Putting the ‘Adaptive’ in Adaptive Monitoring: From Fast Data to Meaningful Ecological Change

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Abstract:

Despite repeated calls for ‘adaptive monitoring’, monitoring programs typically rely on fixed protocols that fail to capture the complex and dynamic natural world. New technologies offer this long sought flexibility, yet paradoxically risk our ability to detect trends by generating fragmented, high frequency data untethered to broader monitoring objectives. Here, we introduce ROAM (Routine-Opportunistic Adaptive Monitoring)--a hybrid framework that pairs goal-oriented baseline sampling with the ability to capture critical, transient events and experiment with optimized sampling protocols. We demonstrate ROAM with case studies of spring phenology shifts, biogeochemical pulses, wildlife demography and early warning detection. Needed developments include: 1) infrastructure for real-time communication and rapid sensor deployment, 2) integrated statistical methods for event detection, sampling optimization, and, importantly, merging high-frequency bursts with long-term collection, and 3) equitable technology transfer, training and funding models. This type of monitoring could finally deliver the adaptive, integrated systems both science and policy demand.

Keywords: adaptive management, biodiversity monitoring, ecosystem dynamics, edge AI, machine learning, trend detection and attribution

Introduction:

Ecological monitoring is essential for documenting the decline and recovery of nature. The general aim of monitoring is straightforward—to enable the comparison of a biological state or trend relative to a baseline or reference conditions. In practice, however, monitoring complex and dynamic ecosystems with limited resources is extremely challenging.

One question is *what* to monitor. Monitoring programs range from broad, multi-taxon (*surveillance monitoring*) to focused field-based monitoring of target species, typically addressing a particular management question (*targeted monitoring*) (Eyre *et al.* 2011; Lindenmayer *et al.* 2022). Because surveillance monitoring is meant to detect broad trends across populations, species, or ecosystems, it is especially valuable for identifying unexpected ecological shifts. Important findings—such as widespread declines in insect biomass (Lister and Garcia 2018; Wagner *et al.* 2021), aerial insectivores (Spiller and Dettmers 2019; Bowler *et al.* 2019), and common North American bird species (Johnston *et al.* 2025) were only possible because of long-term, multi-taxon surveys. Yet surveillance monitoring has been criticised for unclear objectives and risks producing "lots of data but little understanding" (Lindenmayer and Likens 2009; Lindenmayer *et al.* 2022). In contrast, *targeted monitoring* is designed around specific questions and typically yields more actionable insights while remaining cost-effective for smaller budgets (Wintle *et al.* 2010), but targeted designs might overlook broader ecosystem-level change.

Another question is *when* to monitor. Ecological change arises from both gradual pressures and sudden events (Bender *et al.* 1984; McClain *et al.* 2003). Long-term, gradual shifts alter ecological baselines, but extreme events—such as fires, droughts, and heatwaves—can disproportionately impact sensitive species (McClain *et al.* 2003) often exceeding the negative impacts of long term increases in temperature (Harris *et al.* 2018). Fixed-interval monitoring is generally too slow to detect or react to short-term ecological events and to inform management on relevant timescales (Lindenmayer *et al.* 2010; Baho *et al.* 2017).

While long-term monitoring is essential for detecting trends through time, it is no small task. Populations and sub-populations tend to fluctuate strongly on a short-term basis and vary across spatial scales (Dornelas et al. 2023). Sufficient statistical power to detect a trend often requires many repeated samples over time and across populations to avoid concluding a population is not declining when it actually is (Fairweather 1991). We lack the power to robustly detect trends for most population time series around the world and need hundreds or thousands more sampled populations to confidently say a population is recovering from a management action even if that action immediately halted decline (Leung et al. 2019). Even easier-to-measure metrics, such as species richness, require much more sampling than currently exists (Valdez et al. 2023) for lengths of time vastly exceeding most funding cycles (e.g. 30 years). Most data-driven indicators used for standardized, multi-taxon reporting for global assessments, such as IPBES, the Taskforce on Nature-related Financial Disclosures (TNFD 2025) and reporting to evaluate targets of the Kunming-Montréal Global Biodiversity Framework (GBF) lack the ability to detect change by 2030 in their current form (Affinito et al. 2024; Hébert et al. 2025).

The sheer volume of data coming from new technologies (Box 2) is rapidly expanding capacity to detect short-term dynamics (e.g. post-fire change or invasion fronts) or for mobile species missed by traditional monitoring (Abrahms *et al.* 2019; Welch *et al.* 2019). For example, daily estimates of breeding season abundance for the nocturnal whip-poor-will (*Antrostomus vociferus*) are possible with airborne LiDAR and ARUs (Larkin *et al.* 2024a, 2025) and daily estimates of habitat suitability for the blue whale (*Balaenoptera musculus*) by pairing long-term tracking with a daily ocean model (Abrahms *et al.* 2019). These estimates, combined with near real-time whale sightings, are used to report the risk of ship strike in shipping lanes in southern California (https://whalesafe.com/). Several technological applications, such as EarthRanger, have been instrumental in reducing wildlife poaching (reviewed in Lynam et al. 2025) already, and there are endless new possibilities for monitoring nature, such as robotic and autonomous systems (see Pringle *et al.* 2025). But, without the attention to goal-setting of the adaptive monitoring framework (Lindenmayer and Likens 2009) and integration into the long-term records, we risk these being isolated efforts.

Adaptive sampling and monitoring

A last major question is how to monitor *efficiently* given limited resources. One of the best ways to increase efficiency is to update the study design (Lindenmayer and Likens 2009) or the sampling protocol specifically (Henrys *et al.* 2024) to improve trend detection in models (Callaghan *et al.* 2019) or the ability to discriminate between management options (Holling 1978). Adaptive sampling works in theory. Optimizations have shown that redirecting even a modest amount of effort can increase the amount of information available for making conservation decisions (Moore and McCarthy 2016; Hauser *et al.* 2019; Hanson *et al.* 2023; Veylit *et al.* 2025), and efficiency can be gained with small strategic changes in how people record nature (Callaghan *et al.* 2023; Lange *et al.* 2023; Mondain-Monval *et al.* 2024).

However, adaptive sampling has been very rarely done in practice (Henrys *et al.* 2024) due to both *philosophical* and *logistical* (Box 3) barriers including: a general resistance to change, reluctance to change well thought-out sampling designs or biasing results by shifting or narrowing focus too much. Several barriers are based on the assumption that tradeoffs would need to be made, but we argue below that in some cases now, technology can be a net gain, where we do not need to trade-off the overarching study goals. In fact, in many cases, we agree that the overarching design should not be changed as monitoring is difficult under any circumstances and changing protocols mid-monitoring requires extra resources, potentially new permits, and a dedicated and extensive communication effort (Box 3).

Similar to how technology is improving responsive conservation described above, technology can directly address the hurdles to adaptive sampling (Box 2). The most active area of adaptive data collection is not traditional fixed monitoring programs, but through crowd-sourced science. One emerging example is citizen/participatory science, where highly engaged naturalist communities can be redirected toward priority gaps through dynamic maps and behavioral nudges (Callaghan *et al.* 2023; Thompson *et al.* 2023) and active alerts (Sullivan *et al.* 2014), which change as new information is collected. There are more applied examples where conservation tools and platforms have demonstrable outcomes from risk assessment to anti-poaching efforts that iterate through time (reviewed in Lynam *et al.* 2025). However, much of this effort lacks the rigor of long-term systematic monitoring (Balantic and Donovan 2019; Hanson *et al.* 2023; Veylit *et al.* 2025), so how do we pair these efforts?

