Designing optimal biodiversity observation networks

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Abstract: Meeting the goals of the Global Biodiversity Framework (GBF) requires a substantial increase in biodiversity monitoring effort, motivating the development of a Global Biodiversity Observing System (GBiOS). However, GBiOS cannot be built without a practical framework for designing effective biodiversity monitoring networks that balances budgetary constraints with competing policy objectives, which we currently lack. Here we provide the foundations for a theory of optimal biodiversity monitoring design based on: (1) a hierarchical, multi-layer architecture for monitoring networks that matches the multi-scale nature of ecological processes and environmental policymaking, (2) a simulation-based framework for evaluating the efficacy of monitoring network design against the variety of plausible "ecological worlds", and (3) an integrative toolbox for monitoring design, drawing on methods from spatial sampling theory, environmental monitoring design, and optimal decision theory. Together, these form a basis for building the most effective GBiOS possible to best inform policymaking and meet the goals and targets of the GBF.

Keywords: optimal monitoring, biodiversity, global biodiversity framework, essential biodiversity variables, essential ecosystem service variables

Introduction

To counteract threats to biodiversity and the ecosystem services that humanity needs to survive and thrive (Cardinale et al. 2012), the UN Convention on Biological Diversity (CBD) met in 2022 and established the Kunming-Montréal Global Biodiversity Framework (GBF). This agreement hinges on the GBF's Monitoring Framework, which requires parties to the GBF to report a set of biodiversity indicators that quantify various aspects of biodiversity and nature's contributions to people. The ability of data to inform policy making is often hindered by the massive geographic and taxonomic gaps in biodiversity data (Hortal et al. 2015, Hughes et al. 2021, Affinito et al. 2025). The urgent need for improved ecosystem monitoring has driven calls to develop a Global Biodiversity Observing System (GBiOS; Gonzalez et al. (2023a)), inspired by the success of the Global Climate Observing System's ability to provide nearly real time data to relevant parties. To implement a GBiOS that can provide scientifically robust estimates of progress toward GBF targets, we need a methodology for monitoring design to decide where and when to collect biodiversity data, and what type of data to collect, to best inform our understanding of the diversity of life on Earth, to detect when and where biodiversity change is happening, and to attribute this change to causal drivers, following Gonzalez et al. (2023b).

Biodiversity monitoring programs are limited by the pragmatic realities of budgets and logistical constraints on data collection. We can't sample every location at every time, so how do we decide where and when to collect data to best inform our understanding of the status and trends in biodiversity? Monitoring is expensive, so we can only feasibly collect *in situ* data at a small number of places relative to the size of Earth's terrestrial, freshwater, and marine ecosystems. Biodiversity monitoring is therefore an optimization problem where the goal is to select sampling sites that maximize the useful information we obtain from the locations we deliberately choose to sample. While existing tools can solve the problem of a single objective in a single jurisdiction, they do not sufficiently scale to identify efficient sample designs across objectives and ecological and political contexts. Selecting the most informative locations to collect biodiversity data is crucial to building a GBiOS that provides as much actionable information as possible under budgetary constraints, but this requires an integrated and comprehensive theory of optimal biodiversity monitoring that doesn't currently exist. This is both a *people problem* (creating the organization and infrastructure to tackle this massive challenge) and a *scientific problem* (because we lack methodology for multicriteria monitoring design that can adequately answer a variety of scientific and policymaking questions).

The need for a theory of optimal biodiversity monitoring comes at a time of rapid and fundamental change in how we collect data about biodiversity (Pollock et al. 2025). Satellite-based remote sensing can massively scale up monitoring programs (Cavender-Bares et al. 2022), and modern methods for *in situ* species detection (Turner 2014) have the potential to enable real-time biodiversity monitoring (Wall et al. 2014). The explosion in methods for automated detection of species from camera traps (Yu et al. 2013, Schneider et al. 2019), bioacoustic sensors (Salamon et al. 2016, Van Doren and Horton 2018, Buxton et al. 2018, Lostanlen et al. 2019), and eDNA (Rees et al. 2014, Ruppert et al. 2019) have the potential to monitor biodiversity at scales unfathomable only a few decades ago. But to enable the full potential of these tools, we need to be confident in where we choose to place these sensors to obtain as much useful information as possible (Erickson et al. 2019).

