nature reviews biodiversity

https://doi.org/10.1038/s44358-026-00134-4

Perspective

Check for updates

Biodiversity science and policy need more model intercomparisons

Damaris Zurell[1], Cécile H. Albert[2], Greta Bocedi[3], Natalie J. Briscoe[4], Lauren B. Buckley[5], Samuel J. L. Gascoigne[3], Andrew Gonzalez[6], Gurutzeta Guillera-Arroita[4,7], Nick J. B. Isaac[8], Dirk N. Karger[9], Carolyn J. Lundquist[10,11,12], Cory Merow[13,14], Juliano Sarmento Cabral[15,16], Katrin Schifferle[1], Santiago J. E. Velazco[17,18] & Mark C. Urban[13,14]

Abstract

Halting the accelerating decline of global biodiversity requires robust models to project future changes and inform policy decisions. Climate models, especially model intercomparison projects, were pivotal for advancing the mechanistic understanding of climate change attributing to anthropogenic causes. Analogous biodiversity model intercomparison projects (BMIPs), developed only in the past decade, could emulate this success. In this Perspective, we briefly summarize existing BMIPs and highlight the opportunities, gaps and challenges for developing BMIPs by applying lessons learned from the climate model intercomparison projects. BMIPs offer valuable insights into potential global and regional biodiversity trajectories and their uncertainty and can help to attribute changes in biodiversity to drivers when based on standardized, historical benchmark data. Moving forward, BMIPs should adopt mechanistic approaches, establish governance structures and ensure open access to modelling tools and data. With strategic investments in data infrastructure, modelling capabilities and global governance, BMIPs can meaningfully contribute to the delivery of the Kunming–Montreal Global Biodiversity Framework by providing robust projections that support policy and action planning across various spatial scales and scenarios. Achieving this vision requires concerted international coordination, increased funding and proactive knowledge sharing.

Sections

A full list of affiliations appears at the end of the paper. e-mail: damaris.zurell@uni-potsdam.de

Key points

- Biodiversity model intercomparison projects (BMIPs) provide a coordinated and standardized experimental framework to systematically compare biodiversity models, ensuring consistency in inputs, scenarios and outputs.

- BMIPs are particularly useful both for addressing general biodiversity modelling questions and for supporting national to international actions to reach the Global Biodiversity Framework goals and targets.

- Establishing historical benchmark datasets is crucial for validating biodiversity models, enabling impact attribution and a cross-system understanding of predictive performance and model complexity and enhancing confidence in model predictions.

- Strengthening international collaboration, coordination and knowledge sharing and fostering broader community engagement will enhance the relevance, transparency and impact of BMIPs.

- Establishing clear governance structures for BMIPs, including mechanisms for overseeing modelling activities, infrastructure and community consultation and strategies for long-term funding, is essential for ensuring the sustainability and effectiveness of BMIPs.

Introduction

Biodiversity and ecosystem services are deteriorating worldwide as anthropogenic pressures are elevating extinction risk for an estimated one million species[1]. Climate change is already affecting biological processes[2], and as it intensifies, these extinction risks are expected to rise further[3]. The Kunming–Montreal Global Biodiversity Framework (GBF)[4], adopted in 2022, provides an ambitious plan to halt and reverse biodiversity loss, with its importance often compared to the 2015 Paris Agreement for mitigating climate change.

The Paris Agreement was founded on decades of climate modelling and model intercomparisons, whereas biodiversity modelling lags far behind[5]. The GBF relies solely on backward-looking indicators to track progress towards its goals and targets[6] and completely omits the application of models[4]. Yet policy decisions need robust projections to evaluate the potential consequences of interventions before implementation[7]. Although models are widely used in conservation management and policy, a wider synthesis of models for biodiversity projections is still hampered by limited coordination of modelling efforts, lack of funding, and data and methodological challenges[5,8–11]. Improving biodiversity models and their application will be pivotal for designing national action plans that reduce biodiversity loss and meet the GBF's ambitions. Effective policy action will require an assessment of biodiversity response to different future pathways of climate and Earth system changes to support adaptive management actions.