Box 1. Glossary

Term	Definition
Adaptive sampling	An iterative sampling strategy in which observations collected up to a given point are used to update subsequent sampling decisions (e.g., where, when, and how to sample next) to maximise the information gained for a predefined question of interest.
AI Agent (also see Agentic AI)	A software system that can perceive inputs, select actions, and execute multi-step tasks toward goals (e.g., scheduling sensors, requesting labels, generating alerts).
Agentic AI (also see AI agent)	A class of systems that exhibit goal-directed behaviour over time with varying degrees of autonomy. In ROAM, "agentic" behaviour should be bounded by explicit safeguards, budgets, and human oversight.
Autonomous Recording Unit (ARU)	A deployable acoustic sensor that records soundscapes for subsequent or on-device processing (often used for 'passive acoustic monitoring' of birds, bats, frogs, insects).
Burst sampling	A temporary, event-driven intensification of sampling (higher cadence, expanded spatial footprint, or additional modalities) that is bounded by explicit termination criteria to protect long-term continuity and resource budgets.
Continuous integration (CI)	A practice in which code changes are routinely tested and integrated through automated pipelines (e.g., unit tests, data validation checks, deployment builds). In ecological cyberinfrastructure, CI can improve reliability, reproducibility, and safe iteration of models and device software.
Cloud computing	Centralised, remote computing and data storage.
Cyberinfrastructure	The integrated hardware, software, and communications stack that enables distributed sensing, remote data collection, processing, and transmission in the field (including power management scheduling, and device integration).
Edge computing	A distributed computing paradigm in which computation occurs closer to the data source (e.g., on the sensor or a nearby microcomputer), reducing latency and bandwidth demands and enabling low-latency control actions (e.g., trigger based sampling).
Edge AI	The deployment of machine-learning models directly on edge devices for real-time inference locally (e.g., species detection, behavioural classification) and to trigger or prioritise actions without cloud dependency.
Event (in the ROAM context)	A predefined departure from expected conditions requiring attention or response. Events may be rule-based or baseline-relatives thresholds (here, "empirical"), or model-based (parameter shifts, forecast residuals, or changepoints).
Fog computing	A hardware that acts as an intermediary between the sensors and the cloud that provides additional compute, storage and coordination capabilities near the field site (e.g., a field-station with computers aggregating multiple sensors, running heavier models, and managing the network). A fog node is the device implementing this layer.
Human-in-the-loop	A design in which expert review and decision-making are explicitly integrated into automated workflows (e.g., validating detections, adjusting thresholds, authorising escalation, labelling training data, and updating burst protocols).
UAV/UAS	Uncrewed Aerial Vehicle / Uncrewed Aerial System, commonly known as "drones": an aircraft (UAV) plus the supporting system (UAS) including sensors, communications, and control software.
Inference (Ecology)	Drawing conclusions about ecological mechanisms or parameters (e.g., occupancy, abundance trends, treatment effects) from data (individuals in a statistical population) using explicit models.
Inference (AI/Machine Learning)	The generation of predictions from a trained model on new data (a forward pass). In deployment, inference cost is important, and typically integrates latency, memory use, and consumption, which constrains what can run on-device.
Multimodal monitoring	A monitoring design that integrates multiple data types or sensors (e.g., acoustics, imagery, eDNA, microclimate, telemetry), often with different error structures and temporal resolutions, to improve detection, attribution, and robustness.
Telemetry	The remote measurement and transmission of data from sensors or tags (e.g., GPS collars, acoustic modems), often under tight constraints on bandwidth, latency, and power.
Trigger	The operational criterion that initiates a response (e.g., increased sampling cadence, activation of a modality, or stakeholder alert). Triggers should be specified with measurable thresholds, a required duration and persistence, and (where possible) corroboration rules to reduce false positives.

Box 2. Technology for adaptive monitoring

While much of the focus has been on monitoring data streams (e.g. camera traps, acoustic monitoring, environmental DNA), emerging technologies such as edge computing, sensor automation, and AI-powered alert systems are particularly relevant for adaptive sampling. In particular, Edge AI—which performs computations near the data source rather than in centralized cloud servers(Singh and Gill 2023)—is promising because it enables new possibilities for coordination and re-allocating expert knowledge where it is needed most.

This fast-moving technology includes smart camera traps, such as those for insects (Roy et al. 2024; Bjerge et al. 2025) and ground-nesting birds(Chalmers et al. 2025), on-board classification and remote data transfer of particular behaviors (e.g. running) using telemetry on individual animals (Kerle-Malcharek et al. 2025), and smart inertial measurement unit (IMU) sensors to detect horse gaits using a neural network run on a microcontroller (Dominguez-Morales et al. 2021). AI-enabled autonomous drones are inherently adaptive, capable of modifying their flight path based on sensed data. Several cyberinfrastructure solutions now support autonomous operations, including WildWing (Kline et al.),WildLive (Dat et al.) and proposed IoT system to classify camera trap images onEdit with Zotero the edge using optimized ML models (Zualkernan et al. 2022). These could be expanded to support additional modalities, including drones, IMUs, and ARUs across different IoT devices, including Raspberry Pis and NVIDIA Jetson Nanos. Similarly, the 'acoupi' framework for bioacoustic AI models can be expanded or combined with other approaches to support a generalizable cyberinfrastructure (Vuilliomenet et al. 2026). Along with continued improvements in sensors, mobile hardware, power systems (e.g., AudioMoth and SongMeter can run for months in the field), and communication networks (e.g., 5G/6G and distributed computing (Singh and Gill 2023), adaptive sampling is becoming possible at scale for the first time.

Industry projects such as Microsoft's SPARROW project that packages solar power, camera-trap and acoustic sensors, and a low-energy GPU that runs PyTorch Wildlife models at the edge; only distilled results are beamed out via low-Earth-orbit (LEO) satellites, gives researchers near-real-time biodiversity alerts (Ferres 2024). Edge Impulse auto-optimizes hardware agnostic tiny ML models for a variety of edge hardware models, letting small teams drag-and-drop workflows and push them onto field devices, which has been used for poacher-detection and animal-call classifiers ("Improving Camera Traps to Identify Unknown Species with GPT-4o" 2024). The Conservation X Labs Sentinel platform includes a plug-in module that replaces the memory card in existing camera traps or acoustic recorders, runs on-device AI to flag rare species or poachers, and pushes SMS or email alerts over low-bandwidth links (https://sentinel.conservationxlabs.com/) Google Wildlife Insights closes the loop on the cloud side: its SpeciesNet models label camera-trap uploads in minutes, turning bulk imagery into species-level datasets that managers can act on quickly (Ahumada et al. 2020).

Hardware (sensors and compute):

Edge devices with low-cost processors (e.g., Raspberry Pi, Jetson Nano) now support field-ready AI, acting as intermediate processing nodes between sensors and cloud infrastructure. Low-cost compute devices, such as Raspberry Pi and NVIDIA Jetson Nano, enable practitioners to build smart sensors, custom designed for long-term outdoor deployment (Jolles 2021), while biologically-triggered sensor networks reduce storage and energy demands (Besson et al. 2022).

AI (models and edge deployment techniques):

Lightweight AI models deployed on the edge for animal detections (Beery et al. 2019), species classifiers (Stevens et al. 2024), and animal behavior models (Kholiavchenko et al. 2024; Chan et al. 2025), can trigger sampling events and data storage. Techniques like model pruning and quantization enable deployment on resource-constrained hardware (Eccles et al. 2024; Giovannesi et al. 2024), though field validation is needed.

Box 3. Barriers to adaptive sampling

Sociological and philosophical barriers

Sociological barriers stem from a fundamental resistance or hesitation to change in science in general, but also from a deeper epistemological problem linked to changing sampling designs specifically. How can we ensure valid inferences over time as measurement methods evolve? Systems theory, dating back to Von Bertalanffy (Bertalanffy 2008) recognized that feedback-driven adjustment was central to systematic inquiry. Early examples include Odum's (Odum 1969) energy-circuit diagrams for spotting feedback pivots and Tansley's ecosystem concept (Tansley 1935). Both anchored routine measurements tightly enough that purposeful deviations could be decoded. As scientific claims are made from within particular methodological frameworks, comparability requires some degree of protocol stability. When scientific frameworks enter institutional practice, however, this epistemological rationale is often lost. Long-term monitoring typically calcifies into fixed designs and plots—due, in part, to lacking frameworks for managing protocol change while preserving inferential validity—which prevents the flexibility and efficiency needed to adapt to the dynamic of nature's changes and evolving conservation needs.

An intimately related barrier to these sociological and epistemological concerns is statistical: modifying carefully designed sampling schemes risks violating random sampling principles (Henrys et al. 2024) or shifting baselines. Either can bias results, which could compound in successive iterations in updated sampling designs.

While technology cannot solve resistance to change, it can generate data or efficiencies (Box 2) that preserve original study designs while enabling flexibility, or it can improve communication of results/platforms that address statistical concerns. Emerging statistical methods address variable effort and biases across heterogeneous datasets (reviewed in Henrys et al. 2024), though integrated methods are needed (see remaining challenges).

Logistical barriers

Traditional ecological monitoring requires extensive field effort and offline processing. Protocol changes could require field trials that consume critical resources and require coordination among managers, staff, and technicians—often extending to multiple agencies, stakeholders, and policymakers. Permit revisions may introduce delays that undermine adaptive sampling objectives.

Technology, such as Edge AI (Box 2), could help ease the burden of communication in several ways. First, Edge AI could automate some of the steps of adaptive sampling with pre-defined criteria avoiding permit changes and federated and continual learning could iteratively improve deployed AI modes (Velasco-Montero et al. 2024). Second, Edge AI and networking technology could be linked to platforms that alert field teams via real-time dashboards, improving coordination across distributed teams. Third, updated data streams could be linked to data repositories, such as Movebank (www.movebank.org) (Kays et al. 2022) and GBIF (www.gbif.org) via application program interfaces (APIs) for rapid integration into downstream analytics, such as the creation of essential biodiversity variables (EBVs) and indicators. This near real-time feedback, if well designed, could streamline the process from detection to action, provide transparency for partners and regulators, support timely responses to biodiversity threats, and assist in monitoring compliance with conservation policies (Silvestro et al. 2022; Reynolds et al. 2025).

