Reconciling top-down conservation priorities with bottom-up local needs

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Abstract

The success of global conservation goals risks being undermined by conflicts that arise when high-level, data-driven priorities clash with local needs and contexts. While top-down systematic planning efficiently identifies priority areas using large-scale, multi-dimensional data, it neglects the input of local communities and stakeholders. Here, we propose a novel priority-setting process that integrates these potentially divergent perspectives using Reinforcement Learning from Human Feedback (RLHF). Our framework uses an iterative, interactive AI-driven approach to optimize conservation policies by combining initial data-driven proposals with local knowledge and values provided as human feedback. This feedback is converted into a dynamic reward structure, allowing the model to learn and incorporate granular preferences and constraints. Before real deployment, we propose an intermediate calibration step where Large Language Models simulate structured stakeholder feedback to optimize the integration pipeline. Our RLHF approach provides a flexible and powerful roadmap for allocating conservation resources holistically, effectively, and inclusively, thereby increasing the probability of achieving long-lasting biodiversity and societal improvements.

Global conservation targets and local needs

We are in a race to meet the ambitious target of protecting 30% of the world's terrestrial and inland water areas, and of marine and coastal areas, by 2030 – as committed by nearly 200 nations under the Kunming-Montreal Global Biodiversity Framework. However, moving at speed risks creating tension and conflicts, as high-level conservation priorities often clash with local needs and complexities.

Several conservation organizations, such as the World Wide Fund for Nature (WWF), are committed to amplifying "locally-led conservation", a concept that is gaining traction in alignment with the increased recognition of the roles and contributions of Indigenous Peoples and Local Communities (IPLCs) as custodians of biodiversity and as integral partners in its conservation (including both protection and restoration) and sustainable use (1). The upfront participation of IPLCs can contribute critical context-specific knowledge of the territory being considered for conservation, ranging from cultural values of specific sites to a better understanding of nature's contributions to people at a local and regional scale. Bottom-up conservation strategies co-created by IPLCs can also lead to more effective and equitable use of resources allocated for conservation (supporting for instance education and knowledge dissemination efforts), long-term ownership by the communities involved (who feel more responsible for, and committed to conservation outcomes), and additional benefits for biodiversity (such as by promoting the recovery of specific species and habitats) (2).

However, bottom-up local approaches may have limited power to deliver global or even national conservation priorities, which may require most funds being allocated to where the threats are most acute or the outcomes most substantial. They may also be unable to integrate the multiple dimensions of biodiversity, such as functional, genetic, and evolutionary diversity (for which local data and understanding may be lacking); spatial connectivity and complementarity (when local actions are considered in isolation from wider landscape planning); the climate resilience of species, populations, and ecosystems (often based on global or regional models); and the co-benefits of conservation actions, such as ecological restoration, on other outcomes, such as carbon storage (3).

Top-down approaches

Historically, the designation of protected areas and other conservation measures has been performed by government bodies with limited or no local engagement and buy-in (4). They also often proceeded without a prior assessment of how individual interventions across a region would best complement, rather than duplicate each other. This is where systematic conservation planning came in – a more formalized, data-informed approach for locating and designing conservation areas which explicitly considers and attempts to maximize complementarity (5). Under this umbrella, many methods and metrics have been developed to analyze large data sets of various biodiversity indices and create priority maps for conservation (e.g., 6, 7). This work has resulted in influential proposals at the global, regional, and national levels (e.g., 8).

Most recently, artificial intelligence (AI) is now set to revolutionize systematic conservation planning and other forms of conservation science, by becoming incorporated into new tools for biodiversity monitoring and data analysis, and by providing powerful ways to process high-dimensional and high resolution data (9). One such advance introduced by members of our team is the software Conservation Area Prioritization Through Artificial INtelligence (CAPTAIN) (10, 11). This approach uses spatially explicit ecosystem simulations and Reinforcement Learning (a type of AI) to train an agent to identify conservation priorities through time and in space, while considering both biodiversity targets and implementation costs.

While existing analytical approaches have the ability to leverage large amounts of data to generate global conservation priority maps in cost-effective ways, they lack direct contact with local contexts and the communities involved. This disconnect has led to fierce criticism from some conservationists, proposing that "conservation needs to break free from global priority mapping" since "global maps embody a technocratic view of environmental decision-making" erasing "local context and difference" (12).