In climate and Earth system science, model intercomparison projects (MIPs; Box 1) have become a central instrument for understanding past, present and future climate change, fostering model improvement and supporting global and regional scientific assessments. Initiated in 1995, the Coupled Model Intercomparison Project (CMIP) is the most prominent MIP, with a mission to provide climate projections and data infrastructure to the Intergovernmental Panel on Climate Change (IPCC)[12,13]. Following its success, other MIPs have since been developed that address specific questions of the climate system, such as ocean[14] or sea ice modelling[15], or investigate climate impacts on agriculture[16] or fire[17], for example. MIPs provide a standardized experimental and scenario framework for consistent and transparent comparison and evaluation of different models and produce harmonized output that often has direct policy relevance[18–20] (Box 1). They have proved key to understanding the drivers of historical changes, quantifying uncertainty in predicted futures, refining modelling frameworks, improving the credibility of model-based insights, building consensus and confidence, identifying research gaps and facilitating knowledge sharing and international collaboration.

Despite international commitments to halt biodiversity loss, formal biodiversity model intercomparison projects (BMIPs) that address key questions relevant to policy support remain surprisingly scarce, limiting the confidence in model projections. At present, only two BMIPs have been formally established that address some aspects of biodiversity: the Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP)[21–26] and the Biodiversity and Ecosystem Services Scenario-based Inter-Model comparison (BES-SIM)[27,28]. BES-SIM provides a first compelling picture of the uncertainties in future projections of global terrestrial biodiversity. FishMIP additionally enables comparison of global and regional model outcomes by marine ecosystem models[25,26] and highlights key uncertainties about how eco-evolutionary processes will affect biodiversity responses to climate change. FishMIP is part of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)[20,29] that provides climate impact simulations that are consistent across multiple sectors (components of the Earth system or society, such as agriculture, water, fire, energy, health and marine ecosystems) and terrestrial and forest biodiversity. However, unlike FishMIP, terrestrial biodiversity projections within ISIMIP have been limited to correlative models providing global climate impact projections of some well-known vertebrate taxa[30], whereas process-based models have so far only been considered in regional forest MIPs[31]. Although other studies have started to compare different process-based biodiversity modelling approaches at regional scales[32–34], these efforts have not developed into formal BMIPs (Box 1). To the best of our knowledge, model intercomparisons are currently altogether missing for freshwater biodiversity. Therefore, existing MIPs for biodiversity have so far covered only a narrow part of biodiversity complexity and its responses to regional and global changes[22,28], precluding confidence and consensus about the future of biodiversity.

In this Perspective, we discuss the history of MIPs in biodiversity research as compared with climate science and highlight the challenges and opportunities of BMIPs related to policy relevance, model complexity, spatial and ecological scales, data limitations and institutional support. Many lessons can be learned from previous MIPs regarding best practices for how to develop formal BMIPs. Although not every ecological or management question will require a formal model intercomparison, we outline the critical part that they could play and identify areas in biodiversity research and conservation in which formal BMIPs will be particularly useful.

Lessons from climate model intercomparisons

MIPs have a long history in climate science reaching back to the 1970s. Atmospheric scientists recognized that massive data and model deficiencies prevented them from accurately forecasting weather and climate change. As a result, the Global Atmospheric Research Programme was established in 1967 to improve, coordinate and standardize the collection of atmospheric and weather station data for model parameterization

Box 1 | Characteristics of model intercomparison projects

Model intercomparison projects (MIPs) are coordinated scientific efforts that apply a common and standardized experimental set-up to compare multiple models and assess model agreement through harmonized model output[18–20]. MIPs identify differences and similarities in model behaviours, help to understand uncertainty across models and highlight strengths and weaknesses of different modelling approaches. These insights often propel future model developments and refinements[12,24]. As model outcomes naturally differ depending on their input parameters and output metrics, a common modelling protocol and experimental set-up with shared rules for inputs, scenarios and outputs are essential to ensure transparency, a fair comparison of models and uncertainty quantification in outputs. Comprehensively documenting the proposed approach in advance increases the legitimacy of the MIP set-up through peer review. The experimental set-up of MIPs typically comprises historical runs that can be compared against observed data, scenario runs that contain mainly future but sometimes also past projections, and idealized experiments to facilitate impact attribution through counterfactual scenarios and test model sensitivity[12,20,24,29].