A comprehensive theory for optimal design of biodiversity monitoring systems is urgently required to track progress toward the goals and targets set by the GBF and ensure our assessments of this progress are scientifically robust, and guide environmental policymaking. Gonzalez et al. (2023a) articulated the need for GBiOS; here we provide the foundation for its design to provide statistically credible estimates of the state of biodiversity in three parts. First, we formulate a hierarchical, multi-scale framework for designing biodiversity monitoring programs to both inform local and regional scale policymaking and report indicators to the GBF. Second, we construct monitoring design as an optimization problem and propose a simulation-based framework for evaluating candidate designs to ensure they are robust in practice. Finally, we summarize the tools and methods (taken from a variety of fields) that can inform design into a concise toolbox for optimal biodiversity monitoring design. Together, this framework provides the basis for a comprehensive theory of optimal biodiversity monitoring design to enable the implementation of the Monitoring Framework and meet the goals and targets of the GBF.

A Multiscale Theory of Biodiversity Monitoring Design

For GBiOS to be effective, it must both (1) provide adequate data for Parties to the GBF to report monitoring framework indicators that comprehensively quantify the state of ecosystems, their contributions to people, and conservation actions being implemented (Affinito et al. 2024) and (2) inform data-driven policymaking at different scales of governance. To report these indicators and use them to guide policy, nations must develop biodiversity monitoring systems, but they face significant challenges developing systems capable of robustly reporting indicators due to the practical constraints of limited budgets and the numerous logistical challenges involved in collecting biodiversity data.

Environmental policymaking happens at several scales of governance, from local municipalities to global frameworks. Simultaneously, biodiversity is the product of ecological processes interacting across different spatial and temporal scales (Levin 1992), which accumulate uncertainty when aggregated to the level of national indicators. To address the multi-scale nature of monitoring biodiversity, Gonzalez et al. (2023a) proposes a GBiOS composed of a confederated system of Biodiversity Observation Networks (BONs), which are networks of sampling sites and the people who collect and use this biodiversity data for decision making and action. BONs can vary in their scale of governance (national, subnational, regional, local), and scope (type of taxa, ecoregions, and data type). Pragmatically, BONs must be organized to both (i) enable the logistical management of monitoring sites and (ii) inform policymaking at scales that align with governance.

We formulate the structure of multi-scale BONs as composed of four different types of nodes (Figure 1): **(1) Hubs**, which manage the BON at the scale at which governance happens (e.g. subnational governments; states/provinces where applicable), and therefore have *administrative* boundaries, **(2) Ecoregion Sentinels**, which manage field stations within an ecoregion/habitat of interest, and therefore have *environmental* boundaries, **(3) Field Stations**, which implement the logistics of data collection, field surveys, and sensor deployment and maintenance within a given *region of responsibility*, and finally **(4) Monitoring Sites**, the actual places data is collected in different forms (e.g. field plots, camera traps, acoustic sensors, eDNA filters, etc).