Bridging divergent perspectives

To solve this conundrum, here we propose a priority-setting process that integrates available data (biological, environmental, and socio-economic) at large scales, with human feedback (from e.g. surveys and workshops with IPLCs) at local scales. While the co-development of conservation scenarios with local stakeholders and balancing targets for biodiversity protection with budgetary constraints has been previously proposed (13), to our knowledge, no method currently integrates these components directly.

To achieve this, we outline a framework based on Reinforcement Learning from Human Feedback (RLHF). Human feedback has become an integral component in developing and refining AI systems, enabling models to better reflect human preferences, values, and expectations (14). In this context, RLHF has gained increasing traction to improving AI models with applications in different domains such as robot locomotion, video games, and alignment of large language models to human values (15). We consider RLHF particularly promising to devise conservation policies that incorporate large-scale multidimensional data and internationally agreed biodiversity targets, while also learning from the knowledge and input of the local communities involved, through an iterative and interactive process (Fig. 1). In contrast to standard reinforcement learning where the model optimizes actions to maximize a static reward function *R(s, a)* dependent solely on the environment, our proposed framework incorporates human feedback through a dynamic reward structure (16):

$$R_{\text{total}} = R_{\text{standard}}(s,a) + \alpha \cdot R_{\text{human}}(s,a,H)$$

where human feedback *H* is obtained by converting qualitative inputs to quantitative signals using e.g. Bradley-Terry preference models for pairwise comparisons, spatial kernel density estimates to generalize point-based feedback, and semantic embedding of textual feedback to identify preference patterns.

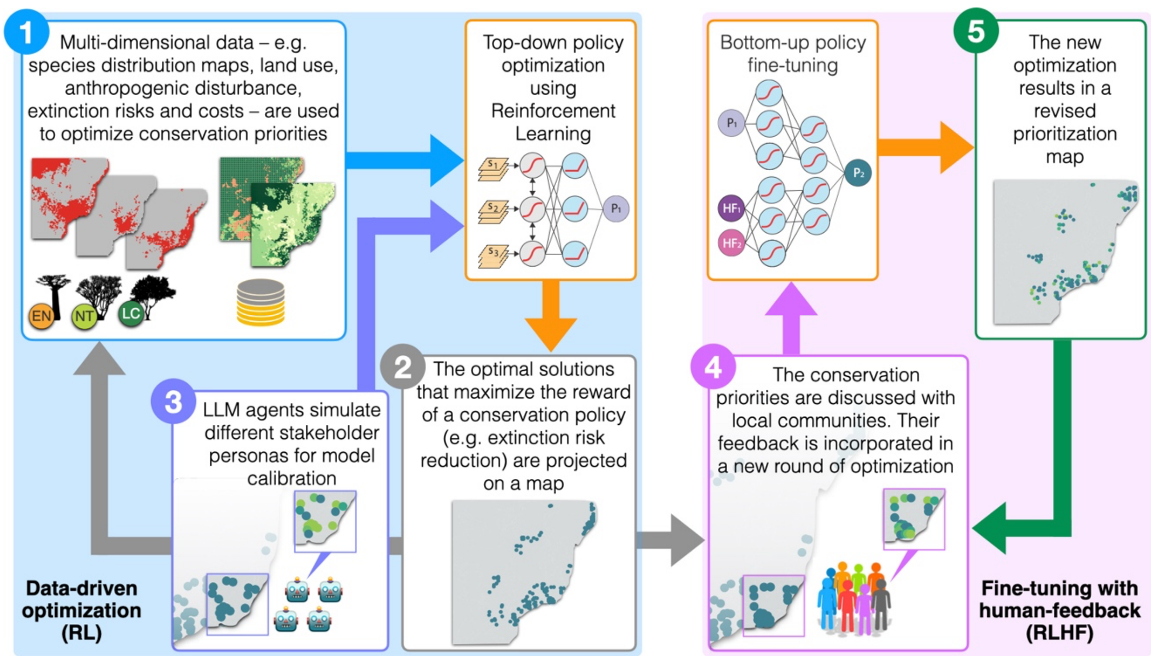

Figure 1 | Identifying conservation priorities through Reinforcement Learning from Human Feedback. Recent advances in artificial intelligence could help break down the divide between top-down and bottom-up approaches to spatial conservation prioritisation. The two loops of optimization outlined can be iterated multiple times to reach an optimal and most socially accepted solution.