Some MIPs (such as ISIMIP[20,29]) explicitly separate an evaluation set-up with only historical runs and a simulation set-up with the scenario runs and idealized experiments. In other MIPs (such as CMIP[12,18]), evaluation of the historical runs is not centrally enforced before using the model for future projections. In either case, evaluation of historical model simulations against observational data provides important insights into predictive accuracy and robust agreement of the participating models and helps to identify uncertainties and knowledge gaps. Comparing model simulations for different scenarios, such as scenarios of climate-related forcings to assess possible futures, allows the capture of model-based uncertainty in future projections in 'ensembles'. Typically, MIPs contain a core set of scenarios that are simulated by all models, whereas fewer models might address additional scenarios and idealized experiments.

Results from MIPs are often used in international and national policy documents such as the assessment reports of the Intergovernmental Panel on Climate Change (IPCC). To maximize their scientific and policy impact, MIPs should be designed as ongoing efforts with plans for iterative phases, ensuring adaptability to new data, evolving methodologies and emerging research questions. Establishing mechanisms for long-term coordination, data updates and methodological refinements helps to maintain relevance and strengthens their role in informing policy and scientific advancements.

and validation, enhance the understanding of and incorporation of mechanisms underlying atmospheric dynamics and create processes to facilitate global coordination and collaboration[12,35]. Early intercomparisons mostly focused on atmospheric models for weather forecasting but already bore an important characteristic of MIPs (Box 1), the preregistration of standard modelling protocols to ensure fair comparisons. In the 1980s, the World Climate Research Programme (WCRP) was established and advocated for the intercomparison of climate models resulting in the creation of the Atmospheric Model Intercomparison Project (AMIP) in 1990 (refs. 12,18) (Fig. 1). AMIP was widely endorsed, with 31 modelling groups participating in its first phase[12]. In parallel, the complexity of climate models increased, and the increasingly sophisticated coupled atmosphere–ocean global climate models finally led to the establishment of CMIP in 1995 to allow a more robust assessment of the mechanisms behind anthropogenic climate change[12,18]. CMIP has since influenced the IPCC assessment reports, and the different CMIP phases are closely aligned with the IPCC assessment cycles. Still, although CMIP supports the work of IPCC, it remains an independent scientific endeavour aimed at understanding climate change and model biases[12,36].

CMIP provided a step change in climate science and supplied the IPCC with defensible results and projections from models developed by worldwide teams to enhance the credibility of climate models, allow attribution to anthropogenic drivers and provide future scenario-based projections. The standardization of inputs, outputs, scenarios and validation and the transparent and global effort to organize and disseminate results and quantify uncertainty were critical to building consensus on human-caused global warming[35]. The standardized comparisons among models quickly allowed researchers to assess the impact of the inclusion of or representation of different processes[12,18]. Ensembles of these consistent model outcomes captured uncertainty owing to modelling choices and considered processes and represented past and current climate data more accurately than single models, thus providing increasing support for projections[37]. The formation of AMIP and CMIP transformed the budding field of atmospheric science from one of many unknowns to the increasingly accurate projection of global climate change. The ability to attribute observed climate change to human activities and project future climate trends based on varying socioeconomic scenarios with increasing certainty was recognized as laying the foundation for efforts to prevent catastrophic effects on humanity – and one of the greatest success stories in science[18,38].

Important elements in CMIP's success included structured governance, standardized protocols, iterative learning and strong community engagement. CMIP has continuously evolved and learned from each phase and now involves approximately 50 modelling centres worldwide[12]. Formal governance structures ensure that CMIP remains a community-driven effort with clear leadership, common standards and guidelines, and coordination across modelling centres worldwide, as well as outreach into the scientific community and beyond[18,36]. CMIP is overseen by the WCRP, directed by subcommittees coordinating CMIP activities and the infrastructure, and is supported by the CMIP International Project Office[18]. The latter manages communication within CMIP as well as the community consultation, which has been initiated in the sixth phase of CMIP[36] and which also seeks input from climate change application experts who rely on CMIP output data for their climate impact assessments[39,40]. Based on their long experience, CMIP also provides best practice guidelines for establishing MIPs[41]. BMIPs can learn from these experiences and can greatly benefit from adopting similar best practices (Box 2), governance structures and community engagement.

