Article submission for *Nature Sustainability* | Manuscript type: Research Article (Invited)

Optimising biodiversity protection through artificial intelligence

Daniele Silvestro[1,2*§], Stefano Goria[3], Thomas Sterner[4], Alexandre Antonelli[1,5,6*§]

[1]Gothenburg Global Biodiversity Centre, Department of Biological and Environmental Sciences, University of Gothenburg, 405 30 Gothenburg, Sweden
[2]Department of Biology, University of Fribourg, Switzerland and Swiss Institute of Bioinformatics
[3]Thymia Limited, London, United Kingdom
[4]Department of Economics, University of Gothenburg, Gothenburg, Sweden
[5]Department of Plant Sciences, University of Oxford, South Parks Road, Oxford, OX1 3RB, United Kingdom
[6]Royal Botanic Gardens, Kew, TW9 3AE, United Kingdom
*Corresponding authors: a.antonelli@kew.org, daniele.silvestro@unifr.ch
[§]Equal contributions.

Abstract: Over a million species face extinction, carrying with them untold options for food, medicine, fibre, shelter, ecological resilience, aesthetic and cultural values. There is therefore an urgent need to design conservation policies that maximise the protection of biodiversity and its contributions to people, within the constraints of limited budgets. Here we present a novel framework for spatial conservation prioritisation that combines simulation models, reinforcement learning and ground validation to identify optimal policies. Our methodology, CAPTAIN (Conservation Area Prioritisation Through Artificial Intelligence Networks), quantifies the trade-off between the costs and benefits of area and biodiversity protection, allowing the exploration of multiple biodiversity metrics. Under a fixed budget, our model protects substantially more species from extinction than the random or naively targeted protection of areas. CAPTAIN also outperforms the most widely used software for spatial conservation prioritisation (Marxan) in 97% of cases and reduces species loss by an average of 40% under simulations, besides yielding prioritisation maps at substantially higher spatial resolution using empirical data. We find that regular biodiversity monitoring, even if simple and with a degree of inaccuracy – characteristic of citizen science surveys – substantially improves biodiversity outcomes. Given the complexity of people–nature interactions and wealth of associated data, artificial intelligence holds great promise for improving the

conservation of biological and ecosystem values in a rapidly changing and resource-limited world.

Keywords: Artificial intelligence, Citizen science, Climate change, Human impact, Marxan, Remote sensing, Sustainable development, Systematic conservation planning.

Biodiversity is the variety of all life on Earth, from genes through to populations, species, functions and ecosystems. Alongside its own intrinsic value and ecological roles, biodiversity provides us with clean water, pollination, building materials, clothing, food and medicine, among many other physical and cultural contributions that species make to ecosystem services and people's lives[1,2]. The contradiction is that our endeavours to maximise short-term benefits are depleting biodiversity and threatening the life-sustaining foundations of modern societies in the long-run[3] (Box 1). This can help explain why, despite the risks, we are living in an age of mass extinction[4,5] and massive population declines of wild species[6]. One million species are currently at risk of disappearing[7], including nearly 40% (or c. 140,000) of all plant species[8,9], which could provide solutions to current and future challenges such as emerging diseases and climate-resilient crops[10-12]. The imperative to feed and house massively growing human populations – with an estimated 2.4 billion more people by 2050 – together with increasing disruptions from climate change, will put tremendous pressure on the world's last remaining native ecosystems and the species they contain. Since not a single of the 20 Aichi biodiversity targets agreed by 196 nations for the period 2011–2020 has been fully met[13], there is now an urgent need to design more realistic and effective policies for a sustainable future[14] that help deliver the conservation targets under the post-2020 Global Biodiversity Framework (https://www.cbd.int/).

There have been several theoretical and practical frameworks underlying biological conservation since the 1960s[15]. The field was initially focused on the conservation of nature for itself, without human interference, but gradually incorporated the bidirectional links to people – recognising our ubiquitous influence on nature, and the multi-faceted contributions we derive from it[1,6,15]. Throughout this progress, a critical step has been the identification of priority areas for targeted protection, restoration planning and impact avoidance – triggering the development of the field of spatial conservation prioritisation or systematic conservation planning[16-18]. While humans and wild species are increasingly sharing the same space[19], the preservation of largely intact nature remains critical for safeguarding many species and ecosystems, such as tropical rainforests.

Several tools and algorithms have been designed to facilitate systematic conservation planning[20]. They often allow the exploration and optimisation of trade-offs between variables, something not readily available in Geographic Information Systems[21], which can lead to substantial economic, social and environmental gains[22]. While the initial focus has been on maximising the protection of species while minimising costs, additional parameters can sometimes be modelled, such as species rarity and threat, total protected area and evolutionary diversity[20,23,24]. The most widely used method so far, Marxan[25] seeks to identify a set of protected areas that collectively allow particular conservation targets to be met under minimal costs, using a simulated annealing optimization algorithm. Despite its usefulness and popularity, Marxan and similar methods[20] are designed to optimize a one-time policy, do not directly incorporate changes through time, and assume a single initial gathering of biodiversity and cost data (although temporal aspects can be explored by manually updating and re-running the models, under various targets[26]). In addition, the optimized conservation planning does not explicitly incorporate climate change, variation in anthropogenic pressure (although varying threat probabilities are dealt with in newer software extensions of Marxan[27,28]), or species-specific sensitivities to such changes.

Here we tackle the challenge of optimising biodiversity protection in a complex and rapidly evolving world by harnessing the power of artificial intelligence (AI). We develop a novel tool for systematic conservation planning (Fig. 1) to explore – through simulations and empirical analyses – multiple previously identified trade-offs in real-world conservation, and to evaluate the impact of data gathering on specific outcomes[29]. We also explore the impact of species-specific sensitivity to geographically varying local disturbances (e.g., as a consequence of new roads, mining, trawling or other forms of economic activity with negative impacts on natural ecosystems) and climate change (overall temperature increases, as well as short-term variations to reflect extreme weather events). We name our framework CAPTAIN (Conservation Area Prioritisation Through Artificial Intelligence Networks). Our framework is particularly applicable to sessile organisms, such as forest trees or reef corals, but implements mechanisms of offspring dispersal (e.g., seeds or larvae) that could be easily adaptable to many other systems.

Within AI, we implement a reinforcement learning (RL) framework based on our spatially explicit simulation of biodiversity and its evolution through time in response to anthropogenic pressure and climate change. The RL algorithm is designed to find an optimal balance between data generation (learning from the current state of a system, also termed ‘exploration’) and action (called ‘exploitation’ – the effect of which is quantified by the outcome, also termed reward). It optimises a conservation policy that develops over time, thus being particularly suitable for designing policies and testing their short- and long-term effects. Actions are decided based on the state of the system through a neural network, whose parameters are estimated within the RL framework to maximise the reward. Although AI solutions have been previously proposed and to some extent are already used in conservation science[30,31], to our knowledge RL has only been advocated[32] but not yet implemented in conservation tools.

We combine these AI components with a module that allows us to maximise various biodiversity metrics (including species richness and phylogenetic diversity) within a given budget constraint (Fig. 1). We investigate through simulations the importance of data gathering, focusing on frequency (a single ‘Initial’, or multiple ‘Recurrent’ inputs of biodiversity data), level of detail (‘Simple’ species reports of species presence, or ‘Full’ monitoring of all species in targeted groups, and their population sizes) and accuracy (no errors in the recording, or allowing for a fraction of mistakes in species identifications characteristic of citizen science efforts). Our platform enables us to assess the influence of model assumptions on the reward, mimicking the use of counterfactual analyses[24].