Technology can also offset the burden and workload of resource managers and technicians and even inspire others to join the effort. While adaptive sampling was traditionally the domain of professional scientists and managers, technology enables a wider breadth of engagement—meaning more public interest, more scientific interest, potentially and more funding. Birders can rush to the scene of a newly arriving migrant using eBird. Land managers can track predator behavior through collars and camera traps. At-risk species monitoring can use eDNA to detect species rather than waiting for a human detection. Managers can now receive automated text alerts from animals equipped with telemetry collars when potential birthing or mortality events are detected.

Introducing ROAM (Routine-Opportunistic Adaptive Monitoring): A tiered solution for adaptive sampling

Here, we introduce a hybrid form of adaptive monitoring—'Routine Opportunistic Adaptive Monitoring' (ROAM)'---that combines ***routine, long-term monitoring*** (Fig. 1) with ***opportunistic burst sampling*** (Fig. 2) using multimodal sensors and coordinated planning (e.g. through edge AI). This design captures both long- and short-term trends by pairing routine data collection with targeted inquiries, initiated either through automation or expert input, for either surveillance or targeted monitoring.

ROAM is meant to be general and usable for any monitoring network that employs some form of automated data collection (e.g. passive sensors) or has an active network of scientists and community members that can collect data. The key requirement is the ability to align systematically collected, long-term data streams with more flexible, targeted sampling. Networks such as the National Ecological Observatory Network (NEON) already implement elements of this hybrid strategy, and the expanding investment in this technology by agencies, NGOs, universities, and governments suggests broad potential for adoption.

Our approach differs from traditional adaptive monitoring (Lindenmayer and Likens 2009) in that it separates the data-decision loop into two parts—an outer loop, which maintains the integrity of the long-term, routine data collection for the study goals (or larger regional monitoring goals such as country-level reporting on indicators), and an inner loop, which allows for opportunistic data collection to pursue early warning signals or targeted questions as they arise.

The goals and data associated with the outer and inner loops would need to be defined on a case-by-case basis but often will align with monitoring goals and ecological scales (Fig. 3). The outer loop is more likely cross-taxa 'surveillance monitoring' that can detect abundance/occurrence/ecosystem shifts over yearly or decadal timeframes typical of indicator trends (Affinito *et al.* 2024; Hébert *et al.* 2025). The inner loop is typically more aligned with shorter-term ecological phenomena, such as individual behavior or hydrological events that could arise within one site, and with more 'targeted' inquiries. While these represent extremes, many questions fall in the middle (e.g. how does a forest thinning trial impact birds). A useful distinction is whether the data collected is an essential baseline for broad (typically long-term) monitoring goals or whether it is a more specific inquiry or more difficult or riskier where experimentation is needed. The real advances come from efficiently linking the scales (e.g. finding behavioral changes across species and ecosystems that could lead to changes in community-level abundance).

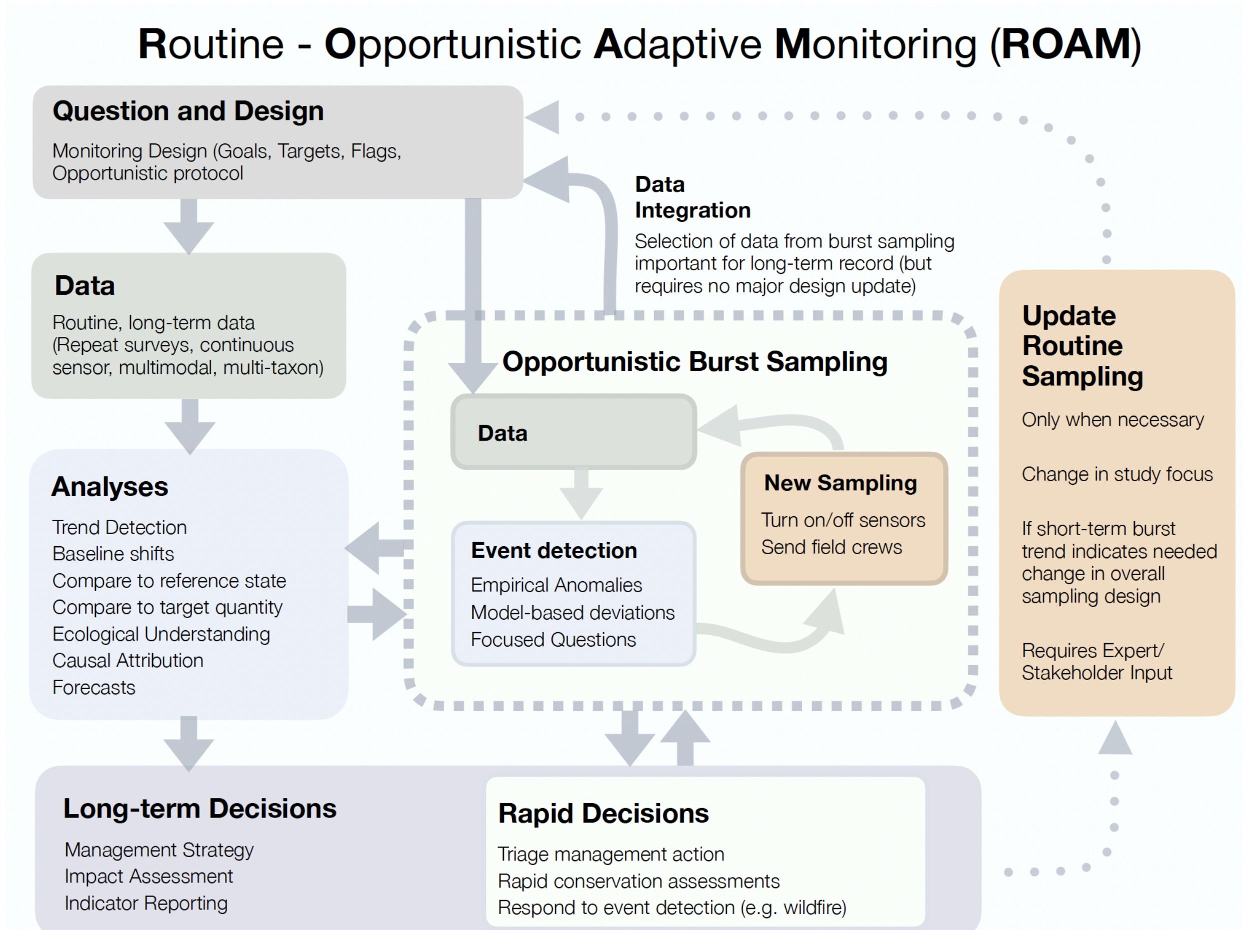

Figure 1. Overview of 'Routine - Opportunistic Adaptive Monitoring' (ROAM), which pairs a routine, long-term monitoring backbone (outer loop) with shorter-term opportunistic sampling (inner loop) to investigate anomalies, rapid ecological change or address conservation concerns. The outer loop is the classic approach to adaptive sampling, which requires clearly articulated goals (e.g. monitoring multi-taxon that match data collection and analysis, but is limited by relatively long times needed to detect trends and the ability to change sampling designs. The inner loop (typically, but not always more tech-focused) overcomes this inflexibility by isolating rapid data collection for short-term inquiries and sample design optimization (Fig. 2).