Existing biodiversity model intercomparisons

Compared with climate science, biologists are more than 20 years behind in their efforts to provide robust projections of future biodiversity changes[5] (Fig. 1). Notwithstanding, biodiversity models have a similarly long history as climate models and cover a diverse set of modelling

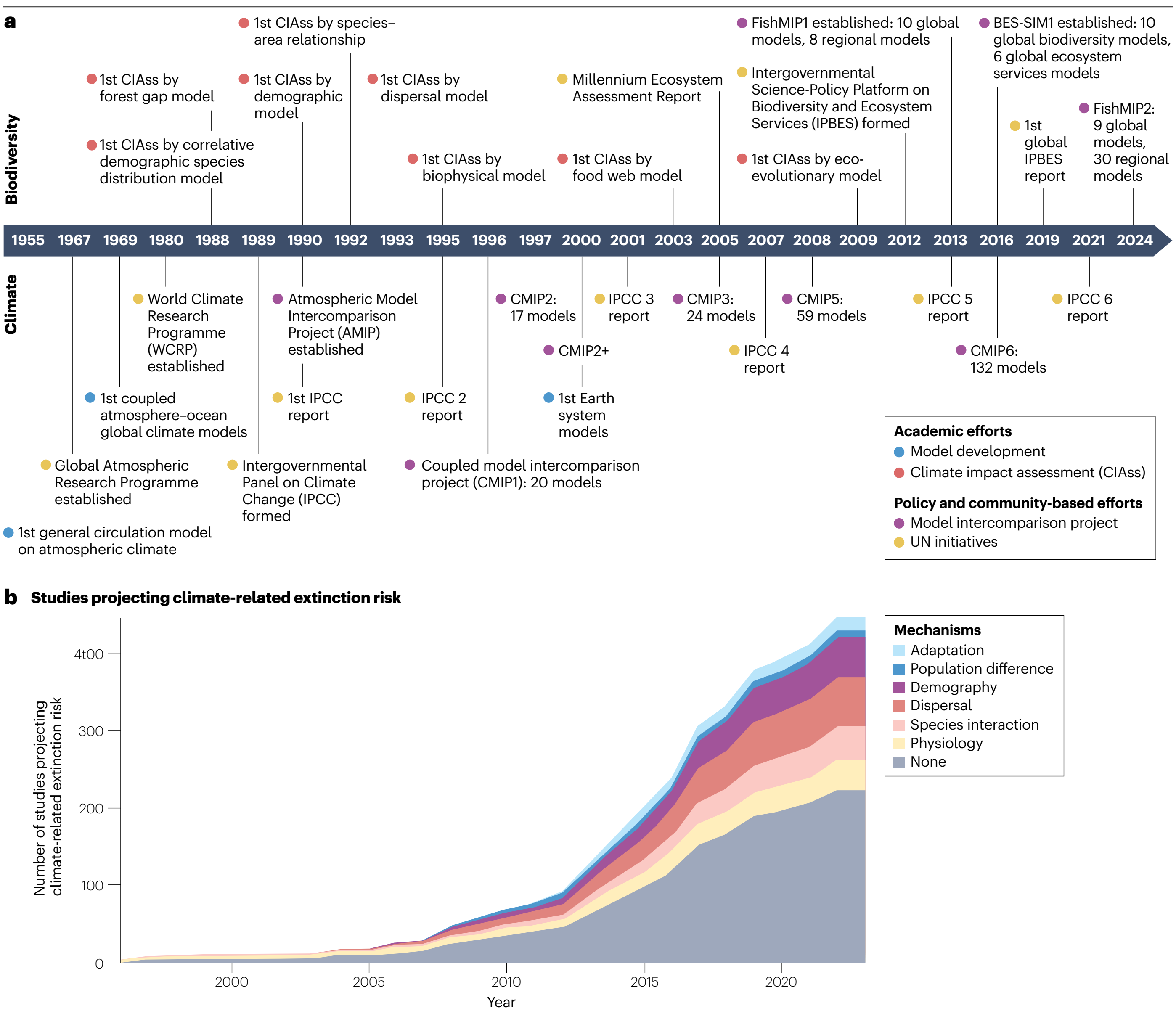

Fig. 1 | Timeline of climate modelling, biodiversity modelling and related model intercomparison projects. a, Events below the timeline relate to climate, and events above the timeline relate to biodiversity. Details on the literature search are provided in the Supplementary Information. **b**, The number of biodiversity modelling studies explicitly projecting extinction risk from climate change and considering different biological mechanisms; data from ref. 3.