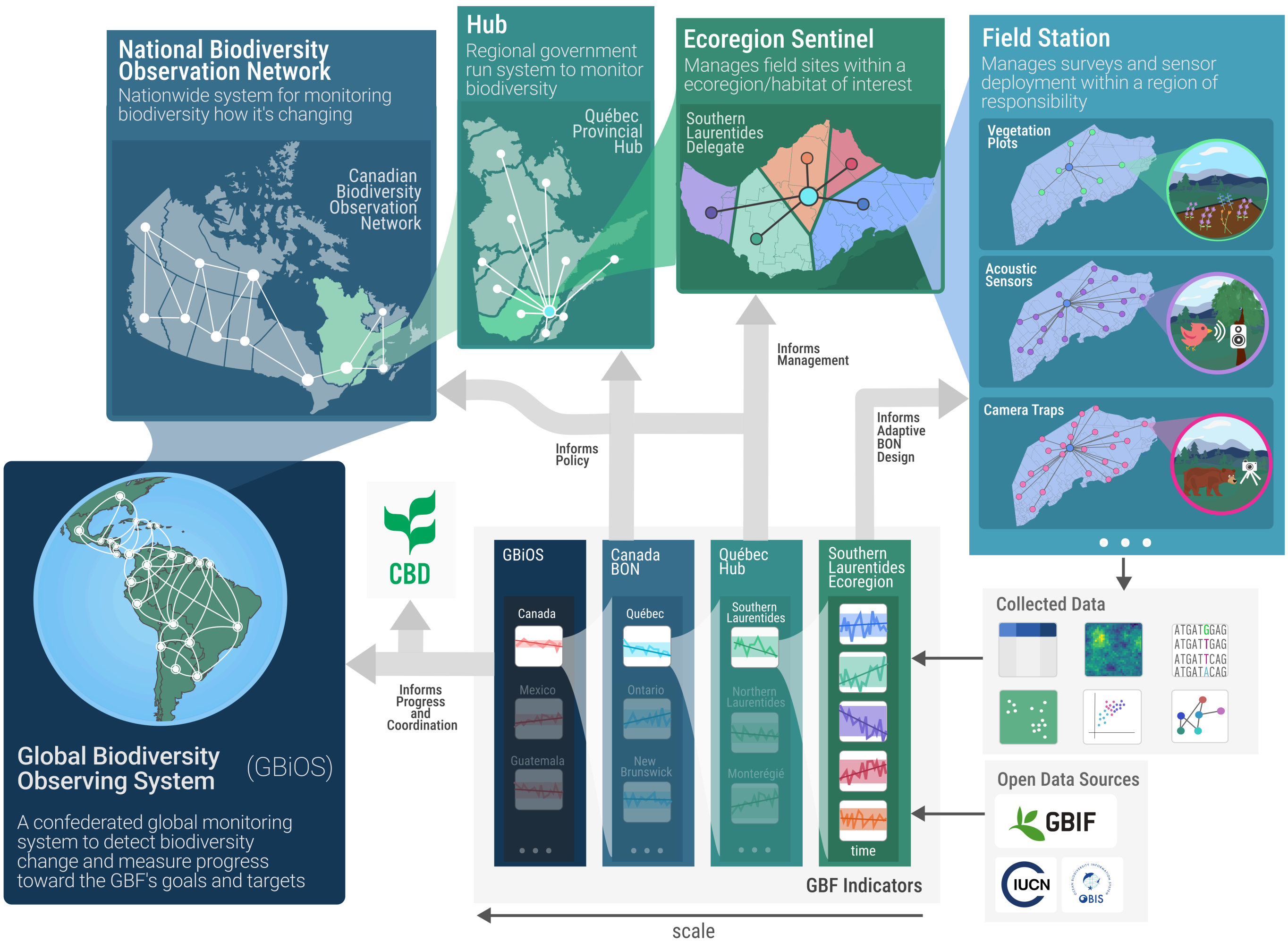

Figure 1
A hypothetical hierarchical design of a national Biodiversity Observation Network (BON) for Canada. Data collected from monitoring sites is then aggregated to form Essential Biodiversity Variables (EBVs; Pereira et al. (2013)) which, in turn, are used to calculate indicators at multiple scales, ultimately to the national scale where parties report required indicators to the GBF.

Hubs

Hubs are the highest level nodes within a multi-scale BON, which correspond to regional governance (e.g. provinces, states) that create and enforce regional policy and are responsible for data aggregation and allocation of funding resources. The geography covered by each Hub will generally be large and therefore will contain various types of habitat and ecosystems. Thus, the role of Hub nodes is to organize monitoring done by the Ecoregion Sentinel nodes within each habitat type in the Hub's jurisdiction, and coordinate monitoring with other regional governing bodies to establish monitoring of ecoregions that span the domain of multiple Hub nodes.

Ecoregion Sentinels

Ecoregion Sentinel nodes monitor particular ecosystem types and have scientific oversight of monitoring with experts on the relevant Essential Biodiversity Variables (EBVs; Pereira et al. (2013)) for each biome. Ecoregion monitoring managers perform organization of multiple Field Stations within each ecoregion and perform aggregation and analysis of data in conjunction with experts on the biome and its taxa to compute indicators and make data-driven policy recommendations.

Field Stations

Field Stations are the primary node responsible for the logistical coordination of monitoring. At this scale, node locations shift from being constrained by the physical location of local governing bodies and ecoregions toward being pragmatically focused on logistics. Each Field Station manages sampling within the region that is most accessible from that station, and orchestrates sensor deployment and maintenance, and the resulting data processing and management.