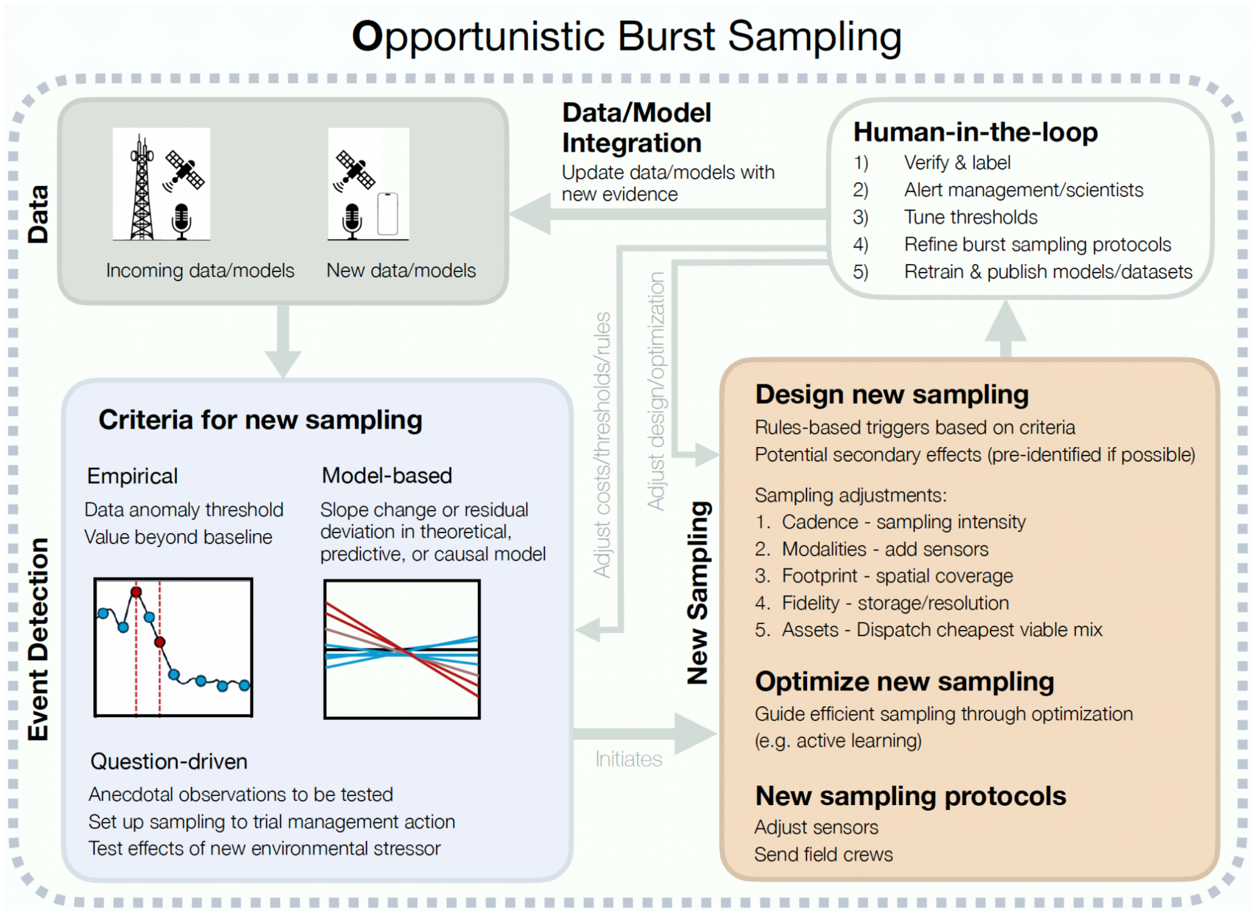

Figure 2. Opportunistic burst sampling is initiated based on automated event detection from routine (long-term repeated or continuous) data collection or monitoring needs (Fig. 1). Events can be empirical or model-based are pre-defined with respect to monitoring goals. Empirical flags surface unknown unknowns, while model-based flags reveal theoretically unexpected events (e.g., a slope change from a statistical model of the biodiversity trend through time or as a response to an environmental variable such as model quality; See Figure 3 for examples). The new sampling module summarizes initial data and implements a sampling plan according to programmed criteria and/or alerts biologists, managers or other stakeholders. This human-in-the-loop step can validate key events and can override policies (e.g., experts can verify and label events, route actions to stakeholders, tune thresholds and refine burst playbooks, and retrain/publish models and datasets with provenance). Over time, these updates also guide careful and strategic revisions to long-term sampling designs.

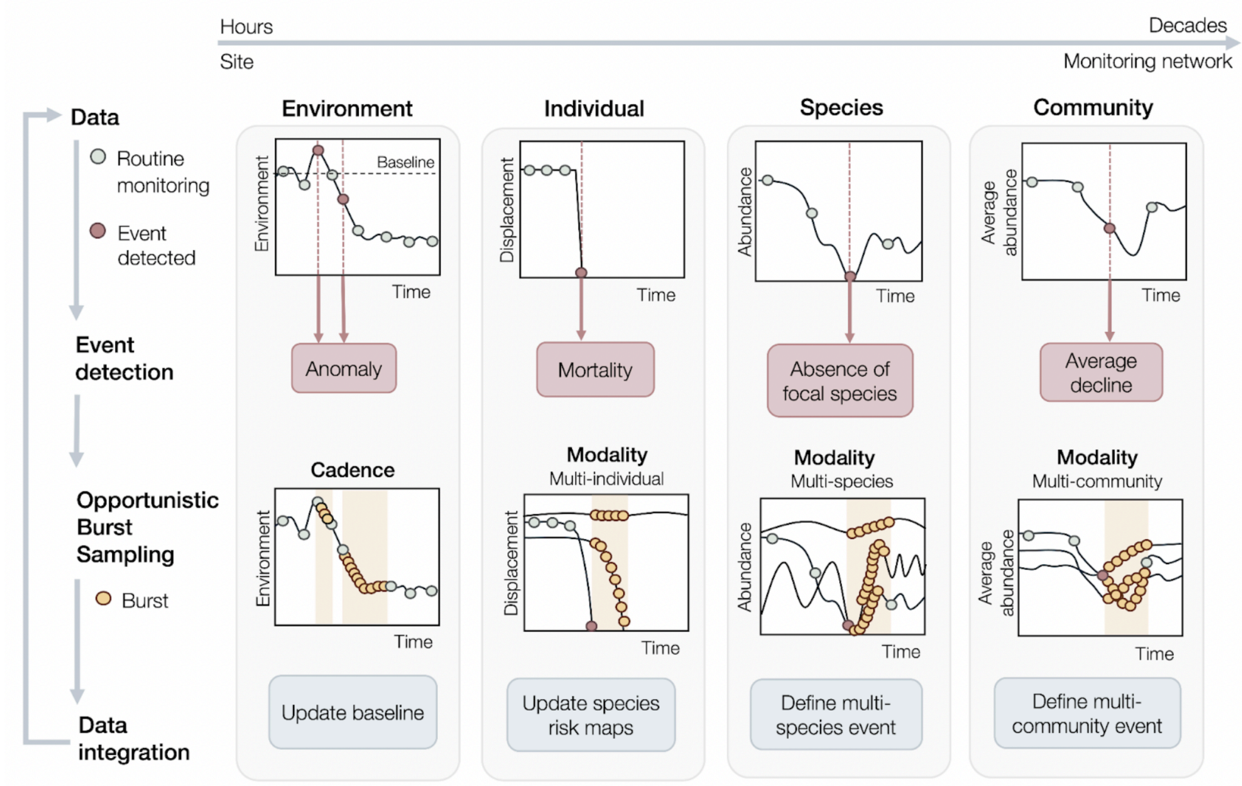

Figure 3. Linking monitoring to multi-scale signals of ecological change through the ROAM opportunistic burst sampling protocol. This example illustrates how this protocol could be applied to track environmental signals alongside changes at the level of individuals (e.g., displacement via movement tracking), species (e.g. abundance of focal species, via acoustic recorders), and communities (e.g. through a combination of species-level data into an average abundance metric). When events are detected, the opportunistic burst sampling protocol can trigger multi-modal sampling to link the levels of ecological organisation (i.e., going from individuals, to species, to communities) at “hot moments” and/or at “hot spots” of interest for the study system. This approach could provide a way forward towards de (sites to regional monitoring networks), and ecological organisation (individuals to communities).

Adaptive opportunistic sampling - the inner loop

The inner opportunistic sampling loop works by strategically collecting new samples when a new ‘event’ is detected (Fig. 2, Fig. 3). Events can be defined empirically (e.g.,outliers in data), relative to process baselines (e.g., departures from ‘normal’ conditions), or deviations from model-based expectations. Each reflects theoretical commitments about what constitutes meaningful change. We seek events through such constructs; what we detect may reveal genuine ecological processes. An event could be as simple as a set of three unrecognized bird calls (empirical) or as complex as a change in a slope parameter in an occupancy model that is being updated automatically based on incoming data (model-based). New questions that arise can also trigger adaptive sampling protocols (Fig. 2). Sampling is then initiated based on triggers, rules and dependencies and continues until a short-term trend (or lack thereof) is established (Fig. 3). For example, the detection of an invasive predator in a wide-lens camera could activate other cameras or ARUs to record any additional predators or prey and turn off when a pre-defined occupancy rate has elapsed. The inner loop is set up to be as efficient as possible to not exhaust or draw resources away from the outer loop long-term trend detection, but also to be the place to trial risky, expensive solutions. In some cases, efficiencies can be gained just from smart sampling for migratory or behaviors (e.g. dawn chorus birds or temperate bats), but in all cases efficiencies can be made from smart deployments of resources that are learned from sampling.

Adapting frequency versus increasing spatial sampling

Adaptive protocols can range from simple, automated changes to more complex multi modal responses across an entire region. Automated changes based on pre-defined rules will often be the easiest path to changing sample protocols, but even these automated changes will require work on how to best optimize for efficiency by balancing power use, data storage and probability of detection. The harder question is what to do if an interesting short-term trend is established, such as local occupancy of the invasive predator. Options would include more intensive, directed sampling, such as predator collars with acoustic and accelerometer capabilities to capture feeding events and prey selection (Studd *et al.* 2021) or issuing a 'rare predator alert' to community scientists in the area. This coordination could enable quick responses to emerging patterns by adjusting data collection across space and time–capturing "hot spots" (spatial variation) and "hot moments" (temporal spikes) (McClain *et al.* 2003). However, the protocols and optimization of new samples become much more complex and will require well-articulated goals and stakeholder input.

When should the inner loop inform the outer loop?