types on a continuum from correlative to mechanistic models[10,42,43]. Mathematical and demographic models have been popular since the 1950s[44], individual-based forest gap models have proliferated since the 1970s[45–47], ecophysiological models were developed in the 1970s[48,49] and correlative species distribution models were first developed in the 1980s[50]. Modelling studies explicitly projecting climate change impacts on species and biodiversity only appeared in the mid-1980s[20,51–60] (Fig. 1) when the threat of global warming became more widely acknowledged and evidenced[61]. In the 1990s, forest gap models dominated climate impact assessments on biodiversity, and in the late 2000s, the number of studies sharply increased, driven by a proliferation of correlative species distribution models (Fig. 1). This increase in biodiversity projection studies was facilitated by the accessibility of generalizable model frameworks as well as availability of digitized biodiversity data and climate data coupled with future climate scenarios that became open access with the third phase of CMIP in the mid-2000s[12]. Despite the variety of modelling approaches available, climate impact projections on biodiversity are strongly biased toward correlative models[3,9].

Biodiversity encompasses various levels of biological organization (genetic, population, species, community or ecosystem), spatial organization (local, regional and global scales) and different components of diversity (from allelic diversity to species distribution to community composition and ecosystem productivity)[62–64]. Modelling these biodiversity components and projecting their potential trajectories over time and at different spatial scales are not easy tasks. Biodiversity models differ widely in the process detail covered, their subsequent data requirements and their output, and thus the essential biodiversity variables (EBVs[65]) that they produce (Fig. 2).

Biodiversity model parameters can be estimated directly from data (such as body mass and maximum reproductive output) or fitted inversely based on their ability to produce known outputs (such as population trajectories)[42]. Living organisms do not behave like physical particles because they also have singular characteristics and the potential to adapt to changing environmental conditions such that no one-size-fits-all solution exists for modelling biodiversity. Hence, models are often calibrated or tailored to specific ecosystems or species and specific management questions[8]. For example, modelling approaches for assessing species-level extinction risks include vulnerability assessments based on species' traits and other characteristics[66–68], demographic models such as population viability analysis[69,70] and species distribution models that estimate habitat suitability of a given location based on climate and other landscape characteristics[71–73]. Calibrating these models requires data types such as species occurrences and abundances, demography and dispersal (Fig. 2), which are often only available in the form of expert opinion, although the availability of digital information is rapidly increasing and starting to resolve data limitations[74–78]. BMIPs thus need to carefully trade off the level of process and biodiversity detail required, data availability and computational efforts for calibrating and running models against the potential gains in system understanding and policy support.

Unlike in climate science, model development in biodiversity science and model use for policy support remain largely uncoordinated. With the notable exceptions of FishMIP and BES-SIM, model comparisons have mostly been developed ad hoc within small teams of collaborators[32–34,79–81]. These ad hoc comparisons have tested the predictive ability of different model types by comparing correlative and process-based approaches for predicting historically observed or simulated species range dynamics[32,33,82] and population growth[81] and assessed uncertainty in future projections of species ranges[34,80]. Most of these comparisons found no single best modelling approach but recommended ensembles to cover a wide range of model types and model parameterizations to adequately capture uncertainty in future projections[82] and identified future avenues for improvements of models and data integration[33,34,81].

Formal model intercomparison projects for biodiversity emerged only in the 2010s, more than 20 years after AMIP. FishMIP[22,23,26] (described in refs. 21,24) was initiated in 2013 and focuses on fisheries and marine ecosystem services. It covers a diverse set of ecological models ranging from correlative species distribution models to ecosystem models that describe the flow of energy through food webs or via partitioning into ecosystem components to project fish biomass, catch and ecosystem parameters. In its first phase, FishMIP produced global projections of marine animal biomass[22,23] that were instrumental in informing international climate and biodiversity science–policy efforts[19]. A 2025 comparison of global and regional models in FishMIP indicated larger uncertainty in projected biomass by regional models, highlighting missing knowledge in key ecological and eco-evolutionary processes at regional scales that should be further explored in the future[26].

BES-SIM[28] (described in ref. 27) was initiated in 2016 by the Expert Group on Scenarios and Models of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). BES-SIM primarily uses correlative models (species–area relationships) and correlative species distribution models to project future terrestrial biodiversity trends (such as species richness) at global scale. It also uses dynamic vegetation models to project ecosystem services. Focusing on correlative biodiversity models was a necessary simplification as BES-SIM covered thousands of species, which makes it difficult to incorporate explicit mechanistic knowledge and processes.