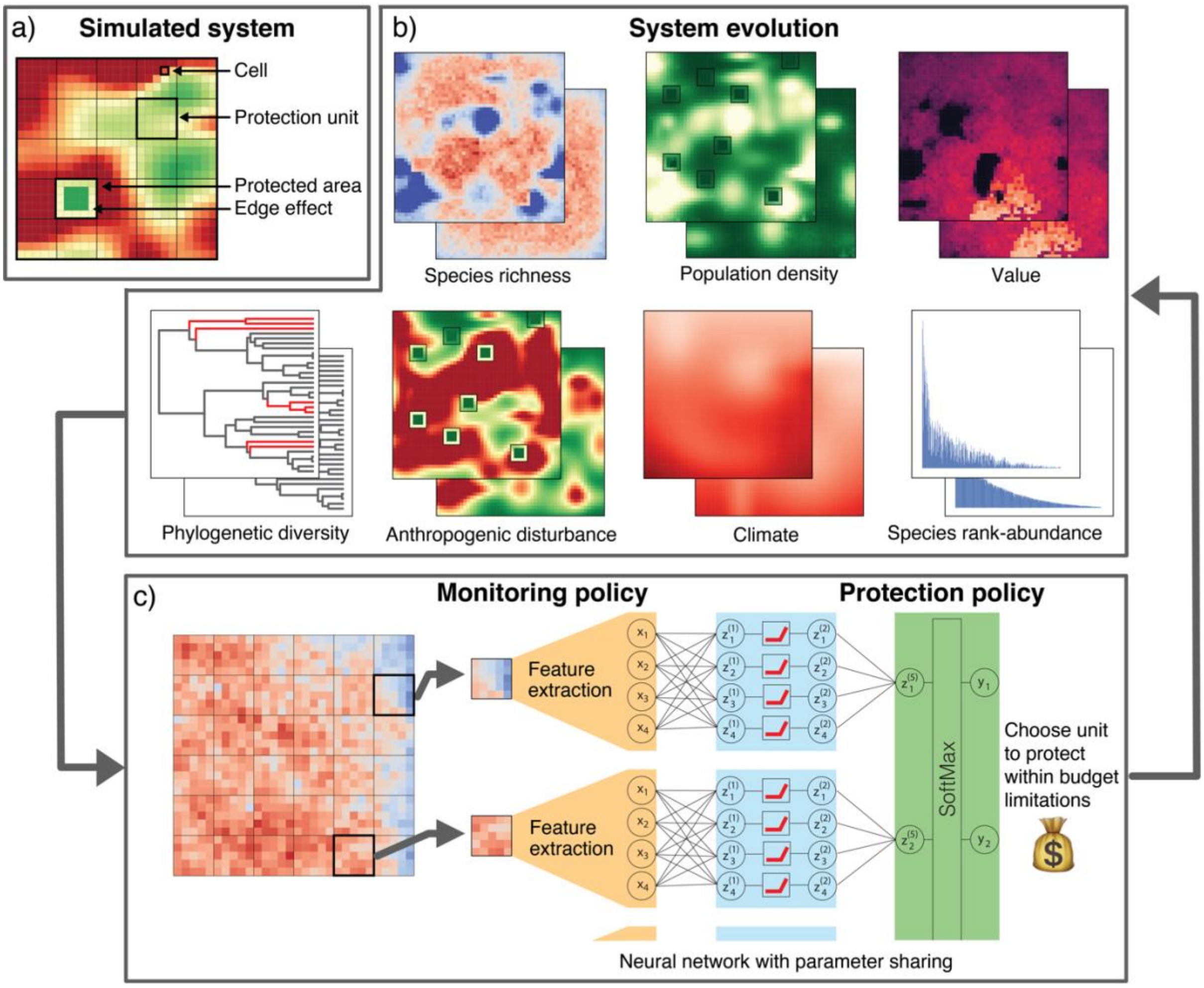

Fig. 1 | The CAPTAIN reinforcement learning framework. a, A simulated system – which could be the equivalent to a country state, an island or a large coral reef – consists of individual cells, each with a number of individuals of various species. Once a protection unit is identified and protected, its human-driven disturbance (e.g., forest loggings) will immediately reduce to an arbitrarily low level, except for the well-known edge effect[33] characterised by intermediate levels of disturbance. All 44 model parameters are provided with initial default values but are fully customisable (see Tables S1–S2). Simulated systems evolve through time (b), which are used to optimize a conservation policy (c) and to evaluate its performance. In empirical applications of the CAPTAIN framework, the simulated system is replaced with available biodiversity and disturbance data. **b-c,** Analysis flowchart integrating simulations and AI modules to maximise selected outcomes (e.g., species richness). **b,** System evolution between two points in time, in relation to six variables: species richness, population density, economic value, phylogenetic diversity, anthropogenic disturbance, climate and species-rank abundance (see Animation S1 for a time-lapse video depicting these and additional attributes). Note that site protection does not protect species from climate change. **c,** Biodiversity features (species presence per cell at a minimum, plus their abundance under full monitoring schemes; see Methods and Box 2 for advances in data-gathering approaches) are extracted from the system at regular steps, which are then fed into a neural network that learns from the system's evolution to identify conservation policies that maximise a reward, such as protection of the maximum species diversity within a fixed budget.

We use CAPTAIN to assess the following questions: i) What role does data gathering strategy play for effective conservation? ii) What trade-offs exist depending on the optimised variable, such as species richness, economic value or total area protected? iii) What can the simulation framework teach us in terms of winners and losers – i.e., which traits characterise the species and areas protected over time? and iv) How does our framework perform compared with the state-of-the-art model for conservation planning Marxan[25]? Finally, we demonstrate the usefulness of our framework to an empirical dataset of endemic trees of Madagascar.

RESULTS AND DISCUSSION

Impact of data gathering strategy. We find that Full Recurrent Monitoring (where the system is monitored at each time step, including species presence and abundance) results in the smallest species loss: it succeeds in protecting on average 35% more species than a random protection policy (Fig. 2a; Table S3). A very similar outcome (32% improvement) is generated by the Citizen science Recurrent Monitoring strategy (where only presence/absence of species are recorded in each cell) with a degree of error (Fig. 2b; see Methods). This is noteworthy because the information it requires, although not currently available at high spatial resolution for most regions and taxonomic groups, could to some extent be obtained through modern technologies, such as remote sensing and environmental DNA, and for accessible locations also citizen science[34] in cost-efficient ways (Box 2).

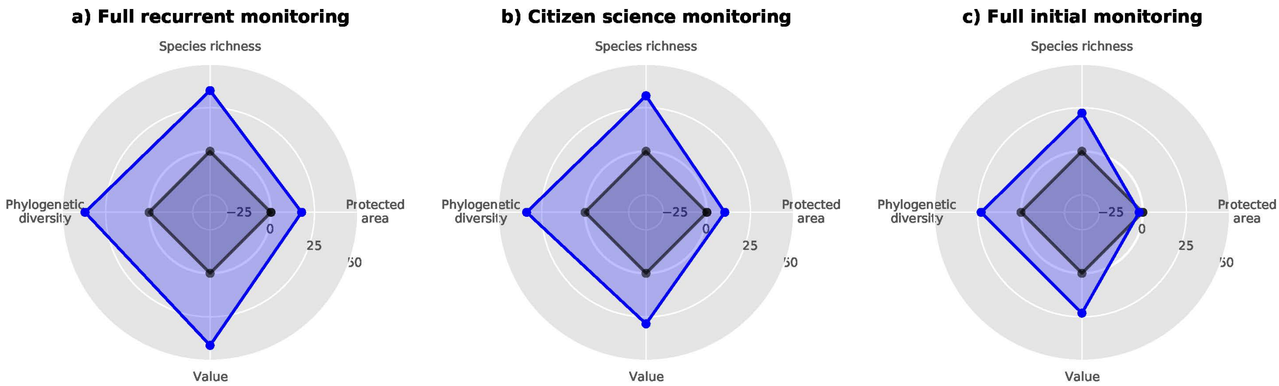

Fig. 2 | Impact of monitoring strategies on biodiversity protection. a-c, Outcome of policies designed to minimise species loss based on different monitoring strategies: **a,** Full Recurrent Monitoring (of species presence and abundance at each time step); **b,** Citizen science Recurrent Monitoring (limited to species presence/absence with some error at each time step); **c,** Full Initial Monitoring (species presence and abundance only at initial time). The blue polygons show the reduced loss of species, total protected area, accumulated species values and phylogenetic diversity between a random protection policy (grey shaded area) and AI-optimised simulations. All results are averaged across 250 simulations. Each simulation was based on the same budget and resolution of the protection units (5x5) but differed in their initial natural system (species distributions, abundances, tolerances, phylogenetic relationships) and in the dynamics of climate change and disturbance patterns.

The two monitoring strategies above outperform a Simple Initial Monitoring with no error, which only saves from extinction an average of 22% more species than a random policy (Fig. 2c; Table S3). This is because the policy ignores the temporal dynamics caused by disturbances, population and range changes, and the costs of area protection – all of which are likely to change through time in real-world situations. Since current methodologies for systematic conservation planning are static – relying on a similar initial data gathering as modelled here – this means their recommendations for area protection may be less reliable.

Our results differ from previous suggestions that area protection should not await prolonged data gathering[29]. This discrepancy can be explained by the nature of changes over time: while some systems may remain largely static over decades (e.g., tree species in old-growth forests), where a Simple Initial Monitoring could suffice, others may change drastically (e.g., alpine meadows or shallow-sea communities, where species shift their ranges rapidly in response to climatic and anthropogenic pressures); all such parameters can be tuned in our model.

To thoroughly explore the parameter space, each simulated system was initialised with different species composition and distributions and different anthropogenic pressure and climate change patterns (Figs. S1–S4). Because of this stochasticity, the reliability of the protection policies in relation to species loss varied across simulations. The policy based on Full Recurrent Monitoring was the most reliable, outperforming the baseline random policy in 99% of the simulations, while the Citizen science Recurrent Monitoring outperformed the random baseline in 92% of cases (Table S3). Both those policies are more reliable than the Full Initial Monitoring, which in addition to protecting fewer species on average (Fig. 2) also results in a slightly lower reliability of the outcome, outperforming the random policy in 89% of the simulations.

Optimisation trade-offs. The policy objective, which determines the optimality criterion in our RL framework, significantly influences the outcome of the simulations. A policy maximizing species commercial values (such as timber price) tends to sacrifice more species in order to prioritise the protection of fewer, highly valuable ones. Under this scenario, species losses decrease by only 2.5% compared with the random baseline, while cumulative value losses decrease by about 70% (Table S3). Thus, a policy targeting exclusively the preservation of species with high economic value may have a strongly negative impact on the total protected species richness, phylogenetic diversity and even amount of protected area, compared with a policy minimizing species loss (Fig. 3a).

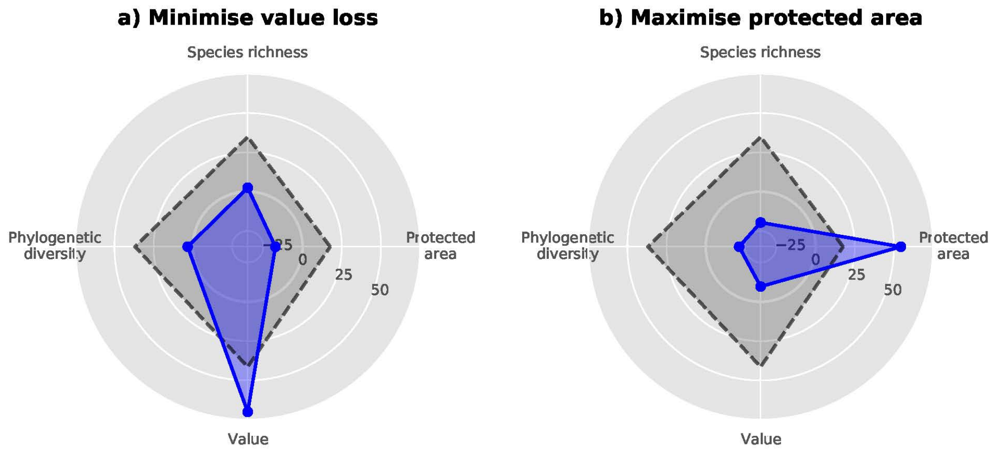

Fig. 3 | Trade-offs in conservation outcomes in relation to policy objectives. The plots show the outcome (averaged across 250 simulations) of different policy objectives based on Full Recurrent Monitoring. The policies were designed to (**a)** minimize value loss and (**b)** maximize the amount of protected area. The radial axis shows the percentage change compared with the baseline random policy, while the dashed grey polygons show the outcome of a policy with full recurrent monitoring optimized to minimize biodiversity loss (Fig. 2a).