This approach would have several advantages over considering top-down or bottom-up planning as alternative strategies. Firstly, it would allow conservation planners to maintain a broad (national, regional or even global) context while optimizing conservation priorities. Secondly, it would allow the integration of granular information about local preferences, cultural values, and implementation feasibility of a conservation program. Thirdly, it would promote the active participation of all relevant stakeholders (e.g., IPLCs, local governments, landowners) in the decision-making process – increasing trust and engagement towards conservation programs. Taken together, these advantages would increase the probability of achieving long-lasting societal and biodiversity improvements.

We envision a workflow integrated in a future development of CAPTAIN where a first top-down optimization is performed leveraging AI to process multiple types of data and variables, such as species distributions and abundances, local and global threats, spatial patterns of anthropogenic disturbance, opportunity and implementation costs, present and future climate sensitivity, among others (Fig. 1, step 1). The optimization will fully account for complementarity of interventions and result in a first proposal for conservation priorities (step 2). After model training and calibration (step 3; see below), this process will then be followed by discussion of the proposed priorities with IPCLs and other relevant stakeholders to collect '*human feedback*' (step 4). This will combine quantitative and qualitative information and will likely be characterized by granular (fine scale) and sparse spatial coverage. Human feedback can cover several aspects including new constraints (for instance dictated by unforeseen limitations in the feasibility of implementation), positive or negative assessments of the initial proposal, proposals for alternative conservation solutions, and modifications to the expected/realistic levels of protection that can be achieved. This will then feed into a new round of AI-driven optimization resulting in an updated conservation plan (step 4). If needed, steps 3 and 4 could be repeated to further fine-tune the solution until a satisfactory scenario is found.

Simulating human feedback for system calibration

Before deploying this RLHF framework in real-world conservation planning contexts, we propose an intermediate validation step using agents based on Large Language Models (LLMs) to simulate stakeholder feedback (Fig. 1, step 3). This approach draws from evaluation methodologies common in human-AI interaction research, where simulated feedback can help assess how the model works across different scenarios before being used by actual people (17, 18). Specifically, LLM agents conditioned on different stakeholder personas (e.g., local community representatives, local government officials, conservation practitioners) can generate structured responses to proposed conservation scenarios, allowing systematic exploration of three critical design parameters: (i) the optimal format and spatial granularity for eliciting actionable feedback (e.g., binary preferences, ranked alternatives, or free-form spatial annotations), (ii) the quantity of feedback samples required to meaningfully inform the initial RL solution as compared to purely data-driven priorities, and (iii) early identification of proposed actions that conflict with known local regulations or community-stated priorities that may not be captured in the training data.

Regardless of how carefully LLM agents are prompted or fine-tuned on regional policy documents and contexts (such as depending on how human population densities and land use change over space), simulated feedback will never be able to capture the full complexity, contextual nuance, and legitimate authority of actual IPLC input – an issue known as the sim2real gap (19). Instead, this simulation phase should be viewed strictly as a system calibration step to optimize the human feedback integration pipeline itself, not as a substitute for genuine stakeholder engagement. By pre-testing the feedback mechanism in controlled evaluation environments, we can ensure that when real human feedback is collected (step 3), the system is able to efficiently and fully incorporate it into the new proposed policy, reducing the number of iteration rounds needed and minimizing stakeholder fatigue while maintaining the authenticity and primacy of community voices in the decision-making process.

From theory to practice

Real-life validations of this approach should include data compilation and analyses, followed by stakeholder engagement through in-person community workshops and (when appropriate) online surveys, where results can be presented and input gathered in the local languages. This interaction should be done in parallel with, rather than instead of, well-tested workflows, such as those established by the Important Plant Areas program (20) – which has so far resulted in the identification of over 2,000 priority areas for plant conservation in nearly 40 countries. And while the methodology proposed here offers a concrete and flexible roadmap ahead, which could be adapted and implemented in many countries and regions, there may be alternative or complementary approaches worthwhile exploring.

We encourage researchers and conservationists to embrace various and sometimes conflicting perspectives, to join forces in ending the top-down vs bottom-up conservation divide. Increased collaboration will support governments, non-governmental organizations, and policymakers with the spatial allocation of conservation resources in ways that are demonstrably holistic, effective, and inclusive.

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