Monitoring Sites

The finest-scale nodes in the system are the monitoring sites themselves. The physical form of monitoring sites depends on the type of data being collected. For example, if we split types of data into the taxonomy of species detection (occurrence/occupancy), species abundance (e.g. individual counts or biomass), species traits (e.g. morphology, physiology, genetics), and species health (e.g. ecotoxicology, disease prevalence), each modality of data could be collected in different forms (e.g. camera traps vs. field surveys for detection data), which would impact the design of site selection.

Evaluating, Optimizing, and Adaptively Iterating Monitoring Design

For a biodiversity monitoring system to effectively guide policymaking and report progress toward GBF goals and targets, it must produce data that are an adequate representation of the true state of nature. This imposes numerous statistical and logistical requirements on the design of biodiversity monitoring programs. Within our framework for monitoring design, some node locations are dictated by the political boundaries of regional governance (Hubs), and some are dictated by the biogeography of habitats and ecoregions (Sentinels). But for smaller scale nodes (Field Stations and Monitoring Sites), it is imperative to organize data collection by choosing locations that most efficiently and effectively quantify the state of biodiversity.

Selecting locations for Field Stations and Monitoring Sites raises two questions that occur at different stages of monitoring design: **(1)** What is the minimum number of Field Stations and Monitoring Sites required to adequately quantify the status and trends of biodiversity in a region? This is essential to determine the overall budget required to report trustworthy information to the GBF. And, **(2)** Where are the best locations to obtain as much useful information as possible under a fixed budget? Answering these questions requires a methodological framework to evaluate a given monitoring design's effectiveness.

We define an Optimal BON, $\mathcal{O}$, as the set of sites that, for a fixed budget $\mathcal{B}$, provides the closest estimate of a set of indicators to the true, latent values of those indicators $\boldsymbol{y} = (y_1, y_2, ..., y_n)$ at the time of sampling. In nature, the latent state of indicators $\boldsymbol{y}$ is intrinsically unknowable, so we can never assess a BON's optimality by comparing the true values of $\boldsymbol{y}$ to the values of indicators inferred from data collected from a particular BON design. Therefore, to evaluate the efficacy of a monitoring design, we must use simulation to determine how robust it is to a variety of "plausible ecological worlds" — different states of biodiversity and how it is changing that are consistent with existing monitoring data.

We formalize the idea of BON optimization as follows. Let $D_{\mathcal{B}}$ be the set of all BON designs possible with a fixed budget $\mathcal{B}$. Let $\mathcal{W}$ be the set of plausible ecological worlds — the true state of biodiversity — that could exist. Let $\boldsymbol{y}_w$ be the true indicator values under a particular plausible world w, and let $\tilde{\boldsymbol{y}}_{d,w}$ be the inferred values of $\boldsymbol{y}_w$ from data collected using a given BON design d. Finally, let $\mathcal{L}$ be the loss function which quantifies how close inferred indicators $\tilde{\boldsymbol{y}}_{d,w}$ are to $\boldsymbol{y}_w$ (where lower is better, e.g. mean-squarederror). The optimal BON $\mathcal{O}$ is then that which minimizes the expected loss across all plausible worlds $\mathcal{W}$:

$$\mathcal{O} = \underset{d \in D_{\mathcal{B}}}{\operatorname{argmin}} \quad \mathbb{E}_{w \sim \mathcal{W}} \left[\mathcal{L}\left(\tilde{\boldsymbol{y}}_{d,w}, \boldsymbol{y}_w \right) \right] \tag{1}$$

The set of plausible worlds $\mathcal{W}$ represents a prior on ecological reality. Initially, these can be constructed using publicly available data from e.g. GBIF, OBIS and IUCN. As monitoring programs get off the ground, they can use the data they collect to better inform the distribution of plausible worlds, thereby enabling *adaptive* monitoring design which continually improves as more data becomes available (Henrys et al. 2024). Further, as more data is collected, candidate monitoring designs can aim to fill spatial and/or taxonomic coverage gaps.

