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The 30 by 30 biodiversity commitment and financial disclosure: metrics matter

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The Kunming-Montreal Global Biodiversity Framework commits nearly 200 nations to protect 30% of their territories. Given financial constraints, the 'easiest' approach to comply would be to protect the cheapest areas. But what would this mean for biodiversity conservation, and how could financial disclosure support — or undermine — success? We showcase and discuss the biological and financial consequences of area protection and restoration selected under various metrics, and highlight the potential of emerging approaches powered by artificial intelligence to guide biodiversity conservation. Through extensive simulations, we show that spatial restoration planning using the CAPTAIN model (Conservation Area Prioritization through Artificial Intelligence) can lead to substantial improvements in predicted outcomes across a wide range of biodiversity metrics. Corporate disclosure provides a common mechanism for reducing environmental damage and increasing conservation, but is often dependent on simplistic and suboptimal metrics, which can lead to significantly lower benefits to nature compared with more comprehensive approaches. Alternative methodologies, building upon technological and computational advances and developed through collaboration between economists, biologists, and data scientists, can provide more cost-effective mechanisms to improve biodiversity outcomes and support implementation of the Global Biodiversity Framework.

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Introduction

In the 'Scramble for Africa', European powers expanded control of the African continent from 10% in 1870 to 90% in 1914. The biggest imperial powers — England and France — competed for strategic control. England tried to extend its East African empire from Cairo to the Cape, while France sought to extend control from Dakar to Sudan. The French seized most of the Sahara and Sahel regions — a vast area, but largely covered by desert with little economic value — while England colonized areas with more economic resources. One of the key reasons was reportedly that the French military were promoted depending on square kilometers conquered, a system referred to as 'Kilométrage'.

Fast-forward more than a century to the United Nations' summit on biodiversity (COP15) in Montreal, December 2022. Its main outcome — the Kunming-Montreal Global Biodiversity Framework (GBF) — was signed by nearly 200 nations and territories and included an area-based target. While the contexts are entirely different — as an international agreement the GBF is inclusive and signing was voluntary — the specific operational aspects of the GBF arguably resemble the 'Kilométrage' system: under its Target 3, 30% of all terrestrial, inland water, and coastal and marine areas shall be protected by 2030, with a similar target for restoration (Target 2).

While the ambition of this '30×30' goal is commensurable with the grand challenge of protecting the world's remaining biodiversity, including about one million species estimated to be threatened with extinction [35], we worry that inadvertently pursuing an *area-based goal* could lead to similar incentives to those faced by the French colonists — leading to the protection of the areas that are cheapest to protect but have relatively little value for biodiversity protection. Instead, the areas selected for protection must deliver on positive outcomes for nature in line with another commitment in the Framework (Target 4): to halt human-induced extinctions by 2030. Yet the kilometrage incentive implies that signatories to the GBF could, within the confines of the small print, attempt to achieve the 30×30 area target at the least cost to their economies and without paying due attention to the impact of those kilometers on biodiversity and ecosystems. Such incentives are not without precedent and would mirror similar experiences with protected areas and so-called 'paper parks' (e.g. [23,9]).

Given the magnitude of the funding required to achieve biodiversity conservation targets, either as part of the Sustainable Development Goals or via commitments to the Convention on Biological Diversity — where the funding gap is estimated at USD 800 billion/year [6] — it is frequently argued that public sector funds will be inadequate and the private financial sector will have to be mobilized [25]. Part of this mobilization will be the movement of capital away from investments and activities that are harmful to biodiversity. While biodiversity can be protected directly through the creation of protected areas and other mandates and regulatory actions, financial disclosure — voluntary or mandatory — may also become a useful instrument if the details are correctly designed. Institutions, investors, and companies are now required, in several jurisdictions, to disclose their environmental footprint, including their impact on biodiversity, as part of their financial reporting. This will hopefully redirect investment by leveraging the demand for biodiversity-friendly investments (or avoidance of reputational loss) that such behavior affords financial institutions and corporations. It is within this framework that the Taskforce on Nature-related Financial Disclosures (TNFD; https://tnfd.global/) released, in September 2023, a set of 14 recommendations for assessing nature-related financial risks, opportunities, impacts, and dependencies from nature, including global disclosure indicators and metrics.

Despite their importance, such instruments are not easy to manage. In many U.S. states, there is a backlash against Environmental, Social, and Governance ratings.[1] To stand a chance to align investors' and financial institutions' incentives with sustainable development, accurate financial disclosures regarding biodiversity impacts are crucial in enabling stakeholders to make informed decisions, manage risks, and identify opportunities related to biodiversity. However, for this incentive to match preferences well, and for the instrument of disclosure to yield satisfactory results in relation to biodiversity and other aspects of nature, accurate, salient, and workable indicators of biodiversity are required.

There are numerous components of biodiversity and measures associated with them [7]. While the extent of protected land is obviously insufficient by itself, it is more difficult to find unique and satisfactory measures among the many possible candidates proposed (e.g. [5,13,26]). Neither is it guaranteed that all measures of biodiversity move together in any given case, nor that the measurement of one biological group (such as birds) reflects the condition for others (such as plants). The choice of metrics for biodiversity could therefore have far-reaching consequences.