So far, adaptive sampling is restricted to the inner loop, but there are two ways that trends/findings from the inner loop could change the outer loop. First, data generated from the adaptive sampling protocols can be integrated with longer-term outer loop datastreams, but this integration is not trivial and risks swamping older data (see Challenges sections). Second, the overall long-term study design could, itself, be changed based on what is learned from the adaptive burst protocols. We recommend that this is only done in certain circumstances given the difficulties (Box 3) and the focus should be on the inner loop through automation, targeted field campaigns, and crowd-sourced initiatives. However, in some cases, inner loop sampling could strongly suggest changes in long-term monitoring protocols or even overall study goals (e.g. a new invasive species detected in the inner loop is causing a potential ecosystem state change). In other words, in some cases a deviation from expected conditions might represent a 'new normal' rather than an anomaly or stochastic event. In this case, expert and stakeholder input would be essential as the baseline layer maintains the critical ability to address long-term study goals (Fig. 1).

Adaptive monitoring for adaptive action

By deploying "bursts" of extra effort when transient events arise, and economy when conditions are stable, this hybrid scheme can deliver more accurate, efficient answers to the ecological and conservation questions we routinely ask (see Table 1 for case studies). The baseline layer maintains the ability to detect long-term trends while burst sampling aligns effort with urgent, shifting conservation priorities without sacrificing breadth. Practically, this design better connects monitoring to action and better matches institutional realities, such as funding cycles and reporting for 2030 targets without letting them wholly dictate epistemic priorities. This tiered approach also manages the conflict between discovery and diagnosis architecturally. The outer loop handles confirmatory trend detection while the inner loop enables exploratory inquiry (Box 3). The result is monitoring that can be simultaneously exploratory and relevant to decision-making.

Case studies

The case studies below are hypothetical monitoring designs intended to make ROAM operationally specific (Fig. 4). They are grounded in published methods and existing components (e.g., PhenoCams and microclimate sensing, high-frequency stream sondes, ARUs with automated classifiers, and event-triggered bio-logging) and illustrate how ROAM's inner and outer loops function across different monitoring systems. In each example, routine sampling baselines—such as vegetational greenness and degree-days, diel stream chemistry, regional acoustic surveys, or low-frequency bio-logging data—anchor the outer loop, providing continuity for trend detection and long-term inference. When anomalies or model departures occur, ROAM's inner loop temporarily intensifies sampling by increasing frequency, adding complementary monitoring modalities, and/or mobilizing observers for targeted data collection. These short bursts capture transient processes, including rapid phenological shifts (Case 1), biogeochemical nutrient pulses (Case 2), localized breeding activity of a declining species (Case 3), or early-warning signs of mortality and disease (Case 4), all of which could remain undetected under fixed-interval sampling designs. Together, these cases show how ROAM integrates discovery with diagnosis by allowing targeted, event-driven sampling without compromising consistent baselines required to quantify change through time.

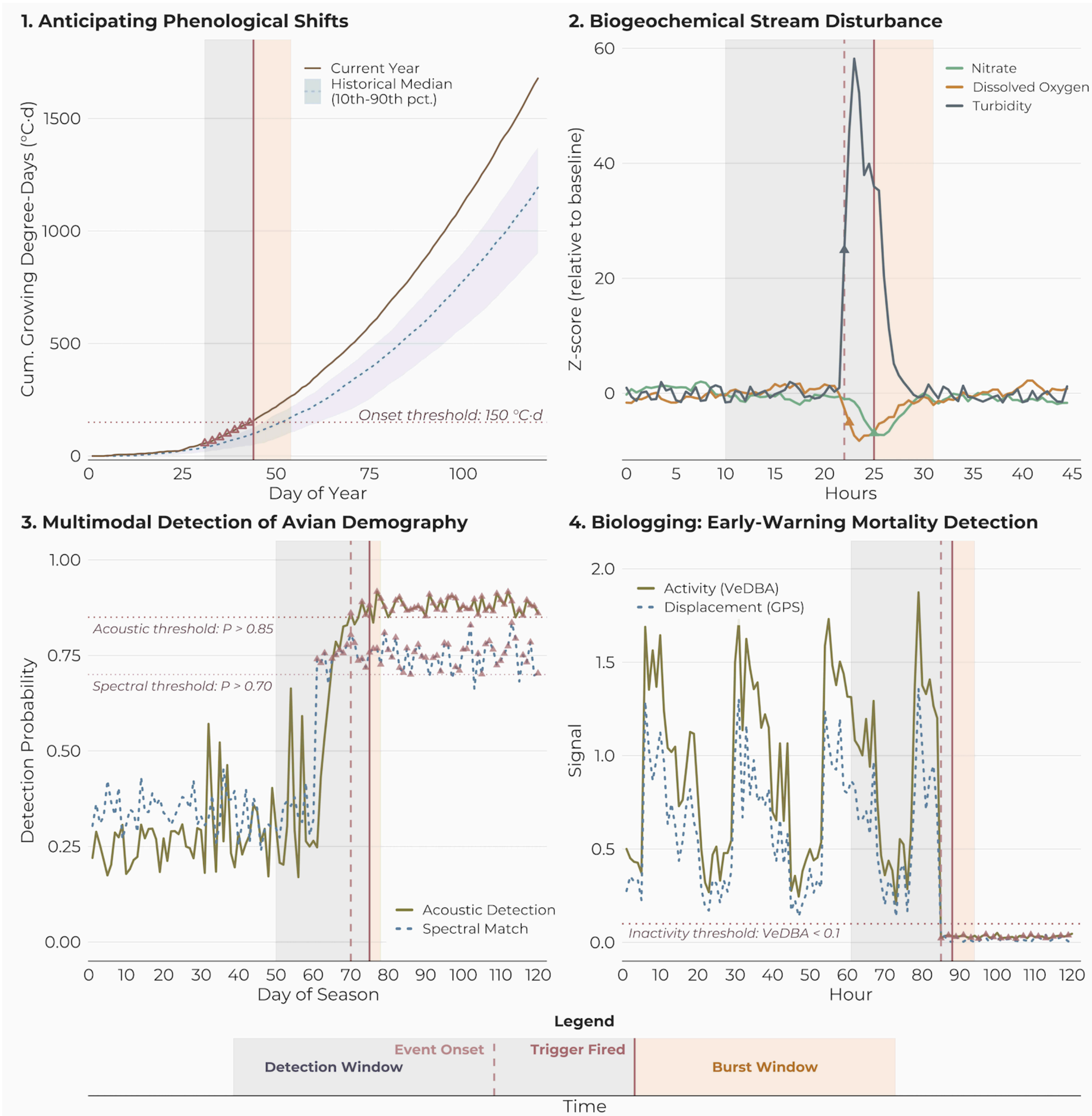

Figure 4. Case study examples of ROAM burst sampling protocols. When routine monitoring detects a predefined event (denoted by triangles), the system activates additional monitoring through automated responses (e.g., increased sampling frequency, additional sensors) and potentially human-deployed measurements. Events can include: (1) surpassing a threshold of growing degree days that indicates an upcoming phenological transition, (2) unexpected stream chemical or physical properties indicating nutrient pulse or disturbance, (3) multimodal evidence of breeding activity in declining bird populations, and (4) biologging signals suggesting mortality events. Burst sampling continues until predefined or updated termination criteria are met. The events and burst sampling period is then refined as data from burst sampling accumulates and is eventually integrated back into routine collection (Fig. 2).

Case Study 1. Anticipating phenological shifts

Phenology is critical for evaluating how climate change alters the timing of flowering, migration, and reproduction, with cascading effects on ecological interactions and ecosystems. Phenological transitions (e.g., leaf-out and flowering) can occur over days and vary strongly among microhabitats, making them easy to miss under fixed biweekly visits (Kudo and Ida 2013; Richardson et al. 2018). Even when paired with near-continuous imagery (e.g., PhenoCam; https://phenocam.nau.edu/webcam), anomalous early-season dynamics may remain undersampled, inflating uncertainty in climate-phenology attribution and limiting tests of microsite-driven mismatch hypotheses (Kudo and Ida 2013; Richardson *et al.* 2018).

Aim: Improve detection and dating of plant phenological transitions (e.g., budbreak, flowering, senescence) using opportunistic sampling.

Event detection: Long-term field visit records define median growing degree-day onset thresholds (Klosterman *et al.* 2014). Two complementary phenophase signals are monitored: (1) greenness chromatic coordinate (GCC) from PhenoCam time-series and (2) cumulative growing degree-days (GDD) from co-located microclimate sensors (McMaster and Wilhelm 1997; Schwartz *et al.* 2006). A burst is triggered when either the rolling z-score of daily GCC increase exceeds 2.0 for three or more consecutive days, or when cumulative GDD reaches the 10th percentile of the historical onset distribution earlier than the median year (Schwartz *et al.* 2006).