A policy that maximises protected area results in a 54% increase in number of protected cells, by selecting those cheapest to buy; but it leads to substantial losses in species numbers, value and phylogenetic diversity, which are considerably worse than the random baseline, by resulting in 20% more species losses on average (Table S3). The decreased performance in terms of preventing extinctions is even more pronounced when compared with a policy minimizing species loss (Fig. 3b). This is an important finding, given that total protected area has been at the core of previous international targets for biodiversity (such as Aichi; https://www.cbd.int/sp/targets), and remains a key focus under the new post-2020 Global Biodiversity Framework under the Convention on Biological Diversity. Focusing on quantity (area protected) rather than quality (actual biodiversity protected) could inadvertently support political pressure for ‘residual’ reservation[35,36] – the selection of new protected areas on land and at sea that are unsuitable for extractive activities, which may reduce costs and risks for conflicts but are likely suboptimal for biodiversity conservation.

As expected, the reliability for optimisations on economic value and total protected area was high for the respective policy objectives, decreasing the value loss in 96% of the simulations compared to the random baseline and increasing the amount of protected area in 100% of the simulations (Table S3). However, these policies resulted in highly inconsistent outcomes in terms of preventing species extinctions, with biodiversity losses not significantly different from those of the random baseline policy (Table S3). This indicates that economic value and total protected area should not be used as surrogates for biodiversity protection.

Winners and losers. Focusing on the policy developed under Full Recurrent Monitoring and optimised on reducing species loss, we explored the properties of species that survived in comparison with those that went extinct, despite optimal area protection. Species that went extinct were characterised by relatively small initial range, small populations and intermediate or low resilience to disturbance (Fig. 4a). In contrast, species that survived had either low resilience but widespread ranges and high population sizes, or high resilience with small ranges and population sizes.

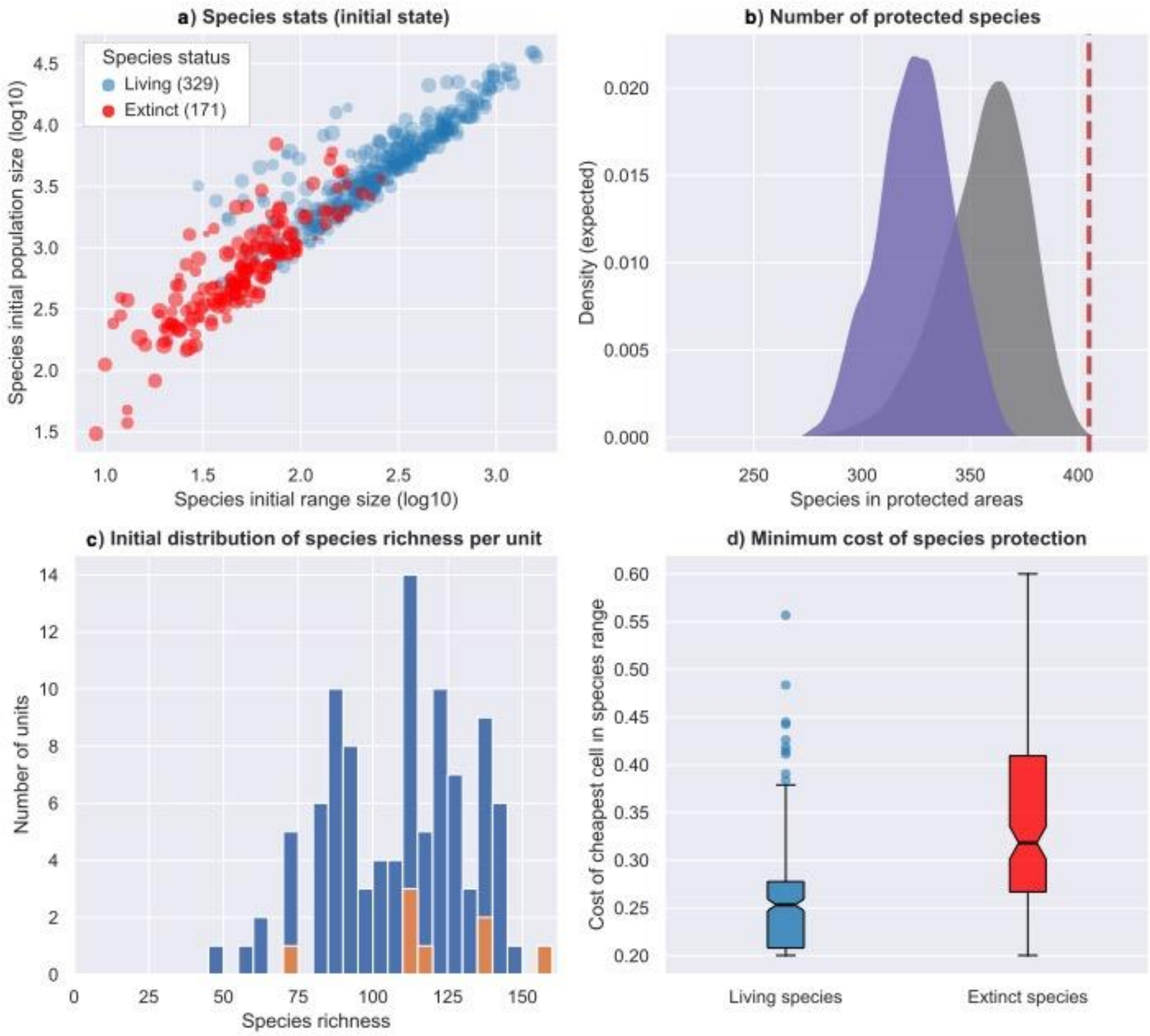

Fig. 4 | Summary statistics for one simulation optimised to reduce species loss and informed through Full Recurrent Monitoring. a, Living or surviving (blue circles) and locally extinct (red circles) species after a simulation of 30 time-steps with increasing disturbance and climate change. The X and Y axes show the initial range size and population size of the species (log10 transformed) and the size of the circles is proportional to the resilience of each species to anthropogenic disturbance and climate change, with smaller circles representing more sensitive species. **b,** Cumulative number of species encompassed in the eight protected units (5x5 cells) selected based on a policy optimised to minimise species loss. The grey density plot shows the expected distribution from 10,000 random draws, the purple shaded area shows the expected distribution when protected units are selected 'naively' (here, chosen among the top 20 most diverse ones), while the dashed red line indicates the number of species included in the units selected by the optimised CAPTAIN policy, which is higher than in 99.9% of the random draws. The optimised policy learned to maximise the total number of species included in protected units, thus accounting for their complementarity. Note that fewer species survived (329) in this simulation compared to how many were included in protected areas (405). This discrepancy is due to the effect of climate change, in which area protection does not play a role (Animation S1). Connectivity of protected areas could facilitate climate-induced range shifts. **c,** Species richness across the 100 protection units included in the area (blue), eight of which were selected to be protected (orange). The plot shows that the protection policy does not exclusively target units with the highest diversity. **d,** Distribution of the minimum cost of protection for living and extinct species. The plot shows the cost of the cell with the lowest cost of protection (as quantified at the last time step) within the initial range of each species.

We further assessed what characterised the grid cells that were selected for protection by the optimised policy. The cumulative number of species included in these cells was significantly higher than the cumulative species richness across a random set of cells of equal area (Fig. 4b). Thus, the model learns to protect a diversity of species assemblages to minimise species loss. Interestingly, the cells selected for protection did not include only areas with the highest species richness (Fig. 4c). This is important because areas with high richness constitute a 'naive' conservation target. Instead, protected cells spanned a range of areas with intermediate to high species richness, which reflects known differences among ecosystems or across environmental gradients and is more likely to increase protection complementarity for multiple species, a key factor incorporated by our software and some others[16,25,37]. Finally, extinct species tend to occur in more expensive regions within the system (Fig. 4d), corresponding to areas with high disturbance, which in turn might explain why they could not be effectively protected within the limited budget of the simulation.

If we instead examine which areas were protected under a policy maximizing total protected area, we find that they often include adjacent cells, for instance areas in a remote region, far from disturbance and therefore cheaper to buy and protect – typical of many current residual reserves, although less so for some newer conservation schemes[35,36].

Empirical applications and benchmarking

We evaluated our simulation framework by comparing its performance in optimizing policies against the current state-of-the-art tool for conservation prioritisation, Marxan[25]. We tested two monitoring policies: the Citizen science Recurrent and the Full Initial Monitoring, for which we could run analogous models within Marxan (see Methods). The analysis of 250 simulations showed that biodiversity loss was smallest in simulations using CAPTAIN with recurrent monitoring. Specifically, species loss using Marxan optimization with recurrent monitoring was on average 24% higher than using the CAPTAIN model (standard deviation, SD =18.9%) and resulted in a higher number of extinctions in 92% of the simulations (Fig. 5). Our methodology was even more successful when applying a one-time monitoring policy, which is the most common approach for identifying and delimiting protected areas worldwide; the CAPTAIN model outperformed Marxan in 96.8% of the simulations, with the latter resulting in a 40% average increase of species loss (SD = 26.7%). We interpret part of this difference in performance as the result of a different optimization objective, whereby Marxan seeks to find the cheapest distribution of protected units that meet a conservation target (e.g., protecting a minimum fraction of all species' initial range), without explicitly incorporating a finite budget as a limiting factor.

