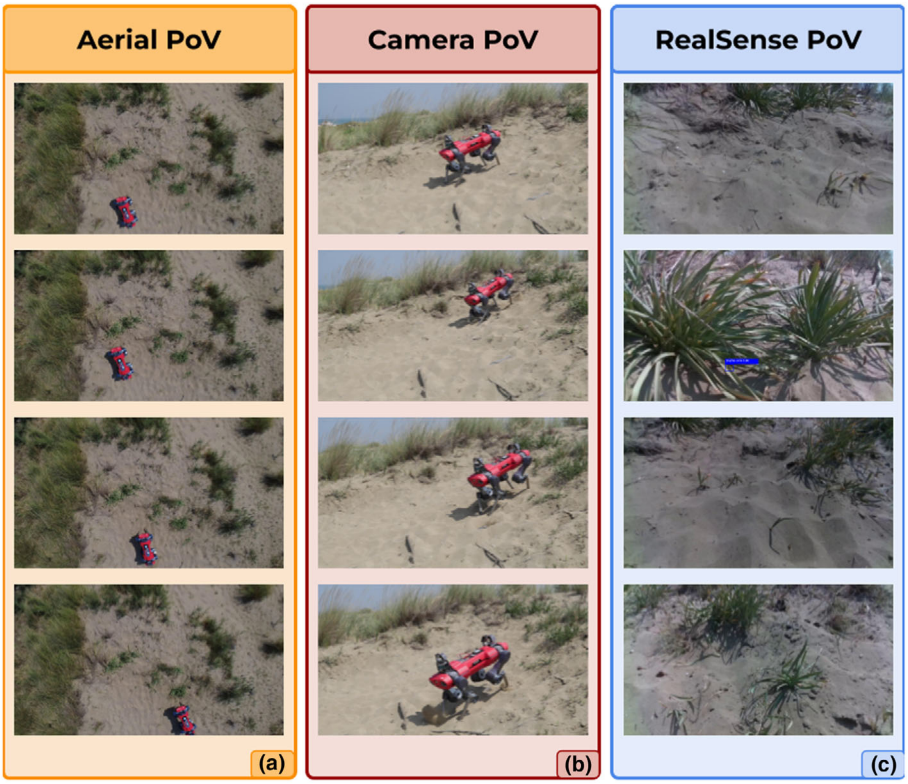


**Figure 5.** Comparative field perspectives during the San Rossore robotic pilot. (a) Aerial view from a multirotor UAV. (b) Ground-level camera view from the ANYmal C quadruped robot. (c) Frontal RealSense camera mounted on the robot.

contributions delivered spatio-temporal capillarity at near-zero marginal cost and first-pass labels that shifted expert time from drawing to verification. The combined citizen and robotic observations thus demonstrate a scalable, integrative framework for near-ground ecological remote sensing.

## Discussion

Our findings demonstrate the feasibility of a citizen-to-robot pipeline that translates community observations into standardized, low-disturbance robotic surveys. The contribution lies not in ecological trends, which will require multi-season replication, but in providing a tested methodological scaffold: dual-model inference (edge vs. offline), a disturbance-aware SOP, QA/QC thresholds, and open metadata standards. Within the broader field of ecological remote sensing, this work represents an example of 'proximal' or ground-based sensing that complements satellite and UAV observations by capturing organism-level information at centimeter resolution.

The monitoring of the *P. maritimum*–*B. crini* interaction illustrates how automated image-based approaches can provide ecological insights into specialized plant–herbivore dynamics. The seasonal shift from foliar to occasional bulb feeding suggests an adaptive strategy by the larvae to overcome host alkaloid defenses (Nair et al., 2020), while avoiding overexploitation of plant tissues, potentially contributing to a balance between herbivore pressure and host persistence (Low et al., 2013). The presence of characteristic damage patterns and nutrient-rich frass highlights additional functional roles, such as localized nutrient cycling (Frost & Hunter, 2004). Furthermore, the incidental detection of natural enemies places this interaction within a broader trophic framework, underscoring how minimally invasive monitoring can reveal complex ecological networks while maintaining reproducibility and scalability across habitats. Although larvae were observed on different parts of *Pancratium maritimum* across images, the present dataset was not explicitly stratified by host–plant organ, and apparent differences in larval positioning are therefore reported descriptively rather than as automated or quantitative AI-driven inference. Future extensions of the framework could incorporate organ-level segmentation of the host plant (e.g., leaves, basal tissues, flowering stems), enabling



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expert-supervised analysis of plant–herbivore foraging patterns across seasons while mitigating potential training-data bias.