Box 2 | Best practices for biodiversity model intercomparison projects

Based on their experience, the Coupled Model Intercomparison Project (CMIP) outlines general model intercomparison project (MIP) best practice guidelines[41] focused on development, design and documentation. These include clearly defining the hypothesis and new knowledge to be gained, as well as the experimental design and data requirements; leveraging past experience and performing prototype experiments; fostering transparent and inclusive collaboration (including co-design of MIPs); thoroughly documenting the approach (including via peer-reviewed description papers); and supporting users and acknowledging contributions.

Clarifying the experimental design and data requirements will be particularly important in biodiversity model intercomparison projects (BMIPs) and will have to be carefully tailored to the system and question under study. Biodiversity data are heterogeneous, and data collation is challenged by diverse data needs of different modelling approaches. Data pipelines could benefit from regular updating as data availability is continuously improving, and modelling teams should work closely with data providers, including Indigenous knowledge, to collate the best possible data.

In addition to the steps outlined by CMIP, we suggest two additional (or refined) best practices for BMIPs related to data availability and equitability. First, BMIPs should provide benchmark datasets with open access to avoid duplicated efforts and encourage broad participation beyond individual, well-linked research groups. The availability of high-quality biodiversity and environmental driver datasets can allow intercomparisons to be efficiently revisited[79,119] and emerging methods to be tested rapidly. Expanding such datasets to cover a broad set of (or all) essential biodiversity variables[65] and world regions should be a priority. Past studies evaluating biodiversity model outputs have relied heavily on a handful of high-quality datasets; for example, bird and butterfly monitoring data from European and North American countries have been used to evaluate the performance of biodiversity models including trait-based vulnerability assessments, correlative species distribution models, dynamic occupancy models and spatially explicit metapopulation models[32,33,120–122]. Second, to ensure equitable opportunities to build national and regional BMIPs, central knowledge platforms are needed that offer comparably easy-to-use toolboxes and extensive guidance to adjust and calibrate models to specific countries and regions (such as BON in a Box[111]). Models should also be shared to allow transfer learning for data-poor regions. As local data become available, these transferred models can then iteratively be refined and updated.