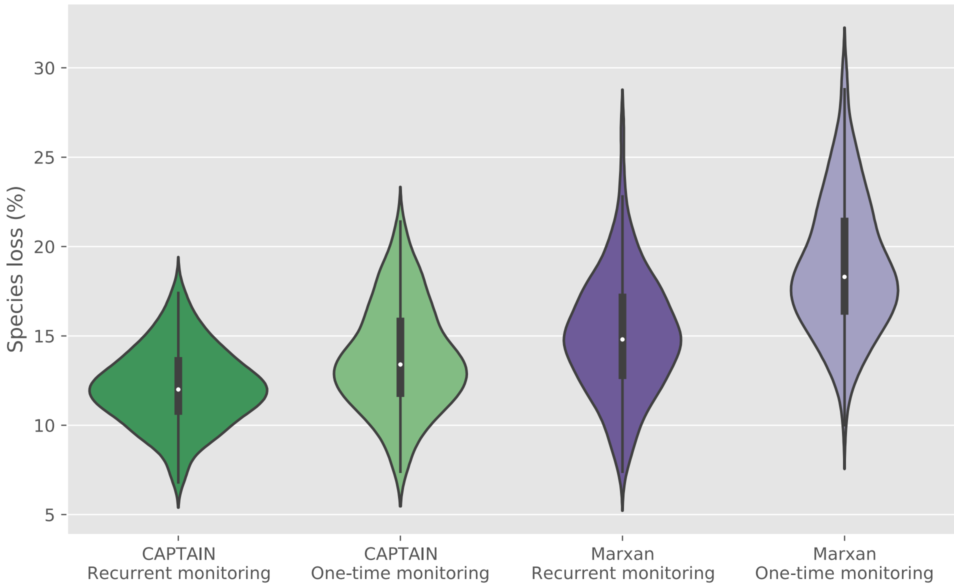

Fig. 5 | Benchmarking of CAPTAIN through simulations. The violin plots show the distribution of species loss outcomes across 250 simulations run under different monitoring policies based on the CAPTAIN framework developed here and on Marxan[25]. Species loss is expressed as a percentage of the total initial number of species in the simulated systems. See text for details of the analyses.

To demonstrate the potential applicability of our framework and its scalability to large datasets, we analysed a Madagascar biodiversity dataset recently used in a systematic conservation planning experiment[38] using Marxan[25]. The dataset included 22,394 protection units (5 x 5 km) and presence-absence data for 1,517 endemic tree species (see Methods for more details). Our results, here constrained to protect the same number of units as in the Marxan analysis, showed some overlap with the Marxan output for the highest priority areas, such as in the north (~ 13º S, 49º E), northeast (~ 15º S, 50º E) and centre (~ 20º S, 47º E) of the country (Figs. 6, S5–S6). Protection units with a Marxan priority greater than 75% were also assigned relatively high priority in CAPTAIN (on average 68%), while units with Marxan rank below 25% had low CAPTAIN rank (< 17%). This indicates a degree of consistency in the ranking of protection units across different methods. However, CAPTAIN additionally identified several other high priority areas across the country, within a wide region ranked by Marxan with only uniform average priority (ranked 25-75%). Importantly, CAPTAIN was able to identify priority areas for conservation at very high spatial resolution (Fig. 6b), making it a useful tool for informing on-the-ground decisions by landowners and policymakers.

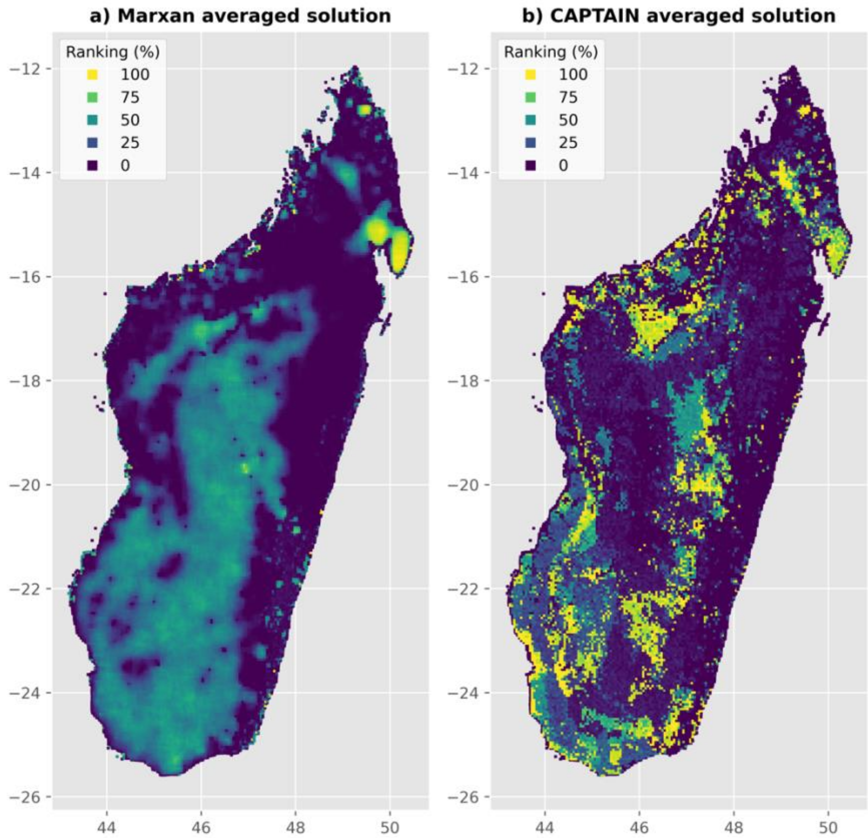

Fig. 6 | Empirical validation of CAPTAIN. The maps show a ranking of priority areas for protection across Madagascar based on the distribution of endemic trees. **a),** protection unit ranks resulting from an analysis using Marxan[25] (as in Fig. S7d of Carrasco et al.[38]); **b),** equivalent CAPTAIN results based on a Citizen science Recurrent Monitoring policy.

Conclusions

In contrast to many short-lived decisions by governments, the selection of which areas in a country's territory should be protected will have long-term repercussions. Protecting the right areas will help safeguard natural assets and their contributions for the future. Choosing suboptimal areas, by contrast, will lead to the loss of species, phylogenetic diversity, socio-economic value and ecological functions. As public funding for nature conservation is scarce and needs to compete with many other important environmental issues such as climate change or the spread of toxins, there is little room for mistakes.

The framework presented here provides a spatially explicit way to explore the complex decisions facing policymakers and conservationists today, focusing on data gathering, placement of protected areas and policy objective – all within the context of a rapidly changing world affected by local anthropogenic disturbances and large-scale climate change. Our results highlight the importance of regularly gathering basic biodiversity information and demonstrate substantial trade-offs in biodiversity outcome depending on the policy being optimised – such as maximizing the protection of species or areas.

As the number of standardised high-resolution biological datasets is increasing (e.g.,[39]), supported by the use of new and cost-effective monitoring technologies (Box 2), our approach offers new opportunities for research and conservation. The flexibility of our model, offered by its nearly 40 variables (see Methods), could be easily expanded and adapted to almost any empirical dataset. Future implementations could model additional variables, such as functional diversity and other biodiversity and socio-economic metrics.

Artificial intelligence techniques should not replace human judgment, and ultimately investment decisions will be based on more than just the simple parameters implemented in our models, including careful consideration of people's manifold interactions with nature[1,15]. More sophisticated measures of value could be incorporated in future work. It is also crucial to recognise the importance of ensuring the right conditions required for effective conservation of protected areas in the long term[40,41]. However, it is now time to acknowledge that the sheer complexity of biological systems, multiplied by the increasing disturbances in a changing world, cannot be fully grasped by the human mind. As we progress in what many are calling the most decisive decade for biodiversity[6,42], we must take advantage of powerful tools that help us steward the planet's remaining ecosystems in sustainable ways – for the benefit of people and all life on Earth.

METHODS

A biodiversity simulation framework

We developed a simulation framework modelling biodiversity loss to optimise and validate conservation policies using a reinforcement learning algorithm. We implemented a spatially explicit individual-based simulation to assess future biodiversity changes based on natural processes of mortality, replacement, and dispersal. Our framework also incorporates anthropogenic processes such as habitat modifications, selective removal of a species, rapid climate change, and existing conservation efforts. The simulation can include thousands of species and millions of individuals and track population sizes and species distributions and how they are affected by anthropogenic activity and climate change.

In our model, anthropogenic disturbance has the effect of altering the natural mortality rates on a species-specific level, which depends on the sensitivity of the species. It also affects the total number of individuals (the carrying capacity) of any species that can inhabit a spatial unit. Because sensitivity to disturbance differs among species, the relative abundance of species in each cell changes after adding disturbance and upon reaching the new equilibrium. The effect of climate change is modelled as locally affecting the mortality of individuals based on species-specific climatic tolerances. As a result, more tolerant or warmer-adapted species will tend to replace sensitive species in a warming environment, thus inducing range shifts, contraction, or expansion across species depending on their climatic tolerance and dispersal ability.