In practice, optimizing over all plausible worlds $\mathcal{W}$ is impossible, so we must resort to evaluating BON design via Monte Carlo simulation. In Figure 2, we outline a framework for iterative optimization of monitoring network design using simulation of many "plausible worlds". This consists of five steps: **Step (1):** Assembling candidate BONs $D_{\mathcal{B}}$ that meet budgetary and logistical requirements. Hub and Sentinel nodes are constrained by political and environmental boundaries, respectively. Assembling candidate BONs then requires selecting locations for Field Stations and the Monitoring Sites they service within the budget. The budget $\mathcal{B}$ can be broken down into establishment vs. recurring costs, the price of sensor units, personnel, data storage, management, and compute, and coordinating data sharing across scales. **Step (2):** Sampling a plausible world via a generative model of plausible ecological realities (i.e. a model that generates various "ground truth" states of biodiversity that are consistent with existing data). **Step (3):** Running standardized pipelines to compute EBVs (Pereira et al. 2013) and resulting indicators from the simulated data collected at each site in the candidate BON (Kim et al. 2026, Griffith et al. 2026). **Step (4):** Computing the monitoring error $\mathcal{L}$. **Step (5):** Repeating 1-4 across a variety of plausible worlds and compare results across candidate BONs.

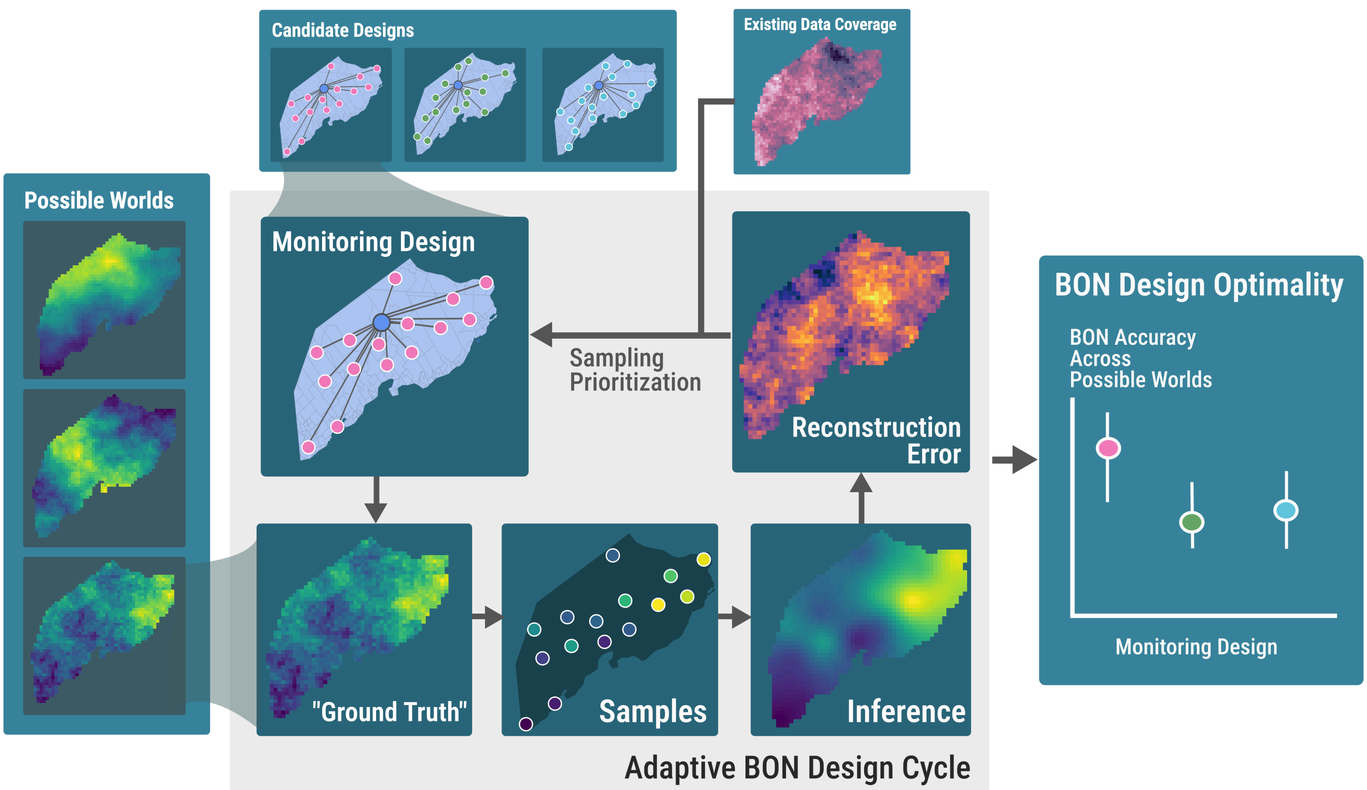

Figure 2
A simulation based framework for iterative optimization of biodiversity monitoring design that is robust to many different "plausible worlds" that represent the change of biodiversity over time.