Although the geographic distribution of the studied populations and the strict association with *Pancratium maritimum* would allow experts to reasonably infer that the observed larvae likely belong to the subspecies *Brithys crini pancratii* (Cyrillo, 1787), this attribution cannot be formally confirmed without targeted taxonomic examination of larval or adult material. Moreover, subspecies-level discrimination within *B. crini* remains the subject of ongoing taxonomic debate (Catania & Mifsud, 2024; Zilli & Romano, 1992). In the context of this study, which relies exclusively on image-based observations and machine learning (ML) models trained on visual features, such inference would exceed the current state of the art and risk over-interpretation. Consequently, all detections are conservatively treated as *Brithys crini* sensu lato. This choice ensures taxonomic robustness and highlights an important limitation of automated recognition systems: While expert ecological knowledge can integrate distributional and contextual cues, such reasoning cannot yet be reliably encoded or inferred by ML algorithms operating on imagery alone.

Importantly, such ecological detail is directly applicable to conservation practice: documenting herbivory regimes, trophic interactions, and habitat functioning contributes to the development of standardized indicators for Annex I dune ecosystems, thereby informing Natura 2000 network reporting and supporting evidence-based management decisions. By using a robotic platform as a ground-based remote sensor, we show how field-scale data can feed directly into multi-scale monitoring frameworks, linking species-level processes with habitat-level indicators measurable by aerial or satellite sensors.

We delineate a practical approach from community observations to standardized, low-disturbance surveys that a single operator can execute and that experts can audit remotely. By synthesizing multi-expert knowledge into complementary model families, we reduce dependence on co-scheduled, multidisciplinary field teams while enhancing repeatability and comparability across sites and years. The San Rossore pilot shows a legged platform executing shoreline-perpendicular transects can satisfy conservative thresholds for image quality and disturbance, with latency margins to support in-run re-takes and same-day offline QC. The citizen component provided the most valuable asset: fine-grained spatio-temporal coverage at near-zero field cost, plus first-pass labels via assisted tools. This integration of citizen-sourced imagery and autonomous robotics exemplifies how participatory data collection can be scaled through automation to produce auditable remote-sensing datasets.

Due to the small target size, platform choice is critical for proximal detection. The UAV pilot revealed a disturbance–resolution trade-off at low altitudes; by contrast, a quadruped with near-ground sensors produced stable, repeatable imagery with minimal vegetation contact under a one-pass, speed-capped SOP. We thus position UAVs as complementary for context and legged robots as primary for close-range, low-disturbance surveys. While ANYmal C provided a proof-of-concept, smaller legged systems or multimodal platforms could further reduce mass/footprint and expand operability in ultra-sensitive sites (Ranjan et al., 2025; Scaldaferri et al., 2025). The pipeline itself is embodiment-agnostic, provided sensing geometry and disturbance constraints are respected. The pilot confirms that legged robots can achieve conservative thresholds for image quality and habitat disturbance, while citizen contributors provide spatial and temporal diversity of inputs that enhance model generalization. Rather than emphasizing ecological findings, this study positions the pipeline as a generalizable monitoring method that agencies and researchers can adopt, adapt, and scale to additional habitats and taxa. Such embodiment-agnostic design aligns with current trends in remote-sensing networks, where multiple robotic and static sensors contribute to integrated biodiversity observing systems (Reddy, 2021; Wang & Gamon, 2019).

Although we refrain from computing indicators in this report, we specify a transferable set with formulas and templates. Adding a dedicated *Pancratium* detector alongside *Brithys* completes the path from raw detections to decision-ready metrics using the same frames, with edge models standardizing capture and offline models providing calibrated, auditable outputs. Although the reported mAP values are moderate, they are consistent with the objectives of this pilot study, which prioritizes feasibility, standardization, and auditability under realistic field conditions rather than optimization for benchmark performance. Limitations include single-class labels for the herbivore (host context via a separate plant detector), pilot-scale temporal coverage, qualitative disturbance baselines, dataset skews (portrait/center/device biases), and potential boundary artifacts from assisted tools (audits suggest limited bias). On-robot performance and energy draw will vary with embedded compute and terrain; broader deployments should verify margins under local constraints. Those limitations do not detract from the methodological advance but instead highlight next steps for operational deployment. Future work should test cross-habitat transferability, quantify uncertainty propagation from edge to offline models, and explore co-registration of these ground data with spectral or thermal layers from UAV or satellite imagery. In this context,

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ground-based robotic sensing is best interpreted as a complementary layer within multi-scale remote-sensing frameworks, trading spatial extent for standardized, high-resolution observation of focal organisms and interactions that cannot be resolved reliably from aerial platforms.