We use time-forward simulations of biodiversity in time and space, with increasing anthropogenic disturbance through time to optimise conservation policies and assess their performance. Along with a representation of the natural and anthropogenic evolution of the system, our framework includes an agent (i.e., the policy maker) taking two types of actions: 1) **monitoring**, which provides information about the current state of biodiversity of the system, and 2) **protecting**, which uses that information to select areas for protection from anthropogenic disturbance. The **monitoring policy** defines the level of detail and temporal resolution of biodiversity surveys. At a minimal level, these include species lists for each cell, whereas more detailed surveys provide counts of population sizes for each species, their temporal trends and geographic ranges. The **protection policy** is informed by the results of monitoring and selects protected areas in which further anthropogenic disturbance is maintained at an arbitrarily low value (Fig. 1). Because the total number of areas that can be protected is limited by a finite budget, we use a reinforcement learning algorithm[56] to optimise how to perform the protect actions based on the information provided by monitoring, such that it minimises species loss or other criteria depending on the policy (see below).

We provide a full description of the simulation system in the Supplementary Methods. In the sections below we present the optimisation algorithm, describe the experiments carried out to validate our framework, and demonstrate its use with an empirical dataset.

CAPTAIN: Optimisation of conservation policy using reinforcement learning

We use reinforcement learning to optimise a conservation policy under a pre-defined criterion (e.g., aiming to minimise the loss of various biodiversity metrics). The CAPTAIN framework includes a space of actions, namely monitoring and protecting, that are optimised to maximise a reward R. The **reward** defines the optimality criterion of the simulation and can be quantified as the cumulative value of species that do not go extinct throughout the time frame evaluated in the simulation. If the value is set equal across all species, the reinforcement learning algorithm will minimise overall species extinctions. However, different definitions of value can be used to minimise loss based on evolutionary distinctiveness of species (e.g., minimising phylogenetic diversity loss), or their ecosystem or economic value. Alternatively, the reward can be set equal to the amount of protected area, in which case the RL algorithm maximises the number of cells protected from disturbance, regardless of which species occur there. The amount of area that can be protected through the protecting action is determined by a budget B_t and by the cost of protection C_t^c, which can vary across cells and through time.

The granularity of monitoring and protection actions is based on spatial units that may include one or more cells and which we define as the *protection units*. In our system, protection units are adjacent, non-overlapping areas of equal size (Fig. 1), which can be protected at a cost that cumulates the costs of all cells included in the unit.

The monitoring action collects information within each protection unit about the state of the system, which includes species abundances and geographic distribution,

$$S_t = \{\mathbf{H_t}, \mathbf{D_t}, \mathbf{F_t}, \mathbf{T_t}, \mathbf{C_t}, \mathbf{P_t}, B_t\} \tag{1}$$

We define as *feature extraction* the result of a function $X(S_t)$, which returns for each protection unit a set of features summarising the state of the system in the unit. The number and selection of features (Table S2) depends on the monitoring policy (π_X), which is decided *a priori* in the simulation. A predefined monitoring policy also determines the temporal frequency of this action throughout the simulation, e.g. only at the first time step or repeated at each time step. The features extracted for each unit represent the input upon which a protect action can take place, if the budget allows for it, following a protection policy π_Y.

Monitoring action

The monitoring action extracts features from the simulated system within each protection unit. These features (listed in Table S2) include the number of species which are not already protected in other units, the number of rare species, and the cost of the unit relative to the remaining budget. Different subsets of these features are used depending on the monitoring policy and on the optimality criterion of the protection policy (π_Y).

We do not assume species-specific sensitivities to disturbance (d_s, f_s) to be a known feature, since a precise estimation of these parameters in an empirical case would require targeted experiments, which we consider unfeasible across a large number of species. Instead, species-specific sensitivities can be learned from the system through the observation of changes in relative abundances of species (x_3 in Tables S2). The features tested across different policies are specified in the subsection *Experiments* (see below).

Protect action

The protect action selects a protection unit, and resets the disturbance in the included cells to an arbitrarily low level. A protected unit is also immune from future anthropogenic disturbance increases, while protection does not prevent climate change in the unit. The model can include a buffer area along the perimeter of a protected unit, in which the level of protection is lower compared to the centre, to mimic the generally negative edge effects in protected areas (e.g., higher vulnerability to extreme weather). While protecting a disturbed area theoretically allows it to return to its initial biodiversity levels, population growth and species composition of the protected area will still be controlled by the death-replacement-dispersal processes described above, as well as the state of neighbouring areas. Thus, protecting an area that has already undergone biodiversity loss may not result in the restoration of its original biodiversity levels.

The protect action has a cost determined by the cumulative cost of all cells in the selected protection unit. The cost of protection can be set equal across all cells and constant thorough time. Alternatively, it can be defined as a function of the current level of anthropogenic disturbance in the cell. The cost of each protection action is taken from a predetermined finite budget and a unit can be protected only if the remaining budget allows it.

Policy definition

We frame the optimisation problem as a stochastic control problem where the state of the system S_t evolves through time as described in the section above, but it is also influenced by a set of discrete actions determined by the protection policy π_Y. The protection policy is a probabilistic policy: for a given set of policy parameters and an input state, the policy outputs an array of probabilities associated to all possible *protect* actions[57]. While optimising the model we extract actions according to the probabilities produced by the policy to make sure that we explore the space of actions. When we run experiments with a fixed policy instead, we choose the action with highest probability. The input state is transformed by the feature extraction function $X(S_t)$ defined by the monitoring policy and the features are mapped to a probability through a neural network with architecture described below.

In our simulations we fix π_X, thus pre-defining the frequency of monitoring (e.g. at each time step or only at the first time step) and the amount of information produced by $X(S_t)$ and we optimise π_Y, which determines how to best use the available budget to maximise the reward. Each action has cost, defined by the function $\texttt{Cost}(A, S_t)$, which here we set to a constant for monitoring and equal across all monitoring policies. The cost of the *protect* action is instead set to the cumulative cost of all cells in the selected protection unit. In the simulations presented here, unless otherwise specified, the protection policy can only add one protected unit at each time step, if the budget allows, i.e. if $\texttt{Cost}(Y, S_t) < B_t$.

The protection policy is parametrised as a feed forward neural network with a hidden layer using a ReLU activation function (Eq. 3) and an output layer using a softMax function (Eq. 5). The input of the neural network is a matrix of J features extracted through the most recent monitoring across U protection units. The output, of size U, is a vector of probabilities which provides the basis to select a unit for protection. The hidden layer $h^{(1)}$ is a matrix $J \times L_1$

$$h^{(1)}_{nl_1} = g\left(\sum_f x_{nf} W^{(1)}_{fl_1}\right) \tag{2}$$

where

$$g(x) = \max(0, x) \tag{3}$$

is the ReLU activation function and the matrix $W^{(1)}$ is the matrix of coefficients we are optimising. The output layer takes the $h^{(1)}$ as input and gives an N vector as output:

$$h^{(2)}_n = \sigma\left(\sum_{l_1} h^{(1)}_{nl_1} W^{(2)}_{l_1}\right) \tag{4}$$

with σ a softMax function

$$\sigma(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{5}$$

We interpret the output vector of N variables as the probability of protecting the cell n.

This architecture implements parameter sharing across all protection units when connecting the input nodes to the hidden layer; this reduces the dimensionality of the problem at the cost of losing some spatial information, which we encode in the feature extraction function. The natural next step would be to use a convolutional layer to discover relevant shape and space features instead of using a feature extraction function. To define a baseline for comparisons in the experiments described below, we also define a random protect policy, $\hat{\pi}_P$, which sets a uniform probability to protect units that have not yet been protected. This policy does not include any trainable parameter and relies on feature x_6 (an indicator variable for protected units) to randomly select the proposed unit for protection.

Optimisation algorithm

The optimisation algorithm implemented in CAPTAIN optimises the parameters of a neural network such that they maximise the expected reward resulting from the *protect* actions. To this aim, we implemented combination of standard algorithms, using a genetic strategies algorithm[58] and incorporating aspects of classical Policy Gradient methods such as an Advantage function[59]. Specifically, our algorithm is an implementation of the Parallelised Evolution Strategies[58], in which two phases are repeated across several iterations (hereafter: epochs) until convergence. In the first phase the policy parameters are randomly perturbed and then evaluated by running one full episode of the environment, i.e. a full simulation with the system evolving for a predefined number of steps. In the second phase the results from different runs are combined and the parameters updated following a stochastic gradient estimate[58]. We perform several runs in parallel on different workers (e.g. CPUs) and aggregate the results before updating the parameters. To improve the convergence we follow the standard approach used in policy optimisation algorithms[59], where the parameter update is linked to an advantage function A as opposed to the return alone (Eq. 6). Our advantage function measures the improvement of the running reward (weighted average of rewards across different epochs) with respect to the last reward. Thus, our algorithm optimises a policy without the need to compute gradients and allowing for easy parallelisation. Each epoch in our algorithm works as:

for every worker p **do**

$\epsilon_p \leftarrow \mathcal{N}(0, \sigma)$ with diagonal covariance and dimension $W + M$
for $t = 1, ..., T$ **do**
$R_t \leftarrow R_{t-1} + r_t(\theta + \epsilon_p)$
end for
end for
$R \leftarrow$ average of R_T across workers
$R_e \leftarrow \alpha R + (1 - \alpha) R_{e-1}$
for every coefficient θ in $W + M$ **do**
$\theta \leftarrow \theta + \lambda A(R_e, R_T, \epsilon)$
end for

where R is the cumulative reward over T time steps, $\lambda = 0.1$ is a learning rate, and A is an advantage function defined as the average of final reward increments with respect to the running average reward R_e on every worker p weighted by the corresponding noise ϵ_p:

$$A(R_e, R_T, \epsilon) = \frac{1}{P} \sum_p (R_e - R_T^p) \epsilon_p. \tag{6}$$

Experiments

We used our CAPTAIN framework to explore the properties of our model and the effect of different policies through simulations. Specifically, we ran three sets of experiments. The first set aimed at assessing the effectiveness of different policies optimised to minimise species loss, based on different monitoring strategies. We ran a second set of simulations to determine how policies optimised to minimise value loss or maximise the amount of protected area may impact species loss. Finally, we compared the performance of CAPTAIN models against that of a state-of-the-art method for conservation planning (Marxan[25]).