Opportunistic sampling: Triggers increase image frequency (e.g., hourly to 10-minute intervals) (Richardson *et al.* 2018) and activate edge-deployed, on-device phenophase classifiers for budbreak and first flower. To minimize false positives, the system requires corroboration via soil temperature increases above baseline (Li *et al.* 2022) and budbreak confirmations across multiple camera viewpoints (Klosterman *et al.* 2014). A subset of events can be verified through targeted field visits and trained observers (e.g., Nature's Notebook volunteers; (Fuccillo *et al.* 2015). Bursts terminate when GCC change rates decrease (Klosterman *et al.* 2014) or after the expected spring greening duration (5–15 days).

Expected outcomes: Targeted bursts can increase precision of onset dating by 1-2 days (Richardson *et al.* 2009), compared to 5-7 days under baseline-only sampling, decreasing residual mean squared-error and improving model fit for temperature and soil-moisture pulses and enabling mid-season calibration of degree-day models (De Pauw *et al.* 2000). Importantly, ROAM treats burst-derived onset estimates as high-information observations that are integrated into the long-term record with bias control, improving interannual comparability while reducing uncertainty where and when phenological change is most rapid. This same design generalises to leaf senescence, insect emergence, and other phenophases where optical and microclimate cues support classification.

Case Study 2. Biogeochemical disturbance in streams

Transient biogeochemical events (e.g., nutrient pulses, oxygen depletion or algal blooms) are can dominate downstream water quality and food-web dynamics, yet their timing and location are difficult to predict (McClain *et al.* 2003; Sprenger *et al.* 2019; Wilkinson *et al.* 2022). Fixed-interval grab sampling provides low-resolution snapshots and often misses "hot moments" such as diel oxygen excursions, hydrologic exchange events, or dissolved organic carbon pulses from leaf-fall or photodegradation (Bernhardt *et al.* 2018; Bi *et al.* 2021). Storm-centric monitoring programs can also lack the spatial resolution needed to localise hot spots across nested tributary networks.

Aim: Detect rare, high-impact stream disturbance events and localise their sensors using a nested ROAM sensor framework.

Event detection: Hourly nitrate (NO_3^-) and dissolved oxygen (DO) concentrations from multiparameter sondes established diel baselines at fixed-monitoring nodes (Bi *et al.* 2021), analysed using 24-hour rolling baselines and 7-day comparison windows (Fig. 4). To reduce bandwidth and power costs, on-logger (edge) processing evaluates two trigger logics. First, an acute disturbance triggers fires when NO_3^- declines exceed 40% along network distance with concurrent DO suppression beyond the diel envelope for two or more hours. These magnitude and duration thresholds reduce sensitivity to electrode drift and transient bubbles or debris (Damala *et al.* 2022). Second, a model-based trigger uses edge, on-chip harmonic regression to predict diel DO, firing when departures from predicted patterns exceed ~2.5 standard deviations for at least three consecutive timesteps (Rode *et al.* 2016; Heathwaite and Bieroza 2021). False positives (e.g., sensor biofouling mimicking DO depletion) are reduced by requiring multi-sensor corroboration (e.g., turbidity, conductivity, dissolved organic carbon proxies), consistency with expected propagation given flow and network structure, and exclusion of normal nocturnal DO minima (Bolick *et al.* 2023).

Opportunistic sampling: After validation, the opportunistic inner loop activates and sampling frequency increases from hourly to 15-minute intervals at the trigger node and adjacent stations to capture event dynamics. Spatial activation follows network topology, expanding to upstream or downstream nodes and sibling tributaries to bracket the anomaly source (targeting localisation within ~50 meters where feasible). Higher-cost modalities can be activated selectively, including UV-vis spectrometers for dissolved organic matter, eDNA autosampling for microbial shifts, and isotope-ready nitrate autosampling for process attribution. Bursts terminate when $NO3^-$ and DO return within ~1 SD of baseline predictions for 12 consecutive hours, or the the source is triangulated and the multimodal sample suite is completed. Where feasible, geofenced notifications can recruit trained volunteers for rapid field verification at predicted locations, scouting for iron-stained sediments, shimmering puddles, redox odours, or visible surface foams at confluences.

Expected outcomes: ROAM converts reactive monitoring into near-real-time surveillance, enabling capture and localisation of hot-moment events within hours that would be effectively undetected under weekly sampling. By concentrating analytical and field effort only when systems deviate from baseline, this approach can reduce uncertainty in annual nutrient flux estimates by observing short pulses that disproportionally contribute to mass export. Long-term value arises because burst-confirmed events are incorporated into flux and process models as explicitly detected episodic components, improving cross-year comparability of watershed function while clarifying when and where mechanisms shift. This framework can be applied to post-fire ash pulses (elevated conductivity and metals), disease-driven canopy losses (altered light and temperature regimes), or other event landscapes with characteristic multi-sensor fingerprints.

Case Study 3. Avian demographic response to management

Widespread avian declines in North America have motivated substantial investment in habitat creation and restoration, but monitoring effectiveness across large regions remains challenging within narrow breeding windows (Corace *et al.* 2010; Rosenberg *et al.* 2019). Autonomous recording units (ARUs) and automated bioacoustic classifiers can estimate presence, occupancy, and abundance and related these to habitat covariates (Czarnecki *et al.* 2024; Fiss *et al.* 2024; Larkin *et al.* 2024b; Chronister *et al.* 2025). However, occupancy-habitat relationships alone are often insufficient to evaluate management effectiveness, such as whether interventions increase reproduction and population growth.

Aim: Improve management interventions of declining songbirds by moving beyond simple occupancy toward fitness and population growth.

Event detection: For challenging cases where vocalisations overlap with heterospecifics and hybridisation occurs, such as the declining Golden-Winged Warbler (GWWA) that hybridises with the Blue-Winged Warbler, standard detection protocols are prone to false positives. ROAM uses edge-capable AI classifiers on ARUs to process daily 2-hour dawn-chorus recordings (Ralph *et al.* 1995) during phenology-informed windows across the breeding season (mid-May to late July in eastern North America). Acoustic detections serve as a conservative primary trigger (high-precision, potentially low-recall), but escalation requires corroboration by secondary modalities, such as camera traps positioned at focal perches near playback sources.

Opportunistic sampling: Upon plausible detection, the inner loop activates short, bounded bursts: playback devices broadcast GWWA song for brief windows (e.g., 10 minutes) while camera traps capture imagery for rapid on-device classifying and review and subsequent human-in-the-loop validation. Once adult presence is confirmed, playback and camera bursts are suspended at that location to reduce habituation and disturbance, while denser ARU arrays can be deployed by researchers to localise singing adult males and improve detection of fledgling calls. If confirmation fails within the burst window, devices power down and the system returns to baseline community monitoring.

Expected outcomes: This multimodal adaptive framework reduces false positives and ensures intensified sampling is spent on true occurrences, improving the efficiency of limited field capacity. Ensuring species presence through multiple data modalities before initiating intensified data collection protocols helps ensure that high-resolution data from localisation arrays contain signals of interest from focal species. By enabling localisation of territories and detection of fledgling begging calls, ROAM supports inference on whether restored sites function as population sources *versus* sinks and identifies microhabitat correlates of reproductive activity. Over the long term, these episodic confirmations can be integrated as validated breeding indicators within the monitoring record, strengthening trend analyses of restoration outcomes beyond presence-absence alone. This framework generalises to other taxa and systems where acoustic ambiguity limits management inference and effectiveness.

Case Study 4. Adaptive bio-logging of early warnings for mortality, reproduction, and risky crossings

Multi-sensor bio-logging supports fine-scale animal movement, habitat usage and behavioural inference but must balance sampling frequency against battery life and transmission costs (Wild *et al.* 2023; Ellis-Soto *et al.* 2025). Fixed GPS schedules and infrequent summary uploads can delay detection of mortality, disease, or reproduction by hours to days, limiting conservation response and obscuring behaviour during critical life-history stages (Yanco et al. 2024). As biologging expands globally (Davidson *et al.* 2025), on-tag edge computing can filter, classify, and selectively transmit high-resolution segments when triggered by behavioural or environmental cues (Kays and Wikelski 2023; Ellis-Soto *et al.* 2025). Commercial systems already support motion-based mortality alerts (e.g., VERTEX Plus collars), making event-driven escalation increasingly feasible.

Event detection: On-tag algorithms monitor multiple sensor streams: GPS displacement, VeDBA (vectorial dynamic body acceleration) tri-axial accelerometer variance, skin and ambient temperature differentials, gyroscope data, and deviation from individual baselines. Detection windows vary by application: sub-daily for rapid responses (e.g., snaring or poaching), daily-to-weekly for behavioural classification and nesting-site identification (Donovan *et al.* 2024), and multi-day windows for disease signature or outbreak surveillance (e.g., Morelle *et al.* 2023; Talmon *et al.* 2025). Triggers target (1) prolonged inactivity with no displacement (suspected mortality), (2) localised activity with limited displacement (reproduction), (3) sustained activity reductions relative to baselines (disease), and (4) projected trajectories intersecting mapped risk zones. For group-living species, triggers can incorporate clustering of synchronised anomalies within a shared area. False positives are reduced through dual-sensor corroboration, species-specific rest patterns, seasonal baselines, laboratory experiments (e.g., accelerometry inferred from behavioral states or energy expenditure), and targeted field validation.