Evaluating monitoring design before deployment is essential to quantify how much trust can be placed in the indicators derived from a given monitoring program. Simulation-based evaluation is a necessary step to both calibrate expectations of how well a monitoring network will perform, and to estimate the cost of monitoring to adequately report GBF indicators to provide empirically grounded estimates of the budgetary requirements of national biodiversity monitoring programs.

Monitoring Trade Offs and Multicriteria Optimization

The Global Biodiversity Framework consists of many biodiversity indicators, each of which quantifies different aspects of biodiversity and its contributions to humanity. The optimal monitoring sites for each indicator may vary considerably. For example, the optimal BON to monitor changes in species population sizes (a fundamental component of the Red List Index, a headline indicator associated with Goal A of the GBF) may be very different from the optimal BON to quantify the provisioning of ecosystem services (headline indicators associated with Targets 10 and 11 and Goal B of the GBF; Vári et al. (2025)). Additionally, there could also be significant differences in the optimal BON design for monitoring the different taxa that comprise a given indicator.

Therefore optimal monitoring design is a *multicriteria optimization problem*, where the aim is to find a solution that adequately meets multiple goals, rather than being strictly optimal for a single goal. An essential concept in multicriteria optimization is the Pareto front, which defines a set of optimally efficient decisions across different prioritizations toward each goal. Each point on the Pareto front is optimal (given a fixed budget) for a particular prescribed balance toward each goal, e.g. how much to focus on species abundances as opposed to ecosystem services. In this context, rather than there being a single optimal BON $\mathcal{O}$, there exists a set of optimal BONs $\mathcal{P}$ that define a Pareto front across all possible prioritizations toward monitoring targets, and monitoring programs must decide what prioritization is best suited toward its policymaking goals.

An additional obstacle is that trade-offs between different monitoring goals are not necessarily linear. A BON where each site is a "happy medium" compromise across all monitoring goals — fine, but not great, at each goal — may result in monitoring that is overall worse than if the same budget were used to select multiple sets of monitoring sites, each targeted toward one specific goal. For example, selecting 50 sites that are mediocre at both monitoring species abundance and ecosystem services may be less effective than selecting the 25 best sites for abundance and the 25 best sites for ecosystem services.

In some contexts, the Pareto front may indicate a positive trade-off (Figure 3, bottom left), meaning the "compromise" BON is the best option, but in other contexts, the trade-off may be negative (Figure 3, bottom right), indicating splitting the budget into smaller systems focused on individual targets may be the better decision. A clear understanding of the trade-offs involved in monitoring to report GBF indicators, and determining which indicators can be monitored effectively using the same sites, is an essential component of optimal BON design.