Initialisation of the systems

Across all our simulations, we used systems of 50×50 cells with uniform carrying capacity across all cells set at $K = 1,000$. Each simulated system was initialised with 500 species with random Weibull-distributed population sizes to reflect empirical rank-abundance plots[60] , totalling 2.5 million individuals (Fig. S3a). Species ranges were generated based on a random diffusion process, with the number of individuals in a cell constrained by the carrying capacity (Fig. S4).

The natural mortality was set constant across species and equal to 0.01, implying that 1% of the individuals of each species die at each time step. We set the growth rate to 1, indicating that, on average, each individual gives origin to one offspring. In our simulations we also assumed dispersal rates to equal across all species ($\lambda = 0.1$), with the distance between adjacent cells set to 1. Species were assigned a random beta sensitivity to disturbance ($d_s \sim \mathcal{B}[1, 1]$) and sensitivity to selective disturbance ($f_s \sim \mathcal{B}[0.2, 0.7]$) (Fig. S3c,d).

To track the effects of biodiversity loss on phylogenetic diversity, we simulated phylogenetic trees describing the relationships and divergence times among all species. Phylogenies with 500 extant species were simulated based on a birth-death process using the TreePar package[61] with a speciation rate set to 1 and extinction rate sampled for each tree from a uniform distribution $\mathcal{U}[0, 0.9]$.

We assigned an economic value to each species using an approach that generates a high variation among species but also a geographic pattern, such that species occurring in some regions tend to be more valuable than species occurring in others (e.g., some types of forest might harbour more valuable species for timber then others, depending on moisture and soil gradients). We first randomly initialised species values such that 20% of the species had a value 100 times higher than each of the remaining 80% of the species. We then randomly selected a cell in the system and divided the value of each species by the distance between the centroid of the species' geographic range and the selected cell. The values were then re-scaled so that that mean value across all species became 1 (Fig. S3b).

In our simulations we defined the cost of protection (C_c) for a cell as a function of the current level (D_c) of anthropogenic disturbance: $C_c = 0.2 + 0.4D_c$, where 0.2 is an arbitrary baseline cost. Under this assumption, the cost of protecting a cell with full disturbance is three times higher than that of a cell with no disturbance. The rationale for this disturbance-dependent cost is that enforcing protection implies removing (or relocating) the source of disturbance. If there is a strong disturbance this can be interpreted as a considerable amount of economic activity (e.g. large town or mine) which will be expensive to remove or relocate.

Monitoring policies to minimise species loss

We performed simulations to assess the effect of different monitoring policies on biodiversity loss. We modelled a dynamic system in which an initial area is subject to a level of disturbance that intensifies and expands spatially over time (Fig. S5). Disturbance values are initialised at 0 across all cells and then increased based on random diffusion processes to create spatial heterogeneity in the disturbance intensity and a trend toward increased total disturbance through time.

We divided the system into 100 protection units of 5×5 neighbouring cells and set the initial budget to 55. Given a baseline cost of 0.2 per cell, the cost of protection for one unit is 5 in the absence of disturbance, thus a maximum of 11 units can be protected under these settings. However, since the cost of protection is also a function of disturbance, the effective number of protected units is lower. The protection policy in these simulations allowed for the selection of a single protection unit at each time step.

We tested three monitoring policies which differ in the frequency of monitoring and the quality and quantity of information obtained through the feature extraction function.

- *Full Recurrent Monitoring*. This policy involves monitoring at each time step with the feature extraction function tracking the number of non-protected rare species, species with a declining population size, and budget and cost of each unit (features x_2, x_3, x_5, x_6 in Table S2). The protection policy included one meta-parameter (defining the threshold for rare species; Table S2) and a neural network with 3 nodes in the hidden layer.

- *Citizen science Recurrent Monitoring*. This policy involves the monitoring of the system at each time step, but with a lower amount and quality of information compared to the full monitoring policy (features x_1, x_5, x_6). Monitoring only tracks the number of non protected species per unit without information about population sizes. The monitoring also includes the available budget and cost of protection. We additionally introduced a fraction of stochastic error in the feature extraction function. Specifically, we assumed that an average of 5% of the species in a unit might go undetected (with probability inversely proportional to their abundance in the unit) and that another 5% of the species can be misidentified. The protection policy included a neural network with 3 nodes in the hidden layer.

- *Full Initial Monitoring*. This policy involves monitoring only at the first time step, with the feature extraction function tracking the number of non protected species, rare species, and budget and cost of each unit (features $x_1 x_2, x_5, x_6$). Since monitoring only takes place once, no information about trends in population sizes is included. We consider the cost feature (x_5) and the protection indicator (x_6) as known even without monitoring, and therefore update them at each step. The protection policy included one meta-parameter (defining the threshold for rare species) and a neural network with 4 nodes in the hidden layer.

The models were optimised using the algorithm described above, running 6 simulations in parallel for 1,000 epochs. Each simulation was based on a different randomly initialised system and ran for 25 time steps.

We then used the estimated parameters to assess the effect of different monitoring policies in 250 additional simulations. Each simulation was run for 25 time steps and we fixed the seeds of the random number generators used in the runs to ensure the simulations were comparable among monitoring policies (i.e. based on the same underlying system and disturbance processes). For comparison, we repeated the 250 simulations using a random protection policy, in which non-protected units are assigned a uniform probability of being selected for protection.

We summarised the outcome of the simulations by measuring at the last time step the species loss, value loss, phylogenetic diversity loss and the amount of protected area. We report all measurements as percentage changes compared to the baseline outcome of the random policy.

We also computed the reliability of the policy as the inverse of the variance (i.e., precision) in species loss across all simulations relative to that of a random policy. Thus a higher reliability value indicates that the policy provides a lower variance in species loss across stochastically different systems and simulations. We interpret high reliability of a policy as a measure of how well it adapts to different systems.

Testing the trade-offs among species, value, and area losses

We ran simulations in which the policy aimed at minimising value loss or at maximising the number of protected units, using the same settings as in the simulations described above.

- *Minimising value loss*. In this policy the negative reward was set equal to the cumulative value of extinct species. We applied a full recurrent monitoring, with the feature extraction function tracking the cumulative value of non protected species, that of rare species with declining population sizes, as well as budget and cost of each unit (features x_4, x_5, x_6, x_7, x_8). The protection policy included one meta-parameter (defining the threshold for rare species) and a neural network with 5 nodes in the hidden layer.
- *Maximising protected area*. In this policy the positive reward was set equal to the amount of protected area, regardless of which and how many species occurred in it. We applied recurrent monitoring, but the feature extraction function here only returned the cost of each unit and the available budget (features x_5, x_6). The protection policy included a neural network with 2 nodes in the hidden layer.

We optimised the models, performed simulations and summarised the results as described in the section above.

Comparison with Marxan

We ran 250 simulations to compare the performance of our model optimised through reinforcement learning framework with Marxan[25], one of the state-of-the-art and most widely used programs for systematic conservation planning. Marxan optimises the placement of protection units to meet a predefined conservation target while minimising the cost. We used a fixed and uniform cost of protection across all units and specified a budget that allowed the protection of 10% of the protection units in the system. Following the settings used in our previous experiments, the system evolved through time with increasing and spatially inhomogeneous disturbance (Fig. S5) and setting one protection unit at each time step if the budget allowed. After 25 steps we measured the extent of species loss.

Within the CAPTAIN framework, we tested two monitoring policies: the Citizen science Recurrent Monitoring and the Full Initial Monitoring. To generate analogous policies in Marxan, we ran the simulations while re-optimising the Marxan model at each step based on the current state of the system (i.e. reflecting a recurrent monitoring strategy) or only at the first step (one-time monitoring) to rank all protection units. Each optimisation involved 100 independent Marxan optimisations using the simulated annealing algorithm followed by iterative improvement, as recommended in the program's manual[62] We summarised the optimisations to rank protection units by the frequency at which they were included in the Marxan solution. As Marxan uses a conservation target in its optimisation, we specified that at least 10 individuals of all species should be included within the designated protected units. This threshold reflects the lower bound of a species' population size below which the species is considered as extinct in all our simulations.

Analysis of Madagascar endemic tree diversity

We analysed a recently published[38] dataset of 1,517 tree species endemic to Madagascar, for which presence-absence data had been approximated through species distribution models across 22,394 cells of 5 $\times$ 5 km spanning the entire country (Fig. S5a). Carrasco et al.[38] used a probabilistic extension of Marxan (MarProb[63]) to identify the units that should be protected to reach a conservation target set to protect at least 10% of the modelled range of all species. Their analyses included a spatial quantification of threats affecting the local conservation of species and assumed the cost of each protection unit as proportional to its level of threat (Fig.

S5b), similarly to how our CAPTAIN framework models protection costs as proportional to anthropogenic disturbance.

Among the analyses presented in their paper, they carried out 100 optimisations of Marxan to rank the protection units based on how frequently they where present in the Marxan solution (Fig. 6b; Fig. S7d in [38]). Their Marxan analyses resulted in a median of 5,336 protected units (23.8% of the total). To analyse the data in a comparable way within our CAPTAIN framework, and because the dataset did not include abundance data, we used the Citizen science Recurrent Monitoring policy (as optimised through the simulations described above) to select 5,336 protection units. In the monitoring step (feature extraction) of our model, we considered a species to be protected only when at least 10% of its predicted range was included within a protected unit, to match the conservation target specified in the Marxan analysis. The selection of protection units was further constrained by their cost, defined as by Carrasco et al.[38] and by a budget, which we set equal to the cost of the best Marxan solution.