Opportunistic sampling: When triggered, GPS fix rates increase from coarse to fine-scale intervals (e.g., hours to minutes), and high-frequency accelerometer and gyroscope data are stored on-board. Full-resolution data upload when high-bandwidth links (LTE or WiFi) become available; otherwise, reduced-resolution features or behavioural summaries are transmitted via GSM, Iridium, or Argos (see Noda *et al.* 2024). This adaptive strategy minimises battery and bandwidth costs while retaining information on critical episodes. Nearby devices (e.g., cameras, acoustic units, or other tags) can be activated to capture collective behavioural responses to environmental events (e.g., natural disasters; Kays and Wikelski 2023). Bursts terminate when movement resumes above threshold for a specified period, the individual safely clears a risk buffer, or a maximum burst duration is reached.

Expected outcomes: ROAM turns bio-logging into an early-warning layer for adaptive management, enabling faster intervention for mortality, disease, and human-wildlife conflict risks than fixed-monitoring schedules allow. Long-term value derives from selectively preserving high-resolution critical episode data while maintaining deployment longevity, improving inference on behaviour near risk zones, disease onset trajectories, and reproductive timing. These burst-sampling resolved episodes can be incorporated into long-term demographic and hazard models as explicitly observed event segments, strengthening trend estimation and management evaluation. This approach is transferable to marine tags, avian migration stopover assessment, and large-carnivore conflict mitigation, where early detection and targeted classification can reduce both ecological and logistical costs.

Table 1. Examples of the ROAM framework in four case studies: phenology, disturbance and water quality, wildlife bioacoustics, and movement ecology (see "Study cases" section). For each case, we summarise the long-term monitoring objective, the baseline monitoring design (outer loop; Fig. 1), the hot spots and/or hot moments targeted by the Opportunistic Burst Sampling protocol (inner loop; Fig. 2), event-detection logic and trigger criteria, the Burst protocol strategies (Fig. 2), and the role of humans in the loop(s).

	1. Phenology	**2. Disturbance & water quality**	**3. Wildlife bioacoustics**	**4. Movement ecology**
Long-term monitoring objective	Vegetation phenology	Water quality status, fluxes, and restoration outcomes	Bird community surveys and management evaluation	Real-time risk, mortality, and demography-relevant events
Baseline monitoring design (outer loop)	Near-continuous imagery with routine field checks	Fixed sondes with routine grab samples	Daily dawn-chorus recordings across a landscape grid with automated species classifiers (edge or near-edge processing)	Low-frequency GPS summaries from with on-tag storage of high-resolution segments
Hot spots & hot moments targeted (inner loop focus)	Rapid phenophase transitions and microclimate-driven asynchrony	Temporal (pulses, diel excursions) and spatial (source localisation) moments	Focal species occurrences, ambiguous detections, and breeding indicators	Mortality or illness signals, risk crossings, parturition, or denning-related behavioural shifts
Event detection and trigger	**Hybrid empirical rules** from slope, z-score, and thresholds relative to historical onset	**Model-based departure** from from predicted diel and seasonal envelopes plus multi-sensor	**Conservative empirical trigger** with high-precision classifier detection or corroborated anecdotal	**Hybrid empirical and model-based** using inactivity and mortality flags, abrupt movement

	1. Phenology	2. Disturbance & water quality	3. Wildlife bioacoustics	4. Movement ecology
		corroboration	observations of focal species paired with escalation requiring secondary confirmation	shifts, and proximity to hazards
Burst protocol strategies: cadence, modality, and footprint	- Cadence: increased image capture - Modality: activate on-device phenophase classifier; add targeted human visits for verification	- Cadence: increased sampling frequency at and near trigger-node - Modality: briefly activate selective high-cost modalities (UV-vis, eDNA autosampler, isotopes) - Footprint: Expand sampling in neighbour sites, along topology	- Modality: activate playback, camera traps - Footprint: deploy denser ARU micro-arraws for localization and fledgling-call detection	- Cadence: increase fix rate - Fidelity: increase sensor fidelity - Footprint: transmit high-value segments only; trigger rapid-response verification
Termination criteria	Until the GCC change rate slows OR burst window elapsed	Sustained return to baseline envelope OR the disturbance source localised and multimodal samples completed	Occurrence confirmed OR if repeated triggers fail within a spatial/time burst window	Distance from risk zones is reached OR event resolved OR until the burst window is elapsed
Human-in-the-loop	Verify and label events, adjust thresholds, targeted verification	Validate, adjust model/envelope parameters, alert management	Confirm detections, manage disturbance constraints, decide escalation to reproduction inference sampling	Respond to mortality/risk alerts, adjust geofences/thresholds, decide intervention
How burst outputs inform the long-term record	Burst-refined transition dates become high-information observations for trend models; preserve comparability via explicit burst flagging/weighting	Burst-captured pulses enter flux/process models as explicit episodic components; improves cross-year comparability of export estimates	Confirmed breeding indicators augment long-term management evaluation beyond occupancy alone	Validated events become structured endpoints for demography/risk trend analyses

Remaining challenges and call to action

Our hybrid approach combines dynamic, actionable data collection with the goal-oriented approach long advocated by traditional adaptive monitoring.

The breadth of rapid ecological responses of ROAM's opportunistic inner loop are highlighted by the case studies. Adaptive sampling can uncover links between anomalous climatic conditions and phenological shifts, detect critical hydrological or nutrient pulses, pinpoint microhabitat features that facilitate successful reproduction in declining species, and clarify how thermal stress, energetic deficits, or landscape hazards give rise to mortality or diseases signatures in bio-logging data. This ability to attribute observed trends to underlying causes is especially valuable.

The ROAM framework also addresses a broader conceptual frontier: the opportunity to borrow strength not only across space and long-term datasets, as is traditionally done, but across diverse data streams operating at different, and increasingly fine temporal resolutions. Integrating such heterogeneous, rapidly collected information is essential for making full use of burst sampling's diagnostic power—but it also exposes the system's operational and analytical limits.

While the value of hybrid adaptive monitoring is evident, successful implementation depends on coordinating sensing, computation, and decision-making in real time. Our case studies reveal common challenges: defining reliable event triggers, synchronizing multimodal data streams, maintaining rapid-response capacity, and balancing automated detection with human validation. Persistent constraints—limited budgets, permitting delays, staffing shortages, and equipment maintenance—restrict how intensively burst sampling can be deployed. To fully realize ROAM's potential, five coordinated advances are essential: (1) technological infrastructure for real-time coordination across distributed networks (e.g., edge compute), (2) integrated statistical frameworks with clear guidelines for trigger design, model selection, and sampling optimization, (3) methods for incorporating high-frequency burst data into long-term records while addressing sampling bias, (4) strategic design of short-term monitoring to address explicit ecological questions, and (5) equitable technology transfer through open-source tools and funding models that extend capabilities beyond well-resourced institutions.

1- Better technology and coordination

Advancements in sensors—camera traps, acoustic recorders, biologgers, drones, mobile apps—enable adaptive protocols through programmable sampling schedules adjusted before or during deployment (Box 2). For example, bioacoustic devices can target dawn and dusk choruses rather than recording continuously, conserving memory and battery. Projects like Sentinel (Conservation X Labs) and SPARROW use edge-deployed machine learning to detect and classify species in real time, filtering blank images at the source. This Edge AI can trigger adaptive responses, such as extending recording time when rare species are detected. While Edge AI promises to revolutionize ecosystem monitoring by enabling scalable real-time adaptive sampling, integrating heterogeneous data from multiple sensor types presents computational challenges. High-quality training datasets, active learning, and few-shot fine-tuning are critical for building versatile detection models that generalize across ecological settings and can be efficiently deployed on resource-constrained edge devices.

Realizing this vision requires user-friendly, scalable cyberinfrastructure that integrates diverse sensors, species, and ecological contexts. We encourage multidisciplinary collaboration among ecologists, biodiversity researchers, edge AI developers, and distributed systems engineers to build next-generation infrastructure for adaptive ecological monitoring. These efforts should leverage the application-driven machine-learning framework (Rolnick *et al.* 2025), ensuring that new systems are tailored to end-user needs and support expert human-in-the-loop control. Federally-funded research organizations, such as NSF's Sage (https://sagecontinuum.org/) and ICICLE (https://icicle.osu.edu/), have made strides in this direction. Sage's continuous-integration (CI) workflows have supported autonomous acoustic monitoring (Dematties *et al.* 2024), air-quality sensing (Balouek-Thomert *et al.* 2023), and wildfire modelling (Altintas *et al.* 2022). ICICLE's CI tooling, in turn, helps teams plan field-deployable ML pipelines (Stubbs *et al.* 2025) and understand the unique systems requirements of AI-enabled camera traps and drones for ecological studies (Kline *et al.* 2024).