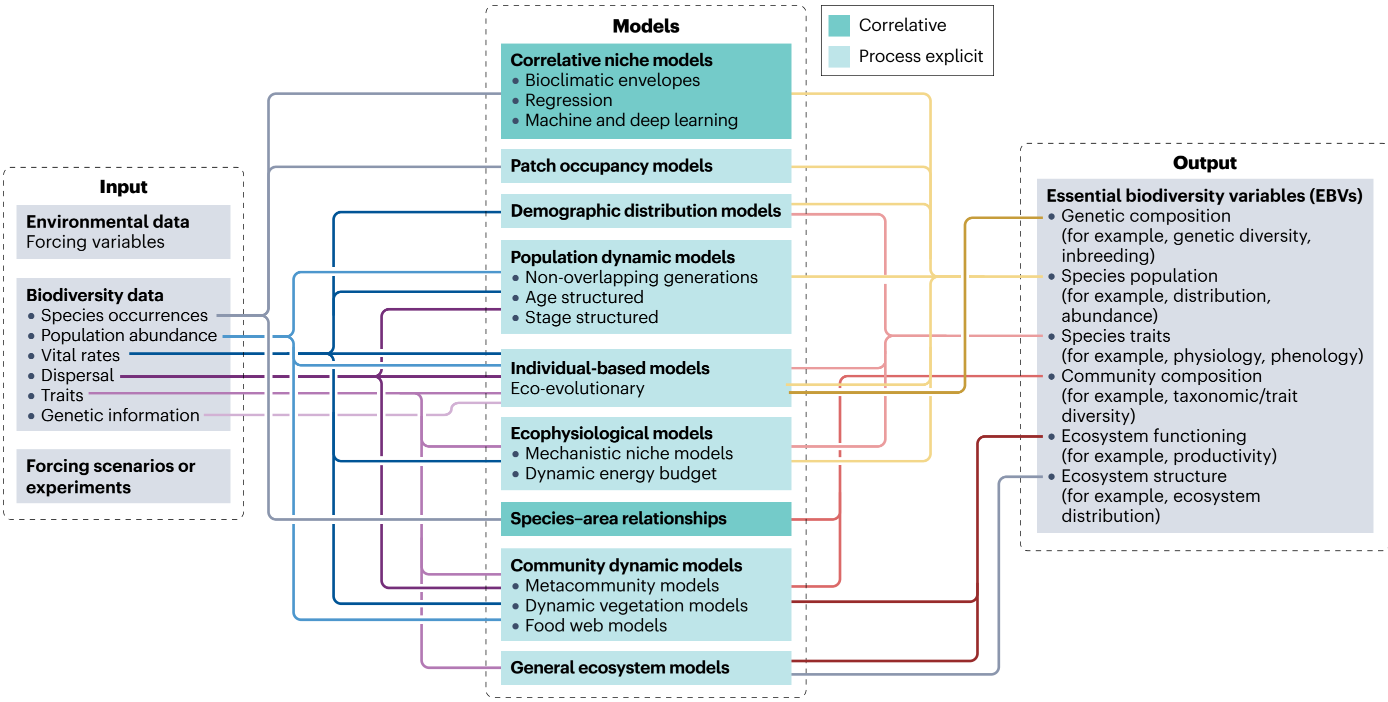

Fig. 2 | Spatially explicit biodiversity models and their typical input data requirements and outputs. Inputs (right) include environmental data (natural and anthropogenic drivers such as temperature, precipitation or land use) and biodiversity data (from monitoring and observing systems and historical collections). Connecting lines signify data requirements of models (centre) and subsequent model outputs (left). Process-explicit models (light blue) require higher data availability (left) than correlative models (teal) but can produce a wider range of expected outputs (right). Running the models with past and present environmental data (forcing variables) allows the output to be compared against observed data for validation and for attribution, whereas running the models with forcing scenarios and experiments will provide critical information about model sensitivity and potential future outcomes that are relevant for informing decision processes. Models are reviewed in refs. 9,10,85.

The large uncertainty in projected biodiversity trends between BES-SIM models could stem from missing processes or be indicative of variation across taxa.

FishMIP and BES-SIM have made substantial contributions to understanding the future of biodiversity and ecosystem services and highlight important next steps for further BMIP developments. These next steps include considering a wider variety of process-based modelling approaches and historic benchmark data for rigorous evaluation of predictive performance. In its second phase (initiated in 2024), FishMIP will emphasize performing an evaluation set-up (sensu ISIMIP[29], Box 1) to detect past changes in biomass trends by assessing model performance to reconstruct historical observations, attribute trends to drivers and provide benchmark datasets for increasing confidence in models[24]. Compared with FishMIP, BES-SIM currently has a limited mechanistic basis. Both BES-SIM and FishMIP use ISIMIP data, but only FishMIP is an official part of ISIMIP that provides modelling protocols to consistently assess climate impacts across sectors[20,29–31].

A few other MIP initiatives exist that are relevant to biodiversity, such as AgMIP[16,83], the Agricultural Model Intercomparison and Improvement Project, and ForMIP[84], the global forest model intercomparison project. However, these MIPs do not explicitly model indicators of the state of biodiversity or nature but agricultural and forest products, and thus we will not further discuss them here.

In the future, a comparison of global models and process-based, regional models — as well as benchmarking of models against historic observations — could produce important insights about relevant eco-evolutionary processes determining past and future terrestrial biodiversity changes. In the terrestrial realm, the uptake of process-based models in the biodiversity community has been slow owing to data and technical challenges[85]. Process-based models explicitly describe the processes by which species respond to environmental variation and consider potentially relevant eco-evolutionary processes such as dispersal, demography, adaptation and species interactions[86]. Compared with correlative models, process-based models are thought to extrapolate better to future conditions and better capture transient dynamics and time-lagged responses[82,87,88]. Using process-based models in BMIPs will also produce more diverse outputs and a broader range of EBVs to inform decision-making (Fig. 2), but their development should be evaluated with regard to the potential trade-off with increased data requirements and computational burdens. Consideration of multiple EBVs and key processes driving biodiversity responses to global change as well as formal model evaluation and impact attribution will be essential steps in the further development and refinement of BMIPs.