We ran two sets of analyses: first we ran the model selecting the 5,336 protection units based on the predicted species presence or absence, i.e. ignoring the fact that species might no longer occur in areas with high levels of disturbance. This means that the monitoring action was based on the modelled theoretical distribution of species, assuming that a disturbed area can be restored to its theoretical natural state. In the second analysis we considered the potential effect of disturbance in the monitoring step. Specifically, in the absence of more detailed data about the actual presence or absence of species, we modelled the presence of a species in a unit as a random draw from a binomial distribution with a parameter set equal to $p = 1 - D$, where D is the disturbance (or "threat" *sensu* Carrasco et al.[38]) in the unit. Under this approach, most of the species expected to live in a unit are considered to be present if the unit is undisturbed. Conversely, most species are assumed to be absent from units with high anthropogenic disturbance. This resampled diversity was used for feature extraction in the monitoring steps (Fig. 1c), therefore assuming that a disturbed area cannot be restored to its theoretical natural level of species richness. While this approach is an approximation of how species might respond to anthropogenic pressure, the use of additional empirical data on species specific sensitivity to disturbance can provide a more realistic input in the CAPTAIN analysis.

We repeated both sets of analyses 60 times using different random seeds and summarised the results by ranking protection units based on how frequently they were selected in the CAPTAIN solution. The resulting maps are shown in Fig. S6b (first set of analyses) and Fig. 6b (second set with binomial resampling).

Implementation and code availability

The simulation framework and algorithms described here were implemented in Python v.3. All the codes and scripts are available here: tinyurl.com/nm29vfcu. and will be made available along with all simulations in a permanent repository on zenodo.org and as an open access repository upon acceptance of the paper: github.com/dsilvestro/CAPTAIN.

Box 1: Socio-economic valuation of biodiversity

The field of economics sees nature as an asset, analogous to diversity in portfolio management[3,43]. It provides valuable insurance that may prove vital[44]. Risks are reduced if two assets are negatively correlated. Weitzman[45] incorporates the idea of redundancy when species share genes, and shows that optimal policy under a budget constraint will involve strict prioritisation of some species.

The value of ecosystem services hinges on ease of substitution by man-made capital. In some respects, man can “replace” a coral reef by artificial structures. Fish still find protection and food, but the artificial reef does not fully “replace” nature. When nature is irreplaceable, we speak of strong (rather than weak) sustainability; meaning more care must be taken to protect natural capital assets[46].

We see massive degradation of natural assets that could have yielded a high return if properly managed by effective owners or stewards. Institutional mechanisms (including secure property rights) are vital to protect nature[47]. Still, private incentives to preserve biodiversity (e.g. research and development in biodiversity-based solutions) remain weak[48], and strong policies are needed[14].

Both benefits and costs of conservation vary considerably across space. Protection is typically expensive for farmland or real estate close to cities. Some land is cheap but protection enforcement expensive precisely because of remoteness. Some areas may be valuable because they have high biodiversity or endemism. What the framework we developed here strives for is high total biodiversity benefits with low land and opportunity costs, at the same time as it reduces risks associated with climate change uncertainties[49]. Spatial targeting of sites that increase biodiversity protected per monetary unit is cost effective, and may also include recreational and other values[22,50] that we hope to develop more in future model versions.

<End of Box 1>

Box 2: New techniques for biodiversity monitoring

Our simulations show that the regular monitoring of species is critical for prioritising areas for conservation under changing anthropogenic and climate pressure (Fig. 2). But given scarce resources and vast areas to monitor, how can this be most efficiently accomplished?

For centuries, biodiversity inventories have been carried out by biodiversity experts. This work has comprised the collection, recording and eventual identification of biological samples, such as fertile tree branches or whole animals – a time- and resource-consuming process, resulting in taxonomically and spatially biased and incomplete biodiversity data[51]. New approaches are now speeding up and popularising biodiversity monitoring, including **environmental DNA**, **remote sensing** and **citizen science**.

Rather than locating and recording each individual species directly, soil samples can be taken by non-specialists (**a**) and their environmental DNA (eDNA) contents subsequently analysed. This approach reveals the biotic composition of whole communities, including plants, animals, fungi and bacteria. Standardised sampling also allows direct comparison of taxonomic and phylogenetic diversity across multiple sites[52], helping to inform on presence and absence of species. Challenges remain in completing reference databases for matching sequences to names, and in separating local versus transported DNA from nearby areas.

Citizen science initiatives such as ‘bio-blitzes’ (an intense period of biological surveying, often by amateurs) can help fill up critical data gaps, reduce monitoring costs and increase local awareness and engagement for biodiversity. An impressive 3.5 billion smartphones are now in use around the world[53], creating unseen possibilities of linking millions of people to nature through species logging (**b**), using platforms such as iNaturalist[54] which increasingly use image-recognition software and geolocations for automated species identification. In our simulations, even identification errors of up to 20% during monitoring steps (a conservative rate for many organism groups, such as birds, mammals or trees) have only a marginal impact on the biodiversity outcomes (Fig. 3c). [Photo credits: a-b: A.A.; c: Justin Moat].

Finally, remote sensing technologies can rapidly scan and characterise relatively large areas. Using 3-D sensing technology, they now hold the promise of automated identification of species using multi-spectrum images[55]. The spectral signatures of species can be produced by combining on-the-ground (visible to NIR spectrophotometry of plant material and terrestrial LiDAR) with from-the-air (hyperspectral and LiDAR UAV survey) data. This allows the isolation of individual objects to record the presence and abundance of species (**c**). The technology can also provide measures of vegetation structure (informing on an areas’ functional diversity) and ecosystem services, such as carbon storage, soil water content, and other parameters that could be easily implemented in our model to help the valuation and ranking of areas for protection, besides greatly improving the quality of habitat data publicly available.

<End of Box 2>

Acknowledgements

We thank Kerstin Johannesson for the initial discussions that sparked this project; Ben Groom, Atte Moilanen, Bob Pressey and Ian Bateman for invaluable feedback on an earlier version of this manuscript; Jesús Carrasco for providing the Madagascar tree distribution data; Justin Moat for input on remote sensing technologies; Weston Testo for suggesting the acronym CAPTAIN; Rhian Smith for editorial support; many colleagues at our respective research groups for discussions; and the editor Monica Contestabile and three anonymous reviewers for suggestions that greatly helped improve this study. AA is funded by the Swedish Foundation for Strategic Research, the Swedish Research Council and the Royal Botanic Gardens, Kew. TS and AA acknowledge funding from the Strategic Research Area Biodiversity and Ecosystem Services in a Changing Climate, BECC, funded by the Swedish government. DS received funding from the Swiss National Science Foundation (PCEFP3_187012) and from the Swedish Research Council (VR: 2019-04739).

Author contributions

T.S. initiated the project with A.A.; D.S. and S.G. developed the AI model and performed all analyses; A.A., D.S., T.S, and S.G. wrote the paper.

REFERENCES

1 Díaz, S. *et al.* Assessing nature's contributions to people. *Science* **359**, 270-272, doi:10.1126/science.aap8826 (2018).

2 Chaplin-Kramer, R. *et al.* Global modeling of nature's contributions to people. *Science* **366**, 255-258, doi:10.1126/science.aaw3372 (2019).

3 Dasgupta, P. The Economics of Biodiversity: The Dasgupta Review. *London: HM Treasury* (2021).

4 Barnosky, A. D. *et al.* Has the Earth's sixth mass extinction already arrived? *Nature* **471**, 51-57, doi:10.1038/nature09678 (2011).

5 Andermann, T., Faurby, S., Turvey, S. T., Antonelli, A. & Silvestro, D. The past and future human impact on mammalian diversity. *Science Advances* **6**, eabb2313, doi:10.1126/sciadv.abb2313 (2020).

6 Leclère, D. *et al.* Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature* **585**, 551-556, doi:10.1038/s41586-020-2705-y (2020).

7 IPBES. Global Assessment on Biodiversity and Ecosystem Services. (2019).

8 Nic Lughadha, E. *et al.* Extinction risk and threats to plants and fungi. *PLANTS, PEOPLE, PLANET* **2**, 389-408, doi:10.1002/ppp3.10146 (2020).

9 Antonelli, A. *et al.* State of the World's Plants and Fungi 2020. (Royal Botanic Gardens, Kew, 2020).

10 Howes, M.-J. R. *et al.* Molecules from nature: Reconciling biodiversity conservation and global healthcare imperatives for sustainable use of medicinal plants and fungi. *PLANTS, PEOPLE, PLANET* **2**, 463-481, doi:10.1002/ppp3.10138 (2020).

11 Kersey, P. J. *et al.* Selecting for useful properties of plants and fungi – Novel approaches, opportunities, and challenges. *PLANTS, PEOPLE, PLANET* **2**, 409-420, doi:10.1002/ppp3.10136 (2020).

12 Seddon, N. *et al.* Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **375**, 20190120, doi:doi:10.1098/rstb.2019.0120 (2020).

13 Diversity, S. o. t. C. o. B. Global Biodiversity Outlook 5 – Summary for Policy Makers. (2020).

14 Sterner, T. *et al.* Policy design for the Anthropocene. *Nature Sustainability* **2**, 14-21, doi:10.1038/s41893-018-0194-x (2019).