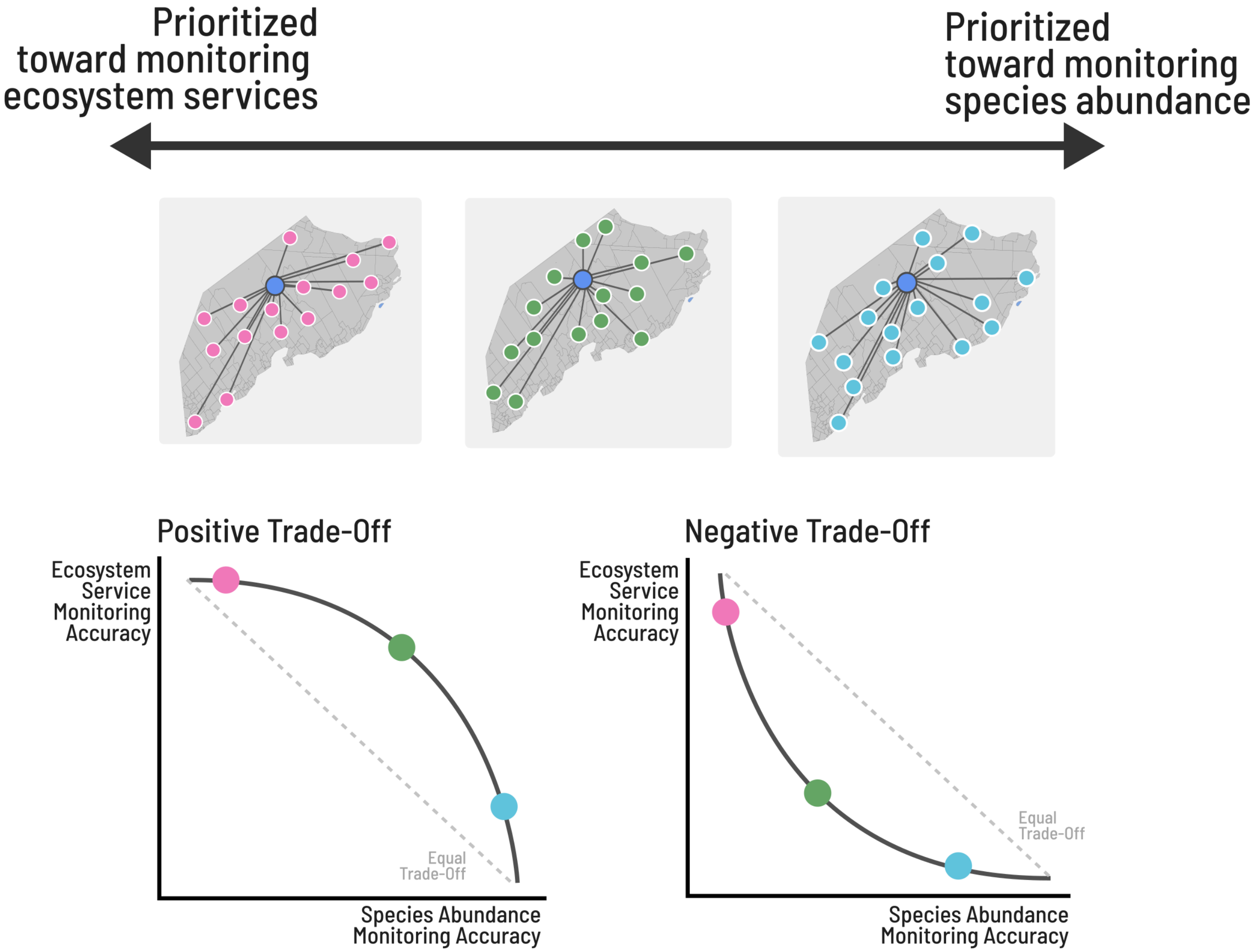

Figure 3
Differently shaped Pareto fronts lead to positive vs. negative trade-offs when designing monitoring networks aimed at multiple monitoring goals.

The Toolbox for Optimal Biodiversity Monitoring

Selecting optimal sites for biodiversity monitoring poses a difficult methodological challenge. Many bodies of research have developed theory and tools that can aid in optimal BON design, which we coarsely summarize in Table 1.

These methods can be taxonomized across two criteria. One distinction is the *design-based* approach versus the *model-based* approach. In the design-based approach, the target of sampling is treated as a fixed value that doesn't change over time. In the model-based approach, the target of sampling is assumed to be a random variable drawn from the result of a biological process, which is stochastically realized during sampling; see Williams and Brown (2019). Another factor is whether each method is *static* or *adaptive*: once a site is established, whether it is fixed in one spot, or if the resources allocated for that site easily change over time to better align with changing priorities.