Despite its global importance for policy and management, biodiversity projections and existing BMIPs are not coordinated by an international body such as the WCRP[89]. IPBES was established in 2012 to synthesize research, assess evidence on the state of biodiversity and ecosystem services and provide policy support. Similar to the IPCC, IPBES is an assessment body only and does not conduct or direct research. Within the Group on Earth Observations Biodiversity

Observation Network (GEO BON), the working group EcoCode acts to coordinate modelling across multiple biodiversity efforts, ranging from monitoring to projections, but lacks the resources to coordinate biodiversity research and model intercomparisons more generally. For both FishMIP and BES-SIM, coordination, administration, communication and scientific activities are handled by volunteers without any dedicated staff, which is in stark contrast to CMIP. Defining the experimental design and data requirements in a transparent and inclusive collaborative process, coordinating the experiments in a timely manner, providing the infrastructure for performing the modelling experiments and accessing the data and outputs, documenting all steps and results and lending support for users are complex tasks[19] (Box 2). Financial and institutional support for BMIPs, analogous to the WCRP, would meaningfully enhance their efficiency and long-term sustainability.

Challenges and opportunities for BMIPs

Advancing the broader use of BMIPs across realms will require overcoming interlinked technical, conceptual and data challenges beyond those already well documented in the literature[8–10,85]. Here, we highlight key challenges for the establishment and refinement of BMIPs related to model complexity, policy relevance, the appropriate spatial and ecological scales and benchmark data. Not every ecological or management question will require a formal model intercomparison. We suggest that BMIPs are particularly useful for (1) questions of broad relevance to understanding and projecting biodiversity changes and (2) national to international action planning toward the GBF goals and targets.

First, broadly relevant modelling questions relate, for example, to the predictability of biodiversity responses to global change and the processes that need to be represented to achieve reliable model projections. These include understanding the role of key ecological and evolutionary processes – such as dispersal, demography, physiology, species interactions and adaptations[86] – in shaping biodiversity dynamics and how the inclusion of these processes affects model transferability[90,91] across scales. Capturing such mechanisms is thought to improve model accuracy[8–10,34,49,85], but no comprehensive evidence exists on how much mechanistic complexity is needed to accurately project biodiversity at different spatial and temporal scales. Model intercomparisons provide a powerful means to answer this question. For example, the comparison of global and regional model projections by FishMIP indicated that larger discrepancies in model outputs at regional scale could reflect missing knowledge on relevant mechanisms[26]. Similarly, a model comparison on virtual terrestrial species data indicated that, although explicit consideration of mechanisms generally improved projections of species range dynamics under climate change, simple dispersal models proved more reliable in highly stochastic systems compared with more complex population dynamic models[82]. The appropriate level of mechanistic complexity might thus depend on spatial and temporal scales, the species and ecosystems analysed, the ecological level and type of biodiversity variable of interest (Fig. 3), and the available data (Fig. 2). A BMIP comparing models across diverse ecosystems and spatial scales could provide important guidance on when additional process representation improves projections and when simpler modelling frameworks are sufficient, helping to balance predictive performance and forecasting efficiency (sensu ref. 92). Explicitly assessing the relevance of different mechanisms across systems will not only improve confidence in future projections but also aid understanding of how different drivers contribute to biodiversity change[93,94].

Second, we advocate for formal BMIPs to support planning for actions toward the GBF goals and targets by comparing the outcomes of alternative management choices[6,10] and assessing their synergies and trade-offs[89]. Some of the GBF's 23 targets for 2030, such as the 30 × 30 target of conserving 30% of land, waters and sea (Target 3), focus on spatial planning at the ecosystem and species levels. Other targets, such as ensuring urgent management actions to halt the extinction of threatened species and restore genetic diversity (Target 4), clearly focus on the population level[95]. Projecting biodiversity outcomes at the population level, and even including genetic diversity, will require models that capture species-specific responses and greater process detail[9] (Figs. 2 and 3). This modelling will be more realistically accomplished at local to regional scales than the global scale[26]. Additionally, whereas GBF goals and targets are formulated at the global level, the targets will be implemented at the national level. Accordingly, BMIPs across local and global scales are needed to inform global outcomes. For parties to the Convention of Biological Diversity, national BMIPs could be used to assess the ambition within National Biodiversity Strategy and Action Plans, specifically, whether planned conservation actions are sufficient to deliver stated outcomes and targets[96]. Developing workflows to effectively integrate local and global scales[25] could then evaluate whether national plans and targets add up to the level of change required to meet the 2050 GBF vision of living in harmony with nature (as defined in Goal A) and contribute to the IPBES Global Assessments and other thematic IPBES assessments. Importantly, to adequately support policy and action planning toward the GBF, BMIPs are required for all realms. FishMIP currently constitutes the most advanced BMIP incorporating a range of correlative to process-based as well as global and regional models[19]. Similar developments are needed for the terrestrial realm and especