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Opinion

Biodiversity modeling advances will improve predictions of nature's contributions to people

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Accurate predictions of ecosystem functions and nature's contributions to people (NCP) are needed to prioritize environmental protection and restoration in the Anthropocene. However, our ability to predict NCP is undermined by approaches that rely on biophysical variables and ignore those describing biodiversity, which have strong links to NCP. To foster predictive mapping of NCP, we should harness the latest methods in biodiversity modeling. This field advances rapidly, and new techniques with promising applications for predicting NCP are still underutilized. Here, we argue that employing recent advances in biodiversity modeling can enhance the accuracy and scope of NCP maps and predictions. This enhancement will contribute significantly to the achievement of global objectives to preserve NCP, for both the present and an unpredictable future.

Highlights

Biodiversity underlies many crucial ecosystem functions and nature's contributions to people (NCP), but they are typically mapped and predicted with approaches that ignore information on species and communities.

At the same time, great progress has been made in statistical biodiversity modeling to predict aspects of biodiversity over space and time. However, breakthroughs in this field have yet to find widespread use in predicting NCP.

In particular, new approaches that employ diverse data sources, estimate different dimensions of biodiversity, incorporate biotic interactions, and address analytical uncertainty could have profound applications for NCP prediction.

Here, we describe the current state of NCP prediction and its challenges, highlight potential benefits of biodiversity modeling advances, and end with how these improved predictions can help to meet goals of international frameworks for biodiversity conservation.

Predictions of ecosystem functions and NCP need more biodiversity information

Many ecosystem functions and **NCP** (see Glossary) are under threat by human-induced environmental change [1]. High-resolution model predictions of key NCP, including decomposition of organic matter, pest control, crop pollination, and seed dispersal for agriculture and habitat maintenance, are essential for targeted management and preservation [2,3]. There are strong links between biodiversity and NCP recognized by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) [1] and supported by a wealth of empirical research [4,5], but despite this, NCP predictions rarely employ biodiversity information [6], which we define here as data describing particular species or the variety of living things and their attributes. Even for NCP directly supported by species, predictions are often made using expert knowledge, **biophysical variables**, land use, land cover, and topography [7,8]. These data are widely analyzed with **decision-support software** (e.g., InVEST [9], ARIES [10], ESTIMAP [11]) that have important limitations: they are typically parameterized based on expert consultation and site-specific measurements and monitoring. These require prohibitive costs and time [12], compromise transferability to new conditions, and can have poor flexibility for the customization of underlying data or model structures [13].

Predictions and mapping of NCP such as crop pollination or pest control that are performed by species or functional groups can be improved by species-level data [14,15]. Even ecosystem functions and NCP like nutrient cycling or water filtration that may not rely on particular species have connections to functional groups or vegetation types, and thus also necessitate consideration of biodiversity [16]. Still, NCP models more typically employ proxies from biophysical variables (Figure 1), such as agricultural land-cover data for pollinators (e.g., [17]). There are multiple reasons why biodiversity is not central in NCP prediction. First, NCP predictions are typically made by land-use modelers that traditionally work with remotely sensed or socioeconomic data [18]. Second, multiple knowledge shortfalls regarding species' natural histories, interactions, distributions, abundances, and others [19] have resulted in persistent barriers to investigation and research biases worldwide that are particular to certain regions and taxa. Using biodiversity data

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for NCP assessments at the very least requires information on where species are and what they do, and difficulties arising from knowledge shortfalls are exacerbated when multiple species or communities are considered. Finally, biodiversity modeling and mapping for multiple species or entire assemblages requires tools and approaches not yet widely used by NCP researchers.

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Biodiversity modeling: an emerging paradigm for NCP predictions

Considering the strong links between biodiversity and NCP, models that predict different aspects of biodiversity have great potential to improve NCP predictions (Figure 1) [20]. For example, **species distribution models (SDMs)** and **macroecological models (MEMs)** are widely applied over space and time for biodiversity conservation and management [21,22]. Modeled

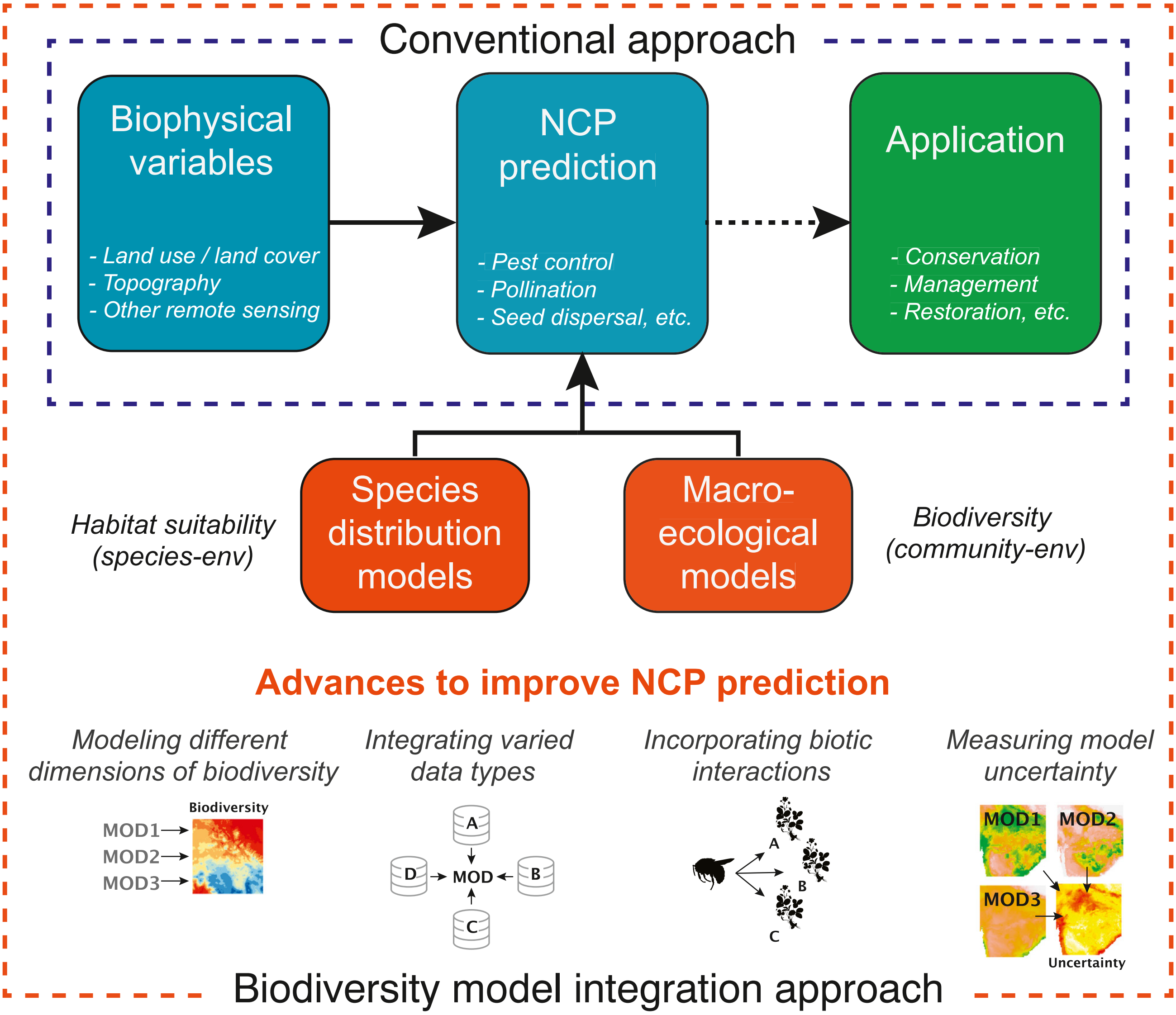

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Figure 1. Conceptual diagram of how advances in biodiversity modeling can improve the conceptual workflow to predict ecosystem functions and nature's contributions to people (NCP).

range or biodiversity estimates of service-providing species and communities indeed provide key information that can potentially improve a wide range of NCP predictions (Box 1) [23,24], but the full potential of these models to predict NCP in space and time or to understand trade-offs and synergies remains underutilized.

In recent years, there has been considerable innovation in biodiversity models. For SDMs in particular, recently established best practices provide methodological guidance [25,26] and new metadata standards promote reproducibility [27]. Moreover, the growing biodiversity modeling community has developed diverse programming tools that automate complex analyses and push the field forward [28], and interactive applications have improved access to new methods (e.g., Wallace EcoMod [29], NicheToolBox [30]). Integration of biodiversity information has been recognized as one of the new challenges for NCP models [31], making it opportune to take advantage of biodiversity modeling innovations for NCP prediction. Here, we argue that these methods have great potential to improve the accuracy and scope of NCP prediction, particularly relating to the mapping of predicted locations of high ecosystem function and NCP provision. We focus our discussion on statistical models as these employ the most readily available biodiversity data for most species, although we also discuss promising applications for mechanistic or hybrid biodiversity models. We conclude with our ideas for how NCP predictions that incorporate biodiversity can directly benefit human society.

Advances in biodiversity modeling that can improve NCP predictions

Harnessing explanatory power from different data types

Recent advances in biodiversity modeling provide new ways forward to combine various data types with unique information. One example is **data integration**, a framework that leverages the complementary strengths of different datasets to improve SDM predictions. Opportunistic species occurrence data are easy to acquire and can cover a broad geographical extent, but

Box 1. Innovative applications of biodiversity models to NCP prediction

Although most predictions of ecosystem functions and NCP have traditionally relied on biophysical variables and decision-support tools, here we highlight some innovative examples that have used SDMs. Polce *et al.* [94] demonstrated how SDM range estimates can be used as direct inputs to decision-support tools, in this case to predict pollinator services in the UK. Ramel *et al.* [95] made NCP predictions with biophysical variables and considered them in tandem with SDMs for spatial prioritization of conservation areas. More typically, however, individual SDM range estimates or stacks to estimate richness have been employed as estimates of NCP provision, sometimes with associated weights. Schulp *et al.* [96] used SDMs and resident survey data to estimate the richness and importance of wild food species in Europe. Modeled range estimates were combined with species trait data linked to NCP by Brasileiro *et al.* [97] for bats (crop pest control) in Brazil and by Perennes *et al.* [98] for bees (crop pollination) in Europe. Ceau u *et al.* [14] used SDMs to estimate richness for multiple species across Europe weighted by medicinal value, edibility, and functional efficiency for NCP. Rey *et al.* [99] assembled a relational table of NCP weights for species in the Swiss Alps and combined SDMs to map broad NCP categories. Future climate change impacts on NCP provision are also increasingly estimated with SDMs. Some examples are Civantos *et al.* [53] for the richness of terrestrial vertebrates (crop pest control) across Europe, Mokany *et al.* [100] for the dispersal capacity of frugivores (seed dispersal) in the Australian Wet Tropics, Moor *et al.* [101] for functional traits of wetland plants (flood attenuation, etc.) in Sweden, and Mori *et al.* [102] for trees and shrubs (biomass production) around the world. Future range mismatch between NCP providers and their food source was found by Sales *et al.* [103] for seed dispersers and pollinators of the Brazil nut tree.

There are far fewer examples of the use of MEMs and dimensions of diversity besides taxonomic richness to predict NCP, although some examples have emerged in recent years. Timoner *et al.* [104] compared predictions of aquatic insect richness based on MEMs and stacked SDMs to predict indicators of stream and river health in Switzerland. Fourcade and Vercauteren [105] used MEMs to constrain stacked SDM richness estimates for earthworms in France and mapped functional richness and evenness based on community composition predictions. An increase in studies employing different kinds of biodiversity models and metrics, as well as those focusing on understudied taxa and regions outside the USA and Europe (e.g., [102]), should improve our understanding of the spatial patterns of NCP provision and help to fill knowledge gaps for the globe. Reducing barriers to such research should be a major goal of the field.

Glossary

Analytical uncertainty: the variance in different possible outcomes that is associated with some aspect of the methodology, such as the processes of data observation and/or generation, the model structure, the model parameterization, or the model predictions.

Biophysical variables: variables describing aspects of the physical environment of the terrestrial biosphere. Typically measured via remote sensing, these can include leaf area index, greenness indices, and vegetation cover extent and type.

Data integration: an approach to combine multiple data sources with different sampling designs and data types in a single statistical modeling framework for improved prediction and inference.

Decision-support software: software that uses environmental data (typically describing biophysical or landscape variables) to produce outputs that support the decision-making process for natural resource management.

Macroecological model (MEM): a model that estimates the statistical correlation between aggregated biodiversity data and relevant environmental variables. Biodiversity data can represent measurements of species richness, species turnover (i.e., community change over space and/or time), phylogenetic relationships, species functional traits, or genetic information. Based on the estimated relationships between biodiversity and the environment, these models can make predictions of biodiversity in space (including unobserved sites) and time (including past and future scenarios).

Nature's contributions to people (NCP): as defined by IPBES, NCP includes both positive and negative contributions to human well-being, with nature playing a vital role. The concept of NCP considers a wide range of relationships between people and nature, including benefits to people often referred to as ecosystem services that tend to be undervalued economically. Ecosystem functions, such as primary productivity, nutrient cycling, and decomposition, underpin these benefits to people. Here, we focus on so-called 'regulating' NCP such as crop pollination, seed dispersal, pest control, water filtration, carbon sequestration, and others. NCP such as these are they are nonetheless often characterized by sampling biases. Most SDM studies lack structured sampling designs that can produce presence/absence and count data with reduced bias. This is because structured designs typically cover smaller geographic extents, have relatively narrower taxonomic representation, and can require sizable financial and labor costs. Further, unlike species' presence data, reliable data on species' absences are much scarcer. Although the prediction of interest for SDMs is the probability of species' presence (or abundance), the use of opportunistic data limits their predictions to those of relative habitat suitability [32]. However, recent methodological developments in SDM data integration, like spatial point process models, can combine opportunistic and structured occurrence (or count) data to make more accurate and less biased inferences on species' environmental responses, distributions, and abundance patterns [33,34]. This approach should help to make quantitative assessments of potential NCP such as pollination, seed dispersal, and food and material production by creating predictions of abundance for service-providing species over a large geographical extent (Figure 2) [35].