Table 1
Relevant tools for optimal BON design

Method	Origin	Description	Static or Adaptive	Design or Model Based	Relevant Literature	Role
Spatial Sampling	Spatial Statistics	The branch of sampling theory focused on selecting sampling sites across space. Common themes here are ensuring samples are *well-spread*, meaning sites are not too close to each other to avoid obtaining redundant information, and *balanced samples*, meaning the average values of auxiliary variables associated with sampled sites is equivalent to the mean of each variable across the whole extent.	Static	Design	(Wang et al. 2012, Benedetti et al. 2017, Williams et al. 2018, Norman and Poisot 2025)	Field Station site selection
Environmental Monitoring Network Design	Environmental Science	A framework for placing sensors that track environmental variables of interest (e.g. water quality, seismic activity), typically with the goal of reducing the difference between the true and observed state using information-theoretic criteria.	Static	Model	(Caselton and Zidek 1984, Dobbie et al. 2008, Zidek and Zimmerman 2019)	Sampling site selection
Facility Location	Operations Research	A set of methods from operations research where the goal is to select optimal locations for a fixed number of facilities (e.g. warehouses, hospitals, etc.) subject to some objective function, often minimizing the maximum distance to the nearest facility across all locations to be serviced.	Static	Design	(Laporte et al. 2019)	Field Station site selection
Adaptive Spatial Sampling	Spatial Statistics	An approach to traditional spatial sampling where the location of the next survey site is influenced by the results of previous observations.	Adaptive	Design	(Thompson 1990, Philippi 2005, Lindenmayer et al. 2011, Williams and Brown 2018, Henrys et al. 2024, Pollock et al. 2026)	Sampling site selection
Active Learning	Machine Learning	A machine learning framework for selecting the most informative sites to improve a model with the fewest samples possible.	Adaptive	Model	(Liu et al. 2009, Settles 2012)	Sampling site selection
Bandit Problems / Reinforcement Learning	Machine Learning	Frameworks for managing the Exploration vs. Exploitation trade-off, to decide whether to monitor sites that are known to provide valuable information or explore sites with unknown value.	Adaptive	Model	(Burtini et al. 2015, Sutton and Barto 2018, Lapeyrolerie and Boettiger 2023)	Sampling site selection
Optimal Experimental Design	Statistics	Statistical methodology for selecting samples that minimize the variance of parameter estimates in a specific model using different criteria related to the model's precision matrix (e.g. A-optimality, D-optimality).	Adaptive	Model	(Pukelsheim 2006)	Sampling site selection
Power Analysis	Statistics	Uses simulation to find the minimum number of sites/years needed to detect a biological effect at a prescribed level of statistical confidence.	-	-	(Steidl et al. 1997, Leung and Gonzalez 2024)	Selecting the number of nodes of each type
Value of Information	Decision Theory	Quantifies the value of additional data collection as the amount it would be worth when being used to make a decision.	-	-	(Canessa et al. 2015)	Selecting the number of nodes of each type
Multi-criteria Decision Making	Decision Theory	A framework for selecting sites when balancing multiple objectives, like reporting on various GBF indicators that may have very different sets of optimal sites.	-	-	(Huang et al. 2011)	Site selection aimed at different goals

Concluding Remarks

To determine if humanity is on track to meet the goals and targets set by the Global Biodiversity Framework, we need transformative scaling up of biodiversity monitoring programs. Establishing a Global Biodiversity Observing System (GBiOS; Gonzalez et al. (2023a)) is necessary to meet this challenge, but we cannot establish a GBiOS with the adequate statistical power to detect and attribute biodiversity change and confidently report progress to the GBF without a theory of optimal biodiversity monitoring design.

Here we've presented a framework for monitoring design built around three pillars: **(1):** the hierarchical design of monitoring networks, consisting of nodes at different scales with different roles: **Hubs**, which coordinate regional governmental policy and allocate budgets for monitoring; **Ecoregion Sentinels**, which perform scientific oversight of monitoring in a given habitat type; **Field Stations**, which organize the logistics of monitoring; and finally **Monitoring Sites**, where data is actually collected in a variety of forms. **(2)**: A framework for evaluating monitoring network design using simulation, to ensure monitoring can adequately report on the status and trends of biodiversity and is robust to all "plausible worlds" of biodiversity change. This framework enables optimization of monitoring design to make the most of monitoring effort under the pragmatic constraints of budget and logistics, and the multi-objective criteria built into the GBF Monitoring Framework. And **(3):** A consolidated toolbox of the methods available to evaluate and optimize monitoring design.

Together, this framework enables development of a GBiOS that has the statistical power to adequately report progress toward GBF goals and targets (Leung and Gonzalez 2024).

This is an essential step in operationalizing the GBF's Monitoring Framework and bending the curve on biodiversity toward positive and just futures for humanity (Chapman et al. 2024) and the rest of life on Earth.

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