Broader application will require better AI tools and wider accessibility across sectors. Imagine NGOs, land managers, or wildlife biologists being able to trigger real-time sampling to answer site-specific questions, rather than relying entirely on the sensors themselves. This co-adaptive approach avoids pure techno-optimism—the idea that advanced sensors alone can resolve longstanding knowledge gaps (see Buchanan 2024; Smits *et al.* 2025). We recognize that even bleeding-edge instruments integrated with AI cannot, on their own, detect the subtle, context-dependent signals of ecological change (Van Stan *et al.* 2023) or or fill global biodiversity data gaps (Pollock *et al.* 2025). Progress instead lies in integrating cutting-edge technology with targeted human engagement at key inflection points. This human-technology partnership enables faster, more precise responses. Finally, hybrid adaptive monitoring is most useful when embedded within the greater ecosystem of regional and national conservation efforts. The use of technologies described above means that interoperability is built-in, greatly facilitating coordination, data and model sharing with existing integration platforms, such as GEO BON's Bon-in-a-Box (Griffith *et al.* 2026)--turning adaptive monitoring into actionable insights.

A practical ROAM cyberinfrastructure treats energy as a priority constraint: burst decisions must be co-optimized with battery state, energy harvesting forecasts, and communication costs so that opportunistic escalation does not compromise long-term continuity. Often the main constraint on edge is power. This implies burst sampling protocols should include: (1) an explicit energy budget (e.g., maximum burst duration given current charge); (2) whenever applicable, filtering and summarization (at the sensor or at the edge) to reduce transmission costs when connectivity is energy hungry or resource limited; and (3) opportunistic scheduling of energy-intensive actions (such as drone activation or high-frequency, high-resolution data gathering) when recharging or harvested energy is sufficient. Some of the infrastructure needed to enable an effective power-aware sampling already exists, including solar-powered devices with edge inference and low-bandwidth satellite uplink (e.g., SPARROW), autonomous drone recharging (ElSayed *et al.* 2022), optimized routing and trajectory (Coutinho *et al.* 2018). Such systems-aware ROAM improve ecological responsiveness while remaining operationally sustainable over seasons and funding cycles, provided maintenance costs could be funded.

2 – Developing and adapting methods and decision rules

While hybrid monitoring may not require entirely new statistical foundations, applying existing methods in this context demands rigorous evaluation and sometimes novel approaches. Integrating diverse data streams and adaptive sampling raises challenges in event detection, counterfactual inference, and detecting trends across different timescales linked to distinct goals (surveillance versus targeted monitoring). These challenges are compounded by ecological data's inherent autocorrelation, bias, and sparsity, especially of multi-modal datastreams.

New methods are needed to incorporate real-time feedback, quantify uncertainty under shifting sampling designs, and prevent high-frequency bursts from obscuring long-term patterns. Building these methods requires integrating statistical innovation, ecological knowledge, and stakeholder objectives to detect both short-term "pulse" events and sustained change.

Event detection can use empirical threshold rules or model-based approaches that update as data arrive and flag parameter changes warranting response. Events can be defined relative to baselines (surveillance) or specific hypotheses (targeted monitoring).

Trend detection methods are well-established for long-term ecological data, but must be adapted to identify when anomalies become trends, particularly across multimodal datasets. Traditional techniques—changepoint analysis, moving-window tests—need evaluation for autocorrelated data with time-varying sampling effort. Machine learning approaches for extreme events (Gonzalez-Calabuig *et al.* 2024; Camps-Valls *et al.* 2025) offer promising directions.

Sampling optimization following event detection remains underdeveloped. Simple pre-programmed rules can automatically activate sensors, but there is great potential in a truly iterative approach to collecting new samples. New sampling can be optimized based on information gain, minimizing costs, and reducing model-based uncertainty (Chadès et al. 2017; Callaghan et al. 2019; Henrys et al. 2024). The value of additional samples can be estimated using Bayesian or information-theoretic approaches, especially if the goal is to reduce model uncertainty. Reinforcement and active learning can also be used to select new samples (Chapman et al. 2023; Xu et al. 2025), especially for real-time dynamic updating, though these methods have limited capacity for addressing uncertainty.

3 - Integrating recent high frequency data into the long-term record

We urgently need cohesive long-term records of populations, species, and ecosystems, so a key question is when and how to update the long-term record with incoming data. This question extends beyond adaptive sampling to any case where recent, high-frequency data is combined with a sparser historic record (Fig 1). Here, machine learning methods might be less useful as estimating uncertainty in long-term trends is critical, although they can be useful for detecting nonlinear patterns. Bayesian methods of model integration are likely the most helpful when data are tied to a particular management decision and methods from structured decision-making (Martin et al. 2009) can be followed. A growing field of model integration for multimodal data (Isaac et al. 2020; Herrera et al. 2025) offer promising strategies for effectively combining diverse data streams, but essentially these average data in different ways, and, in some cases, data might be too different or biased for these techniques.

Hybrid monitoring could introduce new forms of bias that can arise specifically from targeted sampling. Burst sampling may also amplify existing biases because different modes of data collection can have different biases. For example, an easily detectable species could repeatedly flag new sampling, which over time could propagate into the overall trend record. Autocorrelation between populations, areas, and data types is also an important issue that is known to influence trend detection (Hébert and Gravel 2023; Johnson *et al.* 2024). These concerns are not trivial and could lead to systematic errors in long-term trends with the influx of high frequency data that is biased in different ways.

4 - Anchoring technology in goal-oriented monitoring

Rather than post-hoc model integration, a better way to orient new data streams better into the long-term record is to set clear goals for the inner loop that anticipate anomalies or stochastic fluctuation becoming trends. As we have argued here, the barriers for adaptive sampling are being addressed for the inner loop much more rapidly through technology than for long-term monitoring programs, which requires sustained government and other funding, sustained political will, and a long-term commitment by a variety of stakeholders (reviewed in Lindenmayer et al. 2022). But given the rapid rate of technology changes, short funding cycles, we anticipate many situations in which new technologies are being deployed without an existing overarching design (i.e., no outer loop). This is because evidence can only accumulate against a stable ontology: we cannot learn whether X causes Y if the measurement of X keeps shifting. The outer loop stabilizes the ontology (i.e., defining what counts as events, units, and counterfactuals) while also specifying the baseline sampling rule so that deviations from it (and opportunistic burst data) remain interpretable as a signal rather than sampling artifact. We urge any deployment of new sampling to keep in mind clear study goals and link to the goals of relevant regional monitoring.

5 - Technology Transfer

Defining a hybrid network such as ROAM is only the first step. An important aspect of this work is to create a path to technology transfer that aligns with the needs of the ecology and conservation communities. Technology transfer involves many facets, such as coordination, accessibility by and training of operators, cost concerns (both deployment and operation/maintenance), adoption issues (target population, size of monitoring systems, and ease of system adaptation), intellectual property, organizational and cultural barriers, regulatory and legal concerns, and ethical issues.

The ecology community is well poised to enable such technology transfer, given that many of the tools are open source (both academia and industry). Nevertheless, there is a lack of standardization in data formats, not all projects follow FAIR principles or are AI-ready, many open source tools are not modular or industrial strength, and the acquisition and distribution of datasets is still lacking. These challenges make it difficult to train and develop new models.

Some projects are already making inroads towards remote ecological monitoring such as the SPARROW, NEON, and SAGE. These systems typically connect sensors to transmit data to centralized cloud servers through satellite or cell connections. In some settings, the challenge becomes the cost of these sensor nodes when they are not subsidized by industry or governmental agencies. Cost does not necessarily mean financial resources but can also be deployment, installation, management, training, power source, connectivity, and sensor suite, among others. In that sense, this technology is only available to well-funded institutions.

Academic projects in science and engineering have proposed low-cost solutions, which need to be further developed in multidisciplinary teams and deployed in real world environments. Creating a path from such academic projects in laboratories to transferring the technology to actual large-scale deployments will benefit lower-income nations, institutions, and projects. Further, sometimes such lower-cost nodes are also more sustainable, given the fewer resources they consume. New technology does have the potential to address social progress and local communities needs, especially if a participatory approach is taken (Bondi *et al.* 2021). Ultimately, we need technology that works easily, intuitive interfaces, and training for managers and the community to leverage these advances.

Conclusions

Technology gives us the opportunity to finally monitor biodiversity and inform management and conservation flexibly, relatively and at scale, but the integration required to do this is not going to happen automatically. It requires intention. ROAM (Routine-Opportunistic Adaptive Monitoring) couples prolific data collection efforts with monitoring principles designed to detect long-term population and ecosystem trajectories that can disproportionately influence ecosystem function and species demographics. While there are big challenges in developing the technology itself (methods development, infrastructure, and data collection), accessibility to the technology and training are essential for widespread adoption, especially improved access to open-source platforms, training and equitable funding models for democratizing adaptive monitoring beyond well-funded institutions. With these advances, ROAM can improve early warning systems for ecological tipping points, optimize the timing of management interventions, and fundamentally increase the return on investment in monitoring networks.

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