Different types of environmental data from biodiversity monitoring systems can also be employed to improve biodiversity models for NCP. Advances in remote sensing have produced datasets that quantify variables such as land-cover heterogeneity and leaf spectral diversity at increasingly fine spatial resolutions [36]. Such rich landscape information can be harnessed for biodiversity models via new techniques such as convolutional neural networks, which integrate landscape data in spatial windows around occurrence point data to model species distributions [37]. These algorithms could be used to model insect pollinator diversity, for example, using the surrounding land-cover matrix instead of relying solely on point estimates of insect occurrence. In practice, using deep-learning algorithms for NCP prediction could foster more high-resolution mapping, which might be particularly useful in mosaic suburban habitats [37]. Managing biodiversity in interconnected yet patchy networks of land under human use, prevalent in most areas of the world with dense development, will be necessary to meet some of the 30% protection targets of the Kunming–Montreal Global Biodiversity Framework (GBF) (e.g., Target 3, so-called '30 by 30'; Target 2 for restoration). Biodiversity data at high spatial resolutions (<100 m) should capture local-scale differences in land-cover and patch characteristics (e.g., distance to edge) important for habitat suitability in green and blue corridors.

Not just a single variable: modeling the many dimensions of biodiversity

NCP provisions are linked not only to individual species' ranges but also to species richness [38] and turnover [39], as well as other aspects of biodiversity. Making predictions for each requires different modeling strategies, each with multiple approaches [40]. For example, community composition estimates can be made with **stacked SDMs** (e.g., [41]) or joint SDMs that model multiple species together (e.g., [42]). Both are typically made using species' presence data, but they can alternatively use abundance data: in this case, these models can, in theory, estimate community indices like rank-abundance patterns. Species richness can be calculated based on these SDM-based community estimates or modeled directly as a function of environmental variables with MEMs. Although species richness is the most typically estimated biodiversity variable [43], considering it alone is insufficient and can lead to spurious inferences about change in biodiversity and NCP [44]. For instance, species richness can be heavily influenced by wide-ranging species and thus not be informative about diversity centers for rare species, which are also important for ecosystem functions [45]. To address this, species richness can be weighted by range size to calculate 'range rarity', a metric that emphasizes small-ranged species [41]. High spatial community turnover, resulting in more species and more community variability at increasing spatial scales, is important in maintaining crop pollination and can supersede contributions from dominant species alone [39]. Turnover patterns can be estimated with generalized dissimilarity models [22], which have been used to predict trends in global plant diversity linked to NCP and the relative strengths

essential in maintaining human well-being and promoting sustainable development.

Species distribution model (SDM): a model that estimates the statistical correlation between data on species' occurrences (with or without absence data; alternatively, on abundance) and relevant environmental variables. Based on the estimated environmental niche of the species, these models can estimate species' distributions by predicting habitat suitability (or probability of presence or abundance) in space (including unobserved sites) and time (including past and future scenarios). Multispecies models now allow predictions for the whole set of species observed in communities, which should further help in mapping NCP.

Species interactions: spatial or temporal co-occurrence between species that results in population effects on one or more of them. These can be direct, as in predation, competition, mutualism, parasitism, or commensalism, or indirect, as in effects from trophic cascades or apparent competition. The vital functionality of ecosystems often arises from species interactions.

Stacked SDM: the combination of multiple single-species SDMs, often by summing continuous or binary distribution predictions, to estimate biodiversity metrics such as taxonomic richness or turnover.

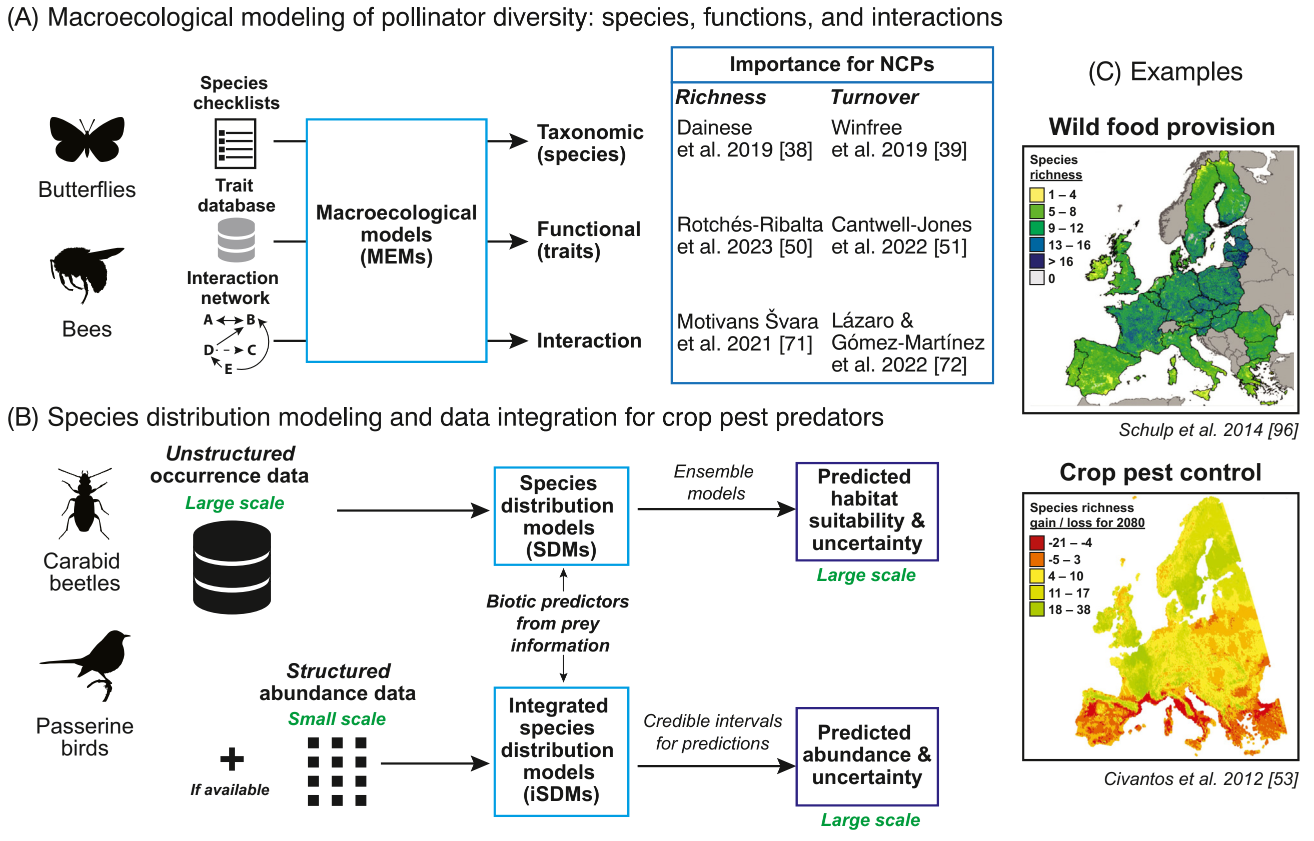

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Figure 2. Example workflows that utilize advances in biodiversity modeling to predict nature's contributions to people (NCP) linked to species and communities. (A) Macroecological models can estimate different dimensions of pollinator diversity, including those describing species interactions, and evidence of importance to NCP is included for each diversity metric. (B) Species distribution models can estimate habitat suitability via ensembles or abundance via data integration, and both can quantify uncertainty. (C) Examples of richness maps focusing on Europe for species that provide NCP. See [38,39,50,51,53,71,72,96].

of different anthropogenic stressors [46]. Phylogenetic and functional (or trait) diversity are two other biodiversity indices whose patterns can differ greatly from taxonomic (i.e., species) diversity. These indices in particular have strong relationships with NCP provisions. It is expected that higher species richness enhances ecosystem functioning and NCPs through species complementarity (niche differentiation and facilitation) and the selection effect (dominance of species with particular traits) [47]. As these effects mostly depend on variation among species, phylogenetic and functional diversity are likely to offer more comprehensive representations of these distinctions than basic measures of species richness [48–51]. For example, woody plant assemblages with high phylogenetic diversity are linked to a richer variety of NCP supporting human habitation [48], and exploring differences between functional and taxonomic turnover of pollinators can improve our understanding of how mutualistic interactions respond to the environment [51].

Models that estimate different dimensions of biodiversity have many applications for NCP prediction. SDMs or MEMs can be used to predict specific trophic or functional groups from basic knowledge on interactions (e.g., [52]) that are directly linked to specific ecosystem services like pest control (e.g., [53]) or carbon storage (e.g., forest biomass, forest functional diversity [54]). Predictions of pollinator richness or trait diversity (pollination type, etc.) with MEMs can identify areas with high potential for pollination services and areas at risk under climate change or land-use intensification. Similar to calculating range rarity, the relative importance of particular species for NCP provisions can be used to define weights to predict NCP. For instance, one might upweight the role of domestic and wild bees over flies for cropland pollination because of their higher pollination efficiency for specific crops [55]. Some aspects of NCP may be more tightly associated with particular species (e.g., specialist pollinators and their hosts) as opposed to functional groups or communities, and for these SDMs may be particularly appropriate. Finally, multiclass classification models, which are developing quickly in the field of artificial intelligence, can be used to model multiple NCP jointly (e.g., pollination, seed dispersal, and pest control) and implicitly account for associations between NCP. These approaches should prove particularly useful for NCP prediction [56], especially because they can incorporate rare NCP with fewer observations that would benefit from joint modeling [57].

Incorporating biotic interactions

The supply of most NCP is the outcome of species that interact with each other. Animals and plants interact to produce pollination provision and seed dispersal, while predators and prey interact to provide pest control. However, knowledge of **species interactions** has long been lacking (i.e., Eltonian shortfall [58]), making it difficult to incorporate this information for NCP prediction. Recently, however, an upsurge of interaction databases (e.g., GLOBI) and initiatives to build macroecological knowledge on species interactions (e.g., [52]) have aided the exploration of deeper relationships between species and NCP [59]. For cases when particular interactions are primarily responsible for NCP (e.g., mutualism between plants and insects for pollination), incorporating information on these interactions into models that are mainly built with abiotic predictor variables (e.g., climate, land cover, soil, topography) can improve not only the accuracy and realism of SDMs [60], but also the utility of species' distributional estimates for NCP prediction.

Integrating species interactions into SDMs requires different strategies depending on the nature of the interaction. When the presence of the focal species has a limited impact on populations of the interacting species, SDM predictor variables can include information on interactors. For example, when predicting the range of a pollinator or seed disperser, information on food plants (e.g., range maps, co-occurrence, diversity) can be used as predictor variables, provided consumption has limited impacts on plant populations (e.g., [61,62]). However, when the focal species strongly impacts the interactor, the interactor should not be used as a predictor for a SDM [63,64]. Examples would be systems where two populations strongly affect each other, such as species that prey on or compete with agricultural pests, or mutualists with plants that promote habitat restoration. In these cases, SDMs can be paired with ecological networks that contain information on interaction strength [65], population-demographic models [66], or joint SDMs that can estimate how the presence of one or more species conditionally affects the probability of another species being present (e.g., [67]). Alternatively, range maps from SDMs built only with environmental predictors (or those from interacting species not affected by the focal species) can be edited to remove areas with negative interactions that make presence unlikely [68]. Techniques also exist to correct biodiversity predictions by removing candidate species from the predicted species pool based on knowledge of biotic filters (e.g., SESAM [69]).

As MEMs can predict taxonomic, functional, or phylogenetic diversity, they can also be used to predict the diversity of species interactions as functions of environmental variables. Hotspots can represent areas with dense interaction networks that are resilient to perturbation and extinctions, making patterns quite different from other diversity indices [70]. Interaction diversity can be particularly suitable for NCP prediction as it summarizes the interactions that generate and maintain NCP, such as those between plants and seed dispersers or pollinators (Figure 2) [71,72], agricultural pests and their predators, and networks of subterranean organisms promoting soil fertility [73]. Interaction diversity is also important to support community stability [74] and thus likely to ensure the sustained provisioning of NCP over time; this topic needs to be explored by further research.

Addressing analytical uncertainty throughout the modeling workflow

As different algorithms, data, and parameterizations can result in very different predictions [75], it is important to explore sources of **analytical uncertainty** in the modeling workflow when implementing policy or management for NCP [76]. As NCP predictions have typically used single models without quantifications of uncertainty (only about 50% of peer-reviewed papers since 2016 [7]), recent efforts seek to integrate uncertainty calculations into biophysical modeling frameworks [77]. Although discrepancies between similar methods remain and more work must be done to standardize best practices, NCP predictions can nonetheless benefit from methods developed to measure and report multiple sources of biodiversity model uncertainty, including data quality and biases [78], choice of predictor variables [79], model algorithm behavior [80], and decisions regarding datasets for model transfer such as future climate scenarios [81].

Uncertainty for biodiversity models can be explored and quantified in different ways. Randomization analyses mimic model behavior but simulate one process randomly, and results can be compared with biodiversity model predictions to estimate bounds of uncertainty. For example, uncertainty in the data observation process can be quantified using simulations that randomize occurrence record locations or the effects of sampling bias [82]. Similarly, null models built with random species occurrence data can help to estimate the significance of empirical performance

Box 2. International frameworks call for NCP–biodiversity modeling integration

SDMs and MEMs have been used in the IPBES Expert Group on Scenarios and Models to generate biodiversity models for biodiversity and ecosystem services scenarios (BES-SIMs) [106]. New challenges have been highlighted in predicting the provision of ecosystem services (NCP), including the integration of species-level biodiversity into NCP models and expansion to consider other aspects of biodiversity [31]. In response, new frameworks were developed to combine NCP and biodiversity models [6] and global NCP estimates using SDMs have been demonstrated [102]. The first joint report by IPBES and the Intergovernmental Panel on Climate Change (IPCC), released in 2021 [107], emphasizes the need to carefully assess the link between climate change and biodiversity change, and biodiversity models that use climatic predictor variables can help to bridge the existing gap. Already, global climate models are beginning to incorporate biological processes more explicitly in addition to geophysical ones, taking into account the feedback effects of the biosphere on the climate system [108].

The launch of the Kunming–Montreal GBF in December 2022 (CBD/COP/15/L25) provides an opportunity to utilize advances in biodiversity modeling for NCP projections, which is critical to the achievement of multiple goals and targets. For instance, Target 11 is aimed at ensuring NCP, including ecosystem functions and services, through nature-based solutions and/or ecosystem-based approaches for the benefit of people and nature. However, the roles of models and predictions are not well represented in the GBF, and we think they are critical to achieve the outcomes of biodiversity targets and goals.

The most closely watched target in the GBF is Target 3, which aims to protect 30% of the planet by 2030 (the '30 by 30' target). However, it is important to note that Target 3 carries the implicit assumption that current climate conditions are static and thus does not consider the potential for species distribution changes and extinctions associated with climate change. As such, it is important to achieve Target 8 focusing on climate change mitigation and adaptation [109], as protected areas established in currently biodiverse areas may have low efficacy if future climate significantly alters the distribution of biodiversity. Therefore, there is much potential for biodiversity models to inform decision-making for Targets 3 and 8 regarding the establishment and management of protected areas based on both current biodiversity predictions and future projections for different climate scenarios (Figure I).

In a more practical context, models can play a significant role in addressing societal issues, as exemplified by GBF Target 15, which focuses on nature-related disclosures by companies and financial institutions. This target highlights the critical needs to evaluate environmental risks and promote sustainability in business sectors. Given the increasing emphasis on the sustainable utilization of natural resources and the imperative for economic valuation [110], initiatives such as the Taskforce on Nature-related Financial Disclosures (TNFD[ii]) and the Finance for Biodiversity Pledge[iii] are gaining prominence. SDMs and MEMS can provide valuable tools to conduct detailed analyses that respond to these emerging socioeconomic frameworks (Figure I). In light of these international policy and business trends, it is becoming ever more vital for business and financial entities to take clear actions toward the conservation and sustainable use of biodiversity.

SDMs and MEMs are instrumental for biodiversity predictions, offering significant potential to enhance emerging frameworks in business, finance, and policy. These models can play a crucial role in ensuring that future biodiversity protection schemes are well informed and effective, aligning with their intended objectives of conservation and sustainable use. By integrating these ecological models into decision-making processes, we can pave the way for more responsible and effective approaches to addressing the complex challenges at the intersection of ecology, economics, and sustainability.

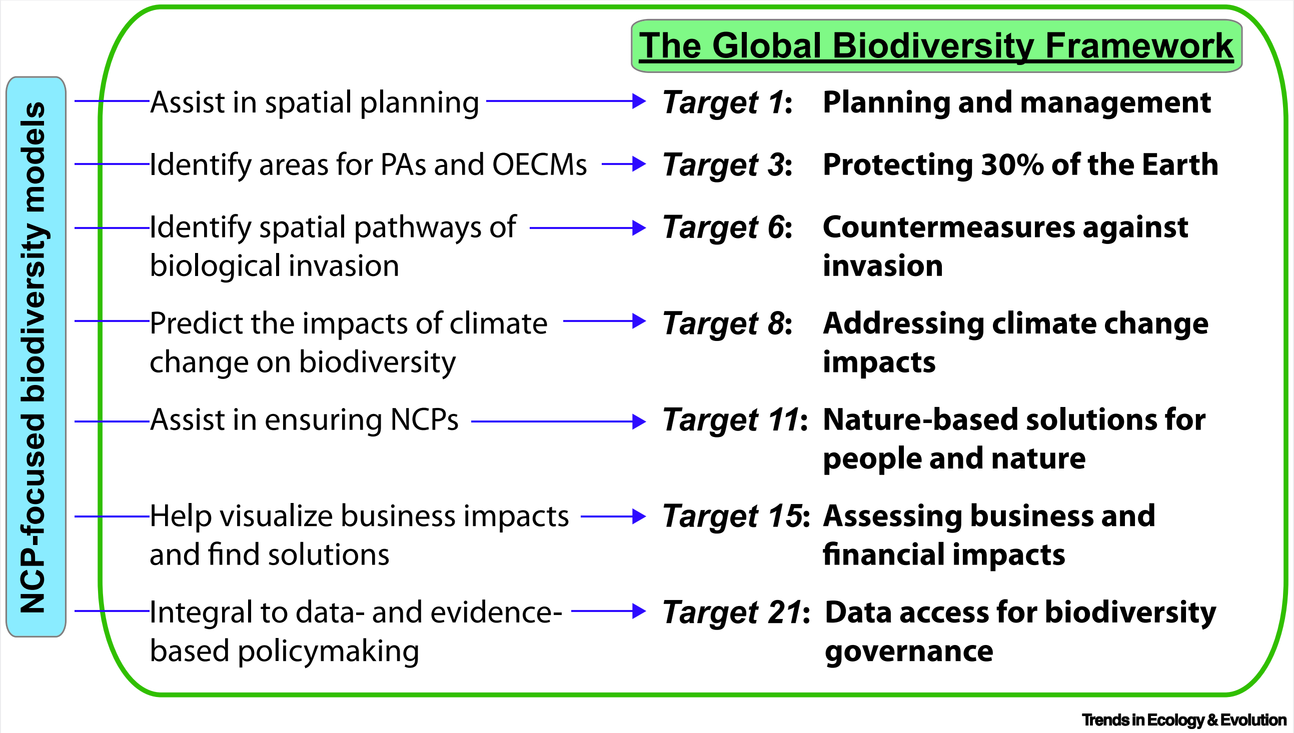

Figure I. Species distribution models (SDMs) and macroecological models (MEMs) can contribute to the achievement of the objectives outlined in the Kunming–Montreal Global Biodiversity Framework (GBF). In this context, we explore several (but not all) potential applications, although the GBF does not explicitly prescribe the use of these models to fulfill its objectives. Abbreviations: NCP, nature's contributions to people; OECMs, other effective area-based conservation measures; PAs, protected areas.

metrics [83] and methodological biases in model transfer to different climate change scenarios [84]. An alternative is to use Bayesian models that explicitly estimate the posterior distribution of parameter values, which enables the calculation of posterior variance and credible intervals (Figure 2) [34]. Model complexity (i.e., shapes of model responses) can be examined with hyperparameter tuning or by building multiple models with different complexity settings and selecting the best performing model [85]. Ensemble modeling combines the outputs of multiple model algorithms, weighted (or not) by model performance on testing data. Ensemble modeling allows the calculation of prediction variance among models and the mapping of algorithm uncertainty caused by differences in model behavior (Figure 2) [75]. Once calculated, measurements of model uncertainty can be incorporated into environmental planning and decision-support tools (e.g., Modern Portfolio Theory [86], Marxan [87]).

Mechanistic biodiversity modeling for NCP prediction

While we mainly discussed how statistical biodiversity models can help to predict NCP across scales, there are mechanistic or semi-mechanistic (hybrid) alternatives. Mechanistic biodiversity models make predictions of NCP that more directly consider the mechanisms that drive ecosystem function. For instance, dynamic vegetation models are able to predict the spatial and temporal dynamics of vegetation types, which can be good proxies for NCP like food and wood production [88], although these remain restricted to vegetation-related NCP. Some mechanistic SDMs consider physiological constraints when estimating relationships with climate to improve the realism of future predictions [89]. Knowledge of thermodynamic limitations should lead to more accurate projections of NCP under climate change scenarios, but such information is not available and/or difficult to acquire for many species. Another promising avenue is the development of hybrid approaches that integrate mechanistic information such as dispersal limits, demographic rates, or physiological parameters into statistical modeling approaches [90,91]. These models require less parameterization than fully mechanistic models and can utilize predictions from SDMs and MEMs. Some new developments also account for species interactions, which have the potential to better represent NCP as discussed earlier. In one example, demographic Lotka–Volterra models, trait relationships, and statistical models were combined to predict the abundance distributions of interacting species in species-rich systems [92]. Although the field is moving in the direction of more integration of statistical and mechanistic models, these approaches still require much data and thus may not be readily applicable to less-studied species groups, such as invertebrates, that play crucial roles in providing important NCP. That said, considering the great potential of mechanistic biodiversity models to improve NCP predictions, more research needs to be done on this front, especially concerning which study systems are most appropriate for each approach [93].

Concluding remarks

The Kunming–Montreal GBF of the UN Convention on Biological Diversity (CBD) has become clear, and the need to jointly conserve biodiversity and derived public benefits has been broadly recognized by international consortia and environmental conservation frameworks. In this context, recent advances in biodiversity modeling have great potential to improve predictions of these benefits and functions that are supplied and supported by biodiversity (Box 2), and this pursuit leads to new and exciting research directions (see Outstanding questions). In addition to these directions, we need more comparative studies that quantify how predictions of NCP are improved (or not) when biodiversity models are employed. The 2050 Biodiversity Vision of the GBF is a world living in harmony with nature, and the next generation of biodiversity models gives us powerful tools to help society realize this nature-positive future.

Outstanding questions

Should weights be applied to taxonomic richness predictions when estimating nature's contributions to people (NCP)? If so, what kinds of weights are most closely linked with NCP provision?

Which NCP are best represented by range estimates of single species and which by estimates of community diversity?

How should we select appropriate spatial resolutions for biodiversity estimates that describe different NCP provisions?

How can the combination of remote sensing data with continuously improving spatial and temporal resolution and artificial intelligence be best harnessed for biodiversity modeling and NCP prediction?

How should we consider species' importance when quantifying their contribution to NCP provision and how should we account for the spatial variation of species' importance?

How should we address NCP correlations and interactions (e.g., synergies, disparities) when modeling them from species and biodiversity estimates?

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Declaration of interests

The authors declare no competing interests.

Resources

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