15 Mace, G. M. Whose conservation? *Science* **345**, 1558-1560, doi:10.1126/science.1254704 (2014).

16 Moilanen, A. Generalized Complementarity and Mapping of the Concepts of Systematic Conservation Planning. *Conservation biology : the journal of the Society for Conservation Biology* **22**, 1655-1658, doi:10.1111/j.1523-1739.2008.01043.x (2008).

17 Margules, C. & Sarkar, S. *Systematic conservation planning*. (Cambridge University Press, 2007).

18 Margules, C. R. & Pressey, R. L. Systematic conservation planning. *Nature* **405**, 243-253, doi:10.1038/35012251 (2000).

19 Obura, D. O. *et al.* Integrate biodiversity targets from local to global levels. *Science* **373**, 746-748, doi:10.1126/science.abh2234 (2021).

20 Moilanen, A., Wilson, K. & Possingham, H. *Spatial conservation prioritization: quantitative methods and computational tools*. (Oxford University Press, 2009).

21 Honeck, E., Sanguet, A., Schlaepfer, M. A., Wyler, N. & Lehmann, A. Methods for identifying green infrastructure. *SN Applied Sciences* **2**, 1916, doi:10.1007/s42452-020-03575-4 (2020).

22 Bateman, I. J. *et al.* Bringing Ecosystem Services into Economic Decision-Making: Land Use in the United Kingdom. *Science* **341**, 45-50, doi:10.1126/science.1234379 (2013).

23 Carvalho, S. *et al.* Spatial conservation prioritization of biodiversity spanning the evolutionary continuum. *Nature Ecology & Evolution* **1**, 0151, doi:10.1038/s41559-017-0151 (2017).

24 Sacre, E., Weeks, R., Bode, M. & Pressey, R. L. The relative conservation impact of strategies that prioritize biodiversity representation, threats, and protection costs. *Conservation Science and Practice* **2**, e221, doi:https://doi.org/10.1111/csp2.221 (2020).

25 Ball, I. R., Possingham, H. P. & Watts, M. Marxan and relatives: software for spatial conservation prioritisation. *Spatial conservation prioritisation: Quantitative methods and computational tools*, 185-195 (2009).

26 Pressey, R. L., Mills, M., Weeks, R. & Day, J. C. The plan of the day: Managing the dynamic transition from regional conservation designs to local conservation actions. *Biol. Conserv.* **166**, 155-169, doi:https://doi.org/10.1016/j.biocon.2013.06.025 (2013).

27 Watts, M., Klein, C. J., Tulloch, V. J. D., Carvalho, S. B. & Possingham, H. P. Software for prioritizing conservation actions based on probabilistic information. *Conserv. Biol.* **35**, 1299-1308, doi:https://doi.org/10.1111/cobi.13681 (2021).

28 Tulloch, V. J. *et al.* Incorporating uncertainty associated with habitat data in marine reserve design. *Biol. Conserv.* **162**, 41-51, doi:https://doi.org/10.1016/j.biocon.2013.03.003 (2013).

29 Grantham, H. S., Wilson, K. A., Moilanen, A., Rebelo, T. & Possingham, H. P. Delaying conservation actions for improved knowledge: how long should we wait? *Ecol. Lett.* **12**, 293-301, doi:https://doi.org/10.1111/j.1461-0248.2009.01287.x (2009).

30 Zizka, A., Silvestro, D., Vitt, P. & Knight, T. M. Automated conservation assessment of the orchid family with deep learning. *Conserv. Biol.* **n/a**, doi:https://doi.org/10.1111/cobi.13616 (2020).

31 Gomes, C. *et al.* Computational sustainability: computing for a better world and a sustainable future. *Commun. ACM* **62**, 56–65, doi:10.1145/3339399 (2019).

32 Spring, D. A., Cacho, O., Mac Nally, R. & Sabbadin, R. Pre-emptive conservation versus “fire-fighting”: A decision theoretic approach. *Biol. Conserv.* **136**, 531-540, doi:https://doi.org/10.1016/j.biocon.2006.12.024 (2007).

33 Murcia, C. Edge effects in fragmented forests: implications for conservation. *Trends Ecol. Evol.* **10**, 58-62 (1995).

34 Kosmala, M., Wiggins, A., Swanson, A. & Simmons, B. Assessing data quality in citizen science. *Front. Ecol. Environ.* **14**, 551-560, doi:https://doi.org/10.1002/fee.1436 (2016).

35 Devillers, R. *et al.* Reinventing residual reserves in the sea: are we favouring ease of establishment over need for protection? *Aquat. Conserv.: Mar. Freshwat. Ecosyst.* **25**, 480-504, doi:https://doi.org/10.1002/aqc.2445 (2015).

36 Vieira, R. R. S., Pressey, R. L. & Loyola, R. The residual nature of protected areas in Brazil. *Biol. Conserv.* **233**, 152-161, doi:https://doi.org/10.1016/j.biocon.2019.02.010 (2019).

37 Dilkina, B. *et al.* Trade-offs and efficiencies in optimal budget-constrained multispecies corridor networks. *Conserv. Biol.* **31**, 192-202 (2017).

38 Carrasco, J., Price, V., Tulloch, V. & Mills, M. Selecting priority areas for the conservation of endemic trees species and their ecosystems in Madagascar considering both conservation value and vulnerability to human pressure. *Biodivers. Conserv.* **29**, 1841-1854 (2020).

39 Bruelheide, H. *et al.* sPlot – A new tool for global vegetation analyses. *Journal of Vegetation Science* **30**, 161-186, doi:10.1111/jvs.12710 (2019).

40 Geldmann, J., Manica, A., Burgess, N. D., Coad, L. & Balmford, A. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. *Proc. Natl. Acad. Sci. USA* **116**, 23209-23215, doi:10.1073/pnas.1908221116 (2019).

41 Geldmann, J. *et al.* A global analysis of management capacity and ecological outcomes in terrestrial protected areas. *Conservation Letters* **11**, e12434, doi:https://doi.org/10.1111/conl.12434 (2018).

42 Díaz, S. *et al.* Set ambitious goals for biodiversity and sustainability. *Science* **370**, 411-413, doi:10.1126/science.abe1530 (2020).

43 Brock, W. A. & Xepapadeas, A. Valuing Biodiversity from an Economic Perspective: A Unified Economic, Ecological, and Genetic Approach. *Am Econ Rev* **93**, 1597-1614, doi:10.1257/000282803322655464 (2003).

44 Goeschl, T. & Swanson, T. The social value of biodiversity for R&D. *Environmental and Resource Economics* **22**, 477-504 (2002).

45 Weitzman, M. L. The Noah's ark problem. *Econometrica*, 1279-1298 (1998).

46 Barbier, E. B. The concept of natural capital. *Oxford Review of Economic Policy* **35**, 14-36, doi:10.1093/oxrep/gry028 (2019).

47 Dasgupta, P. The Dasgupta Review –Independent Review on the Economics of Biodiversity. Interim Report. (2020).

48 Simpson, R. D., Sedjo, R. A. & Reid, J. W. Valuing biodiversity for use in pharmaceutical research. *Journal of Political Economy* **104**, 163-185 (1996).

49 Ando, A. W. & Mallory, M. L. Optimal portfolio design to reduce climate-related conservation uncertainty in the Prairie Pothole Region. *Proc. Natl. Acad. Sci. USA* **109**, 6484-6489, doi:10.1073/pnas.1114653109 (2012).

50 Bateman, I. J. *et al.* Conserving tropical biodiversity via market forces and spatial targeting. *Proceedings of the National Academy of Sciences* **112**, 7408-7413 (2015).

51 Meyer, C., Weigelt, P. & Kreft, H. Multidimensional biases, gaps and uncertainties in global plant occurrence information. *Ecology Letters* **19**, 992-1006, doi:10.1111/ele.12624 (2016).

52 Ritter, C. D. *et al.* The pitfalls of biodiversity proxies: Differences in richness patterns of birds, trees and understudied diversity across Amazonia. *Scientific reports* **9**, 19205, doi:10.1038/s41598-019-55490-3 (2019).

53 Deyan, G. 61+ Revealing Smartphone Statistics For 2020. (2019). <https://techjury.net/stats-about/smartphone-usage/#gref>.

54 Wäldchen, J., Rzanny, M., Seeland, M. & Mäder, P. Automated plant species identification—Trends and future directions. *PLoS Comp. Biol.* **14**, e1005993, doi:10.1371/journal.pcbi.1005993 (2018).

55 Baena, S., Moat, J., Whaley, O. & Boyd, D. S. Identifying species from the air: UAVs and the very high resolution challenge for plant conservation. *PLOS ONE* **12**, e0188714, doi:10.1371/journal.pone.0188714 (2017).

56 Barto, A. G. Reinforcement Learning and Dynamic Programming. *IFAC Proceedings Volumes* **28**, 407-412, doi:https://doi.org/10.1016/S1474-6670(17)45266-9 (1995).

57 Weng, L. 2020).

58 Salimans, T., Ho, J., Chen, X., Sidor, S. & Sutskever, I. Evolution strategies as a scalable alternative to reinforcement learning. *arXiv preprint arXiv:1703.03864* (2017).

59 Sutton, R. S., McAllester, D. A., Singh, S. P. & Mansour, Y. in *NIPs.* 1057-1063 (Citeseer).

60 ter Steege, H. *et al.* Hyperdominance in the Amazonian Tree Flora. *Science* **342**, doi:10.1126/science.1243092 (2013).

61 Stadler, T. Simulating trees with a fixed number of extant species. *Syst. Biol.* **60**, 676-684 (2011).

62 Game, E. T. & Grantham, H. S. Marxan user manual. *For Marxan version* **1** (2008).

63 Tulloch, V. J. *et al.* Incorporating uncertainty associated with habitat data in marine reserve design. *Biol. Conserv.* **162**, 41-51 (2013).