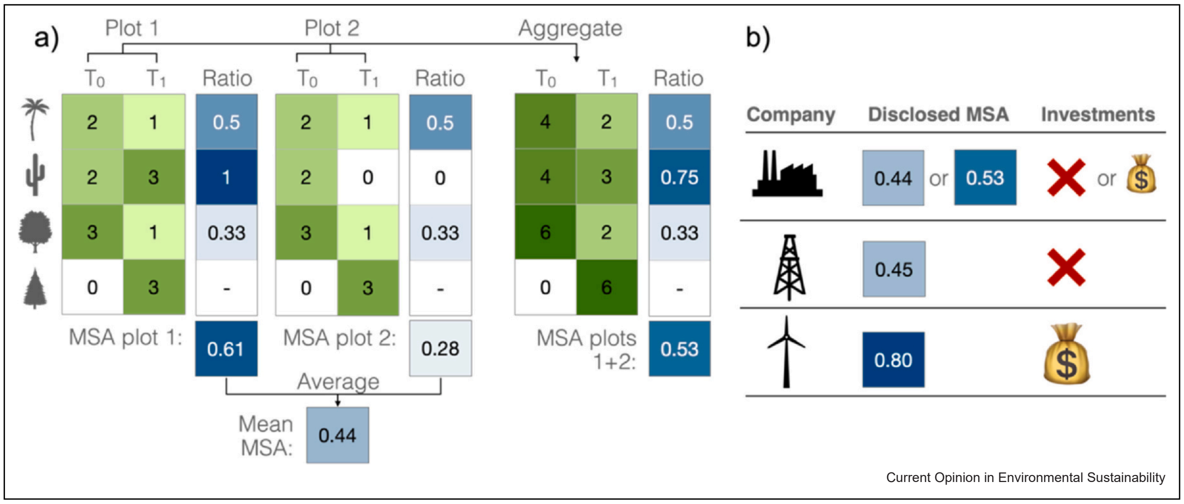
One of the most widely used metrics in the financial sector is the Mean Species Abundance (MSA), which measures the population intactness of a particular area of land or marine environment, compared to an assumed status of intact nature before human intervention. MSA is routinely proposed as a measure of biodiversity footprint for financial institutions and corporations [11] partly because it provides global coverage via the Globio model [29].[2] Consequently, many footprinting tools now use MSA to provide an indication of corporate impacts on biodiversity [11]. The government of the Netherlands, among others, undertook an assessment of the biodiversity footprint of their central bank using MSA as the outcome. Similarly, many large companies use MSA and similar metrics, according to the information disclosed on corporate websites at the time of writing. These tools enable companies to quantify their impact on local biodiversity across their value chains, helping them document the effects on biodiversity protection [3,7]. Numerous Biodiversity Credit offerings also use MSA as an indicator of the quality of their products (e.g. [24]).

There is a pronounced need for objective measures when companies engage with their stakeholders or the authorities about their efforts to protect biodiversity. Despite its popularity, the MSA metric suffers from

[1] See, for instance, https://www.csis.org/analysis/what-does-esg-backlash-mean-human-rights.

[2] The Iceberg Labs (https://iceberglabs.ai) tool uses MSA in the construction of the Corporate Biodiversity Footprint measure of biodiversity footprint.

Figure 1



Examples showing scale issues in the MSA metric. **(a)** The number of individuals for each of the four species found in two plots is reported at its natural level (at time T_0) and in the present state (time T_1). The MSA calculated across two plots is 0.53, which differs from the average MSA between individual plots: (0.61 + 0.28) / 2 = 0.44. **(b)** These scale issues can potentially have repercussions on (de)investments aimed to reward businesses with lower impact on nature, that is, disclosing a higher MSA. If, for instance, in a hypothetical scenario, only companies with a disclosed MSA greater than 0.5 were rewarded with investments or incentives, the approach taken to calculate this index could determine whether a company obtains the reward.

several limitations.[3] Typically, the motivation for using MSA stems from the idea that it is a close indicator of some other elements of biodiversity, such as species richness or extinction risk. However, this relationship is not necessarily strong, nor does it reflect the nonlinearity of extinction risk in populations of species found in other metrics (e.g. [10]). Similar arguments can be leveled at measures of habitat intactness [33]. Therefore, maximizing solely MSA does not necessarily protect threatened species, and the pursuit of MSA may not be cost-effective, since costs are not included in the metric. There are also challenges of aggregation and scale of nonlinear biodiversity metrics. Maximizing MSA, for instance, in each adjacent plot is not the same as maximizing MSA over a larger area, and the MSA for a larger area is not the average MSA for each of the component areas separately (Figure 1). At a practical level, this could have several implications. When considering estimating biodiversity footprints and allocating capital, two portfolios could have differing footprints, not because their impact on biodiversity differs, but because the scale at which MSA is measured differs. For conservation more generally, this relationship may penalize or reward larger areas, depending on the distribution of more granular measures of MSA.[4]

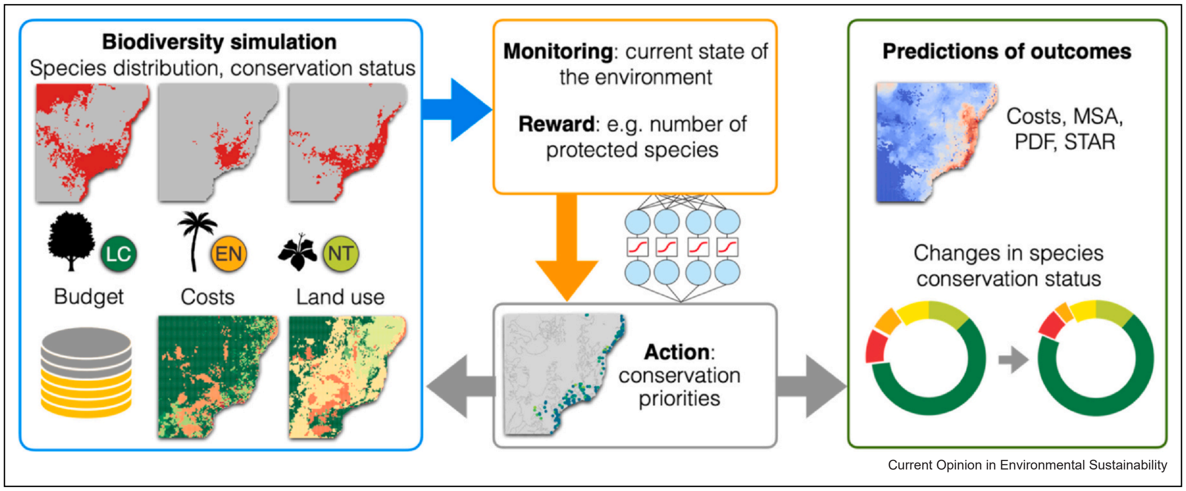
The challenges exemplified above are not unique to MSA: by focusing on one aspect of biodiversity, all metrics have advantages but also deficiencies. Species richness ignores genetic diversity [38], while both ignore population size, the extent of habitat, and the functionality of biodiversity [18,36,5]. Similarly, the Potentially Disappeared Fraction (PDF; Table 2), another measure used in biodiversity footprinting, focuses on local extirpation rather than the arguably more essential measure of global extinction risk [4]. Even more recent and comprehensive metrics, such as the Species Threat Abatement and Restoration Metric (STAR) — which focuses on activities that may reduce the extinction risk of species [22] — contain shortcomings, such as a lack of explicit consideration of genetic diversity and the requirement of widespread and recurrent Red List assessments.

An alternative to single metrics guiding biodiversity protection or impact disclosure is the use of more complex, but potentially more powerful, quantifications based on spatially explicit models of biodiversity that can identify priorities (e.g. [21,37]). One such model is

[3] Other intactness measures exist. For instance, the Natural History Museum's PREDICTS model uses the 'Biodiversity Intactness Indicator' [25], and the Species Habitat Indicator (SHI) measures habitat intactness [17].

[4] The argument can be understood as a manifestation of Jenson's Inequality where the average of a function f(S) over different values of S: E[f(S)], is not equal to the value of the function evaluated at the average value of S: f(E[S]) if the function f(S) is non-linear in S. With S representing a vector of species, and f(S) representing the biodiversity metric, e.g., the MSA, E[f(S)] can be understood as the average of plot level MSAs, while f(E[S]) is the MSA estimated across all plots. The sign of E[f(S)] - f(E[S]) will depend on whether f(S) is concave (> 0) or convex (< 0).

Figure 2



A model to identify conservation priorities based on a dynamic system trained through reinforcement learning. New AI-powered technologies can provide valuable alternatives to standard metrics, such as MSA, to quantify conservation priorities while incorporating biodiversity and socio-economic data. Simulations of biodiversity can help us to predict the outcomes of different implementations of biodiversity conservation policies.

CAPTAIN (Conservation Area Prioritization through Artificial INtelligence [32]), which uses biodiversity simulations to optimize the identification of conservation priorities using reinforcement learning and to account for the spatio-temporal dynamics of the environment (Figure 2). CAPTAIN models use a neural network to translate biodiversity and economic information (including the spatial distribution of species, threats, costs, and the current conservation status of species) into a prioritization of areas for protection. The advantage of this approach is that it can take multiple types of data as input and can adapt the estimated priorities through time based on how the system evolves.

The overarching issue is that the biodiversity metric chosen inevitably affects decisions. When incentives are steered by a particular target, as in the case of disclosure mechanisms in the financial sector, the choice of biodiversity metric will be particularly important. Although the pitfalls of policies that blindly focus on maximum area protected have been discussed (e.g. [1]), the financial and biological consequences of choosing sub-optimal areas to protect remain poorly quantified.

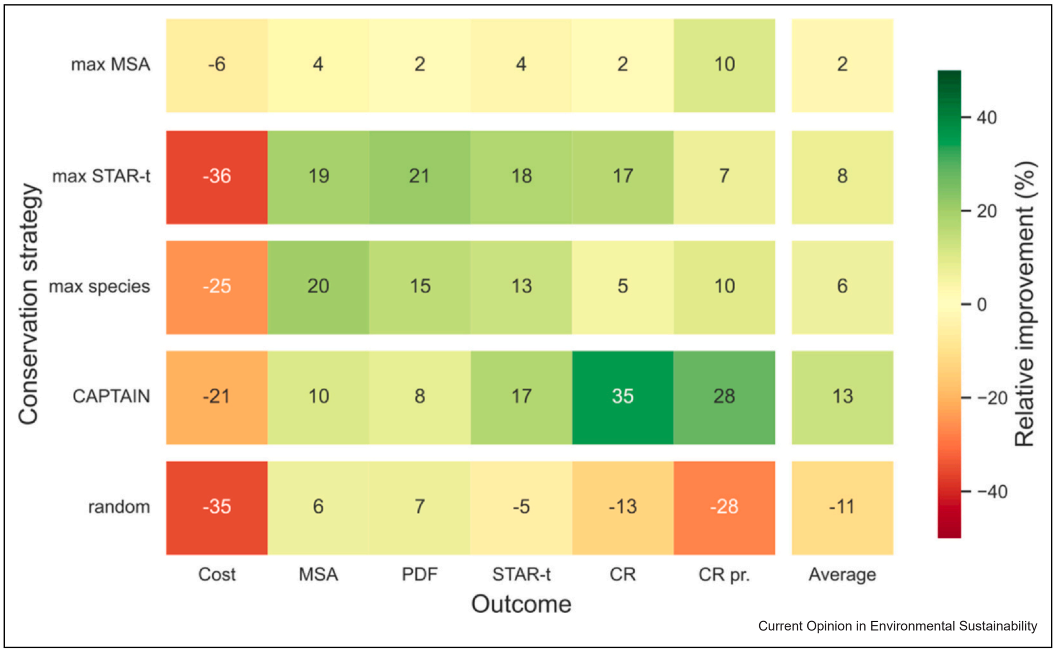
Here, we propose the use of computer simulations of biodiversity, habitat degradation, and restoration to predict the outcomes of alternative implementations of a 30×30 policy, guided by different metrics. We posit that a policy guided by a comprehensive use of biodiversity and socio-economic data powered by artificial intelligence will help guide more effective biodiversity protection and potentially improve the estimation of biodiversity footprints in the financial sector.

Using simulations to predict the effects of different 30×30 strategies

We used spatially explicit simulations to evaluate the impact of different implementations of a 30×30 target on biodiversity (see Appendix). These showed that alternative conservation strategies result in significantly different outcomes depending on the metric chosen. Protecting the cheapest 30% of the available area results, as expected, in significantly lower costs compared with all other strategies (Figure 3). However, it resulted in worse outcomes along all other metrics (MSA, PDF, STAR-t, and number and protection of threatened species; Table 2) compared with all other strategies except for the random selection. Thus, designating the cheapest areas as conservation units leads to strongly negative effects on biodiversity conservation compared to virtually any alternative strategy. For the following comparisons, we used the cost-minimizing strategy as the reference to measure relative changes in other strategies (see detailed results in Table S1 and the Supplementary plots).

Selecting conservation units based on their local MSA did not lead to significant improvements across most metrics compared to the reference (Figure 3, row 1). Specifically, it did not lead to a substantial improvement in terms of global MSA (where MSA is measured over the entire area under consideration rather than aggregated over the MSA at the level of the constituent conservation units), which increased significantly (p-value < 0.01) but only by 4% compared to the reference and was strongly outperformed by other strategies.

Figure 3



Relative change (reductions in red shades, improvements in green shades) of different conservation strategies relative to a strategy that minimizes the costs. Each strategy 2–5 is a row, and the results reported are compared to strategy 1, which is the lowest cost strategy. All strategies resulted in the protection of 30% of the available area. The outcomes (columns) measure different metrics at the end of the simulations to evaluate the performance of the strategy along different axes. The 'Average' column reports the mean of the outcomes for each conservation strategy. These results show that substantially different outcomes are predicted depending on how the protected areas are selected, showing tradeoffs between the cost of protection and its effectiveness in reducing species extinction risks.

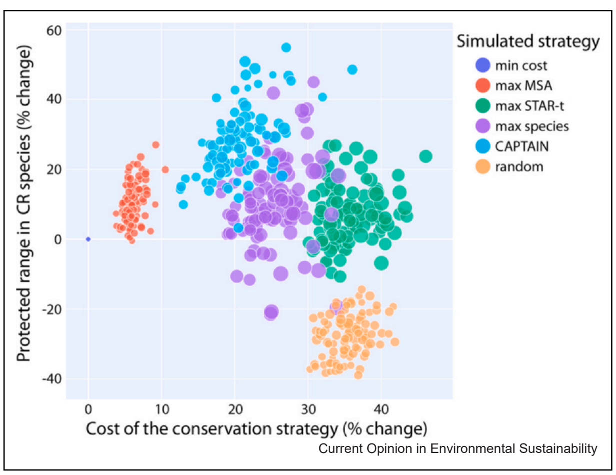
Changes in the resulting PDF and STAR-t were also minimal, with improvements (i.e. reduction) of 2% and 4%, respectively, compared with the PDF and STAR-t scores obtained under the reference strategy. Prioritizing conservation based on local MSA did not significantly reduce the number of species classified as Critically Endangered (p-values of 0.15). These results show that, while the MSA might be a valuable metric to measure the pristineness of a region, it is not strongly correlated with other measures of biodiversity that are arguably equally or perhaps even more important. Given that this metric is also sensitive to the spatial scale applied (Figure 1), it seems doubtful that MSA is an effective metric to guide conservation action.

A conservation strategy guided by STAR-t (Figure 3, row 2) led to positive outcomes across all biodiversity metrics, with improvements of 19% in MSA (p-value: < 0.01) and 21% in PDF (p-value: < 0.01). However, it also led to significantly higher costs, increasing by 36% (p-value: < 0.01). While a STAR-t–driven strategy led to a substantial reduction in the proportion of Critically Endangered species (mean reduction: 17%), there was also a high variance in the outcomes that led these improvements to be weakly or nonsignificant compared with the reference baseline (p-value: 0.05). The average fraction of protected geographic range in Critically Endangered species did not improve significantly compared to the baseline (mean increase: 7%, p-value: 0.79; Figure 3). These results show that STAR-t, which uses the extinction risk classification of species in its calculation, is better than most other strategies in the overall biodiversity outcomes, although it substantially increases the costs and shows relatively high volatility in its ability to effectively protect species at risk of extinction.

A prioritization strategy focused on areas with the highest species richness (Figure 3, row 3) resulted in the highest global MSA across all strategies, with an improvement of 20% compared with the baseline. It also significantly improved (i.e. reduced) the resulting PDF by 15% (p-value < 0.01). However, it did not significantly reduce the fraction of species classified as Critically Endangered (mean reduction: 5%, p-value: 0.21). This shows that while protecting species-rich areas leads to a good average outcome measured across all species (MSA, PDF), it neglects highly threatened species, potentially leading to substantial biodiversity loss in the long term.

Finally, a conservation strategy driven by a CAPTAIN model (Figure 2, row 4) led to improvements compared to the baseline in all biodiversity metrics, although the change in MSA (mean increase: 11%, p-value: < 0.01) and PDF (mean decrease: 8%, p-value: < 0.01) was smaller than for the STAR-t driven policy. Importantly, CAPTAIN resulted in a strong and significant reduction of the fraction of species at risk of extinction. Critically Endangered species dropped by 35% compared to the reference (p-value < 0.01). The fraction of protected range increased by 28% (p-value: 0.01) for Critically Endangered species (Figures 3 and 4) and by 18% (p-value: 0.04) for Endangered species (Table S1). The costs implied by this strategy were higher than the baseline (mean increase: 21, p-value: < 0.01), but significantly lower than the cost of the STAR-t strategy (mean reduction: 11%, p-value: < 0.01). Interestingly, the resulting global STAR-t metric was almost identical to that obtained under a STAR-t–driven strategy (mean improvement: 17.43, p-value: 0.01 for CAPTAIN; mean improvement: 18%, p-value: < 0.01 for STAR-t strategy). These results show that the deployment of a model trained through reinforcement learning can lead to a more efficient protection of highly threatened species compared with a strategy driven by the STAR metric, while still improving almost equally well the final STAR value.

Figure 4



Relative change for different conservation strategies compared to the cost-minimizing strategy plotted across each of the 100 simulated datasets. The change is shown for costs (x-axis) and the average fraction of protected range for Critically Endangered species (y-axis), obtained after protecting 30% of the area. The size of the circles is proportional to the change in MSA. The ideal strategy would minimize costs and maximize the protection of Critically Endangered species, that is, fall in the top left of the plot while reaching the largest MSA (large circles). Our analyses highlight, however, the tradeoffs between costs and biodiversity protection. Our CAPTAIN model generally reached the highest levels of protection for Critically Endangered species at lower costs compared to other strategies.

Discussion

We showed that the exploration of conservation strategies using a realistic but simulated framework allowed us to evaluate potential outcomes while removing the uncertainties related to biodiversity monitoring and the estimation of species extinction risks. The implementation of these strategies in the real world might therefore be affected by the incompleteness or errors in the biodiversity and socio-economic data (e.g. costs and threats). This is particularly the case for metrics that require knowledge about the ‘natural’ state of the environment or detailed knowledge of the current species conservation status, even though imputation methods can be used to fill some of the knowledge gaps (e.g. [39]). While ground validation remains of fundamental importance to improve our models and independently evaluate their accuracy, the use of simulated data — covering a wide range of realistic values — can help us to assess the sensitivity of individual metrics in relation to multiple scenarios, and make robust predictions on the outcomes of different conservation policies.

Our analyses show that protecting the cheapest area is the worst conservation strategy for biodiversity. It is also the least additional action, since areas protected based solely on their cost are generally those with the fewest inhabitants — meaning that their land would more likely be left undisturbed anyway than those closer to urban environments. We acknowledge that our simulations used a simplistic approximation of costs, here set proportional to the intensity of human activities in each area as a proxy for opportunity costs. Real-world conservation will need to consider implementation and maintenance costs and potential benefits such as spillover effects and improved ecosystem services.

Different metrics capture different aspects of biodiversity, so their use in conservation strategies highlights the inevitable trade-offs in goals such as protecting as many species as possible, prioritizing species at risk, or optimally allocating a limited budget — all while meeting a 30% area protection goal. Our analyses indicate that prioritization based on species extinction risk or STAR is effective at improving the average state of a biological system, as measured by an increased resulting MSA and reduced PDF. Yet, CAPTAIN achieved the highest equally weighted average across all metrics considered (MSA, PDF, STAR-t, Critically Endangered species and their protected range; Figure 2). Our simulations show that reducing extinction risk, the main objective of our CAPTAIN model, leads to the improvement of many other metrics of biodiversity as well. In contrast, a focus on simpler metrics, such as MSA, will fail to achieve wider objectives. Thus, while commonly used metrics in financial disclosure might provide good summaries of the overall state of an environment, their use to guide the protection of biodiversity is at best flawed, and potentially misleading — largely depending on how the metrics are aggregated.

CAPTAIN provides a flexible framework to optimize a conservation strategy based on predefined targets and priorities. While the model tested here was trained to prioritize the protection of endangered species, the same framework can be used to train a model to optimize other metrics, such as global MSA. This allows for a direct comparison of the spatial priorities identified under different conservation targets. The use of artificial intelligence in CAPTAIN leads to a more flexible and comprehensive use of biodiversity and socioeconomic data that is captured by the parameters of an underlying neural network and that cannot be easily included in a single metric. While we demonstrated its use with simulated data that might not capture the full range of heterogeneities and complexities of real-world conservation action, the method can be further developed to include the use of more complex data. For instance, the cost of conservation could be expressed as a space- and time-varying quantity that incorporates economic and societal benefits of nature conservation areas and implementation costs. Additionally, multiobjective optimization can be implemented to optimize conservation action along multiple biodiversity and economic metrics [31]. This framework therefore provides new opportunities to further enhance existing prioritization metrics (e.g. [22,12]).

While the simulated biodiversity settings and outcomes presented here are informative of the behavior and properties of different metrics and conservation strategies, the analysis of empirical data remains central to evaluating them in real-world scenarios and across different contexts [19]. This requires accurate information about the distribution and abundance of biodiversity, which remains incomplete and spatially heterogeneous (e.g. [28]) but will likely benefit from technological advancements in environmental DNA sequencing and remote sensing [14,2,34]. Benchmarking biodiversity metrics and conservation strategies with real data should ideally also incorporate information about the costs and feasibility of conservation policies while incorporating societal factors [15]. Although the compilation of such datasets remains challenging, the optimization algorithms implemented in CAPTAIN can be used on subsets such as species distribution models and proxies for land use and costs [32].

Conclusions and prospects

Our study demonstrates that vastly different biodiversity outcomes can be obtained within a 30×30 protection framework, depending on the metric and methodology used. We are however left with the question of which approach to 30×30 is best. The answer to this requires introspection concerning which biodiversity metrics society should consider. If, as suggested by certain studies (see [4]), minimizing extinction risk is the key to biodiversity conservation, then several conclusions can be made. Firstly, maximizing local MSA (the objective in many financial-biodiversity disclosure tools) is a problematic approach to achieving a reduction in extinction risk. Secondly, optimizing for other metrics of biodiversity (such as STAR or PDF), while better, is only imperfectly related to extinction risk reductions. Finally, there may be additional considerations relating to the functionality of biodiversity *in situ* that are more directly related to intactness type measures (such as MSA) or simple species richness metrics. Consequently, the priorities for biodiversity conservation will have to balance these considerations when designing the implementation of 30×30, and in the objectives and incentives for biodiversity disclosure mechanisms in finance.

We hope that this contribution will help the financial sector to better understand the challenges and opportunities associated with the financial disclosure of environmental impacts. Above all, we call for strengthened collaboration between governments, companies, and scientists to bring about further improvements in this important area for nature and society.

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Data Availability

The CAPTAIN software is available at captain-project.net under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International license. The updated version used in this study along with all data are available in a permanent repository at zenodo.org (DOI: 10.5281/zenodo.17403206).

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships that may be considered as potential competing interests: Daniele Silvestro, Alexandre Antonelli, Stefano Goria, and Thomas Sterner are co-founders of CAPTAIN Technologies LTD. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Methods and data

To address the research questions on the implementation of 30×30 and the role of biodiversity metrics, we carried out a series of realistic simulations using the Conservation Area Prioritisation through Artificial INtelligence (CAPTAIN) software, developed by members of the team [32]. Each simulation consisted of a spatially explicit dataset gridded into a 100×100 cell matrix, with 250 species. Every species was characterized by a specific geographic range, population size, dispersal ability, growth rate, and sensitivity to anthropogenic disturbance. CAPTAIN was then used to evaluate different conservation policies, including 30×30, based on cost, area, different biodiversity metrics, and based on a prioritization model informed by AI (see *CAPTAIN optimization*).

Data

Rather than initializing species ranges randomly as done in previous simulations [32], we opted to use realistic species distributions obtained from species distribution models. These were generated from occurrence data of 6000 tree species occurring in an area of South America delimited at latitudes of 30° to 5° South and longitudes of 35° to 60° West, roughly corresponding to the Atlantic Forest biome, but also including portions of the Cerrado savannahs, and of Amazonia (Fig. S2). Occurrence data were downloaded from the Global Biodiversity Information Facility (gbif.org; accessed on April 5, 2023). We combined the occurrences with the 19 climatic variables of the CHELSA database [20] to generate distribution models for each species through a random forest classifier. We implemented all the data retrieval and processing functions in Python within the CAPTAIN software and provided the code as Supplementary Information. We then gridded the species distribution models to a 100 by 100 cell resolution (i.e. 0.25° or ca. 27×27 Km) and used them to initialize the natural species ranges for our simulations. The total continental area, excluding cells in the ocean, included 7636 cells. We note that the choice of area and taxa here is arbitrary, and that this approach was taken simply as a way to initialize realistic species richness maps and species ranges.

Simulated environments

We generated 100 datasets based on subsets of 250 species randomly sampled from the full set of 6000. In each dataset, we drew species-specific growth rates from a U-shaped Beta distribution B(0.5, 0.5) and sensitivities to anthropogenic pressure from a uniform distribution U(0, 1). We initialized the species abundances based on habitat suitability as inferred by the species distribution models. We set cell-specific carrying capacities based on the prevalent biomes found in the cell, based on the Terrestrial Ecoregions of the World [27], with the maximum capacity of a cell arbitrarily set to 10 000 individuals for rainforests, 8000 for dry forests, and 3000 for grasslands.

The anthropogenic disturbance affects the carrying capacity of the cell and is described by an index that can range from 0 (no disturbance) to 1. Disturbance leads to a reduction of the carrying capacity of the cell, with consequent mortality of individuals living in it if they exceed the carrying capacity. Because of variation in species sensitivities, the increased mortality will affect some species more than others, leading to a change in relative abundances and potential extirpation of some species. We initialized the anthropogenic disturbance as a random multivariate normal function, generating strong spatial heterogeneity with an overall mean disturbance of 0.75 and with the highest disturbance capped at 0.9. The heterogeneity reflects a pattern in which some regions are heavily impacted by human activities, for example, urban, industrial, or intensive farming areas, while others are less affected, for example, forests or areas with limited accessibility. Each dataset was subjected to randomly different disturbance patterns.

We used the CAPTAIN framework to simulate the evolution of the biodiversity system through time. This involved an individual-based spatially explicit simulation of biodiversity that tracks all species (here 250 in each dataset) through time and space. Species' geographic ranges and abundance can change at each time step based on mechanistic processes of dispersal, death, and reproduction, reflecting the natural processes governing the dynamics of species and populations. Species' ranges and abundance are also affected by anthropogenic disturbance, altering natural mortality [32], and by the establishment of protected areas, in which the disturbance is lowered, thus enabling natural growth and re-colonization through reproduction and dispersal.

The features included in the CAPTAIN simulation framework are important to answer the questions at hand because they allow more explicit and realistic predictions of conservation outcomes while accounting for the dynamic responses of species and populations to a changing environment (e.g. modifications of the disturbance patterns). Here, we extended the software to implement different prioritization strategies (see *Conservation strategies*) to reach the protection of 30% of the area within six time steps, emulating the number of years until 2030. Independent of the chosen strategy, our simulation framework allowed us to evaluate their outcome based on a range of biodiversity metrics, including MSA and PDF (see *Metrics and evaluation of the outcome*). The exact value of the metrics could be calculated because, in our simulated systems, unlike in nature, we can afford perfect knowledge of the natural state (e.g. population sizes and range before human impact) and of the current state (e.g. population declines and local extinctions).

Simulating extinction risk

We initialized the conservation status of each species following a classification into five classes, intended to emulate the conservation status scale of the International Union for Conservation of Nature (IUCN) Red List (www.iucnredlist.org), namely: Least Concern, Near Threatened, Vulnerable, Endangered, Critically Endangered. In assigning the conservation status of species, we approximately followed available guidelines [16,8] and based on the ratio between the current population size of each species (i.e. after applying the effect of disturbance) and its natural population size. We used the thresholds shown in Table 1 to assign species to a threat class.

Because of changes in disturbance or the establishment of new protected areas, the extinction risk of species might change over time. We updated the extinction risk of species based on the following rules: 1) species move to the next higher risk category (e.g. from Endangered to Critically Endangered) if they have a declining population size over time; 2) species move to a lower risk category if their population size is larger than the initial one and increasing over time; 3) species with a ratio between current and natural population size greater than 0.6 and at least 50% of their current population found in protected areas are set to Least Concern, even if they show a declining trend. We stress that our approach does not attempt to perfectly reflect the application of the IUCN guidelines but is intended as an approximation for the purpose of our comparative analyses across metrics.

Table 1

Thresholds used to approximate the extinction risk across simulated species within five classes, with labels inspired by the IUCN Red List.

Ratio between current and natural population size	Extinction risk category	Associated reward
0.6 – 1	Least Concern	+1
0.5 – 0.6	Near Threatened	0
0.3 – 0.5	Vulnerable	−1
0.1 – 0.3	Endangered	−3
< 0.1	Critically Endangered	−12

Within the context of our AI-driven conservation strategy (see CAPTAIN optimization), we trained a model using reinforcement learning and based on positive rewards associated with species in the LC category, while increasingly negative rewards were associated with higher extinction risks. Thus, the CAPTAIN-trained model used here was optimized to find areas to protect such that they minimize the number of species in the highest risk classes, while attempting to keep the costs low. We note that the definition of rewards is user-defined and can be modified to reflect different priorities, for example, minimizing costs.

CAPTAIN optimization

The CAPTAIN program includes a *simulation module* (as described above) and an *agent*, which, in a reinforcement learning framework, represents the policy maker. The agent performs two tasks: 1) monitoring the current state of the environment, and 2) selecting conservation units, where the anthropogenic disturbance is reduced and maintained low. In our analyses, the information (features) obtained through monitoring included, at each time step and for each protection unit, the extinction risk status of all species (using the simplified criteria described above), the ratio between observed and potential species richness (based on the natural species ranges), the relative number of species in each extinction risk category, and the cost of protecting the unit, which is proportional to the current disturbance and approximates opportunity costs.

To define the objectives of the model, we implemented a reward system that favors the protection of the largest number of species, giving priority to the most endangered ones. Specifically, we defined the objective function of the model as the maximization of the total reward based on the number of species found in each extinction risk category, with a positive reward for least concern species and increasingly negative scores for species at higher risk (Table 1).

After defining the objective function, the program uses reinforcement learning to optimize how the agent uses the information gathered through monitoring and translates it into a decision, that is, the selection of a protection unit. CAPTAIN uses a neural network as a flexible, non-linear function to map the features of each spatial unit onto a probability of choosing it as the next protection unit. The parameters of the neural network optimized to yield the highest total reward are then used as the CAPTAIN trained policy seeking to minimize the overall number of species at risk of extinction and to move as many of them as possible to lower risk categories. We optimized the model based on simulations of 50 by 50 cells with 500 randomly initialized species following the default procedure and algorithm described in [32]. The trained model was then applied, along with other conservation strategies outlined in the section below, to select protected areas in the 100 simulated datasets.

Conservation strategies

We performed simulations in which 30% of the total area was protected. The effect on a parcel of land of obtaining protected status is a reduction in the level of disturbance from a maximum (in the model) of 0.9 to a maximum of 0.4. Protection of a disturbed area will therefore increase its carrying capacity to at least 60% of its natural state, allowing populations to grow through natural regeneration (based on the species-specific growth rates) and individuals from other areas to migrate and colonize them (based on their distance and dispersal rate).

The environment was divided into protection units of 2 by 2 cells, and 100 protection units were established at each time step (e.g. one year), thus reaching 30% of the total continental area in less than six time steps. Each cell was assigned a cost for protection ranging from 0 to 1, here set equal to the disturbance in the cell. The implicit assumptions are that there is an opportunity cost that depends on the human activities occurring in each cell (here approximated as *disturbance*) and that monitoring and enforcement are in place to maintain the reduced disturbance level. At each time step, the species extinction risks were re-evaluated based on their current population sizes. At the end of the simulation, we calculated the metrics listed in Table 2 to evaluate different outcomes of the implemented strategy.

We compared alternative conservation strategies in which the selection of protected units was determined through six different criteria. Specifically, we selected: 1) the cheapest protection units to minimize the overall costs, 2) the units with the highest unit-level MSA, 3) units with the highest STAR-t score [22], or 4) units with the highest number of species. We additionally 5) selected protection units based on the CAPTAIN model described above, and 6) applied a random selection of protection units as a baseline.

Metrics and evaluation of the outcome

We analyzed 100 simulated datasets, each initialized with a different set of species, random disturbance, sensitivities, and growth rates. We analyzed the datasets under the six conservation strategies described above and measured six metrics to compare the outcomes along different axes. Specifically, we measured the metrics as described in Table 2. We acknowledge that many other metrics exist [7] and could be, in principle, evaluated within our approach. Our selection was based on the inclusion of metrics commonly used for financial disclosure (MSA and PDF, also discussed in the main text), the quantification of conservation impact on species with the highest extinction risk (CR, EN metrics in Table 2), and a more sophisticated index that combines extinction risks with species potential and occupied geographic range (STAR).

Table 2

List of metrics used to evaluate the outcome of our biodiversity protection simulations.

Metric	Acronym	Method
Potentially Disappeared Fraction[30]	PDF	Mean difference between the species abundances (total number of individuals) and the natural abundance (number of individuals in the absence of disturbance), relative to the natural abundance
STAR-t and STAR-r metrics[22]	STAR	Indices based on the fraction of suitable area or restorable area in a region for each species, weighted by the species' extinction risk
Mean Species Abundance[29]	MSA	A measure of the intactness of an environment based on the ratio between current and natural abundance averaged across species
Number of species in the highest extinction risk categories: Critically Endangered and Endangered	CR, EN	Species counts in CR and EN categories after the implementation of a protection policy
Degree of protection in Critically Endangered and Endangered species	CR_pr, EN_pr	Average fraction of protected geographic range across CR and EN species after the implementation of a protection policy
Cumulative cost of the areas selected for protection	Cost	Total simulated cost of selected protected areas

We selected the conservation strategy aiming to minimize the overall costs (strategy n. 1) as a reference and summarized the outcome of the remaining five conservation strategies as the percentage change compared to the reference. This was computed for each metric, e.g., for MSA:

$$\Delta_{MSA} = \left(\frac{MSA(alternative\ strategy)}{MSA(reference)} - 1\right) \times 100$$

We note that for some of the metrics, namely: cost, PDF, and number of species with the highest extinction risk, an improvement is obtained through a lower score. For these metrics, the relative change was computed as, e.g., for PDF:

$$\Delta_{PDF} = -\left(\frac{PDF\,(alternative\ strategy)}{PDF\,(reference)} - 1\right) \times 100$$

Thus, in our analyses, positive change always indicates an improvement compared to the reference, while negative change indicates a lower performance. We computed the percentage change across all simulations to evaluate the relative performance of each strategy. In summarizing the results from the 100 datasets, we computed the mean percentage change, the standard deviation, and a p-value obtained as the fraction of simulations in which the alternative strategy outperformed the reference. We believe that our methods will be useful for the analysis and planning of investments that affect biodiversity, whether at the company level or that of regulators, be they municipalities, countries, or even globally.

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.cosust.2025.101587.

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