Data contributed by citizens introduced significant variability in terms of framing, resolution, and metadata quality, reflecting the diverse skills, devices, and engagement levels of contributors. Although this heterogeneity necessitated meticulous curation and expert verification, it also served as an asset by enhancing the diversity of training inputs and improving the models' generalization capacity. In practice, the pipeline benefited from a broader range of conditions than could have been captured by a small team of experts alone, illustrating that the structured integration of citizen observations can enhance model robustness without compromising data quality. Notably, this approach is applicable beyond the specific *Pancratium–Brithys* system. In this case study, species were intentionally selected due to their clear, unambiguous diagnostic traits, which minimize misidentification.

However, the minimal requirement for volunteer training suggests that the same citizen-to-robot workflow could be extended to more complex taxa or interaction systems, provided that diagnostic criteria are explicitly defined and expert verification is maintained. This citizen-to-robot workflow provides a standardized, transferable foundation for ecological monitoring, contributing directly to operationalizing Essential Biodiversity Variables (EBVs) for species populations and species interactions by providing repeatable, comparable measures of occupancy, condition, and interaction intensity across spatial and temporal scales. The modular structure of the pipeline, comprising data ingestion, expert curation, model training, and standardized robotic deployment, renders it adaptable to a wide array of monitoring contexts, from pollinator–plant interactions to invasive species surveillance. Decoupling data capture from expert presence, the framework reduces entry barriers and offers a reproducible pathway that other research teams and conservation agencies can adopt, adapt, and scale to their own taxa and habitats. This framework aims to demonstrate how ground-based robotic sensing can serve as a key link among citizen science, field ecology, and large-scale remote-sensing programs, integrating technology, ecology, and conservation.

## Conclusions

We introduce a methodological framework designed to transition biodiversity monitoring from community-based observations to standardized, minimally invasive robotic surveys. Utilizing the interaction between *Pancratium maritimum* and *Brithys crini* within Annex I dune habitats as a proof-of-concept, we illustrate the process by which expert-validated citizen observations can be converted into deployable models for autonomous field surveys. The primary contributions of this study include: (i) the development of an expert-curated instance-segmentation corpus for a focal herbivore; (ii) the implementation of a dual-model architecture that integrates lightweight edge models with more robust offline models; (iii) the establishment of a disturbance-aware standard operating procedure, incorporating explicit pre-, in-, and post-run quality checks and complete provenance; and (iv) the creation of a transferable set of decision-ready indicators specified for future computation. Pilot trials demonstrated that a quadruped robot can meet conservative image quality and disturbance thresholds, while a small UAV trial revealed disturbance–resolution trade-offs that favor legged platforms for proximal invertebrate detection. Future extensions may include the incorporation of larval volume analysis as a proxy for herbivore pressure and the expansion of AI-based recognition to encompass additional trophic elements, thereby facilitating more comprehensive ecosystem assessments. Overall, the significance of this framework lies not in the specific case study but in the standardization pathway it offers. By reducing field burden, decoupling expert presence from data capture, and enhancing repeatability and comparability across sites and seasons, this approach provides a scalable, transferable tool for multi-site biodiversity monitoring and evidence-based management.

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## Author Contributions

**Giovanni Di Lorenzo:** Conceptualization; software; methodology; data curation; investigation; formal



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analysis; visualization; writing – original draft; writing – review and editing. **Simonetta Bagella:** Conceptualization; writing – review and editing; validation; resources. **Micaela del Valle Rasino:** Methodology; data curation; validation; writing – review and editing. **Maria L. Carranza:** Writing – review and editing; conceptualization; validation. **Manolo Garabini:** Writing – review and editing; supervision; funding acquisition. **Franco Angelini:** Supervision; funding acquisition; writing – review and editing.

## Conflict of Interest

The authors declare no potential conflict of interest.

## Inclusion Statement

This study brings together expertise from engineering, robotics, ecology, and botany, ensuring that ecological and conservation perspectives were integrated from the outset. Field specialists in Mediterranean dune ecosystems (Simonetta Bagella and Maria Laura Carranza) contributed domain knowledge, validation, and contextual interpretation of ecological results. Local authorities and experts from the protected areas where the work was conducted were also engaged throughout the study to ensure that methods and outcomes were aligned with site-specific conservation priorities. Early collaboration across disciplines and institutions enabled the research to address management-relevant questions in a way that is transferable beyond the case study system.

### Data Availability

Data and code supporting this study have been uploaded to the following anonymized repository: Zenodo Britcat20251027MEEyolov12 repository. The repository includes the annotated image dataset used for model training and evaluation, with representative examples shown in Figures 3 and 4.

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## Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

**Data S1.**
**Data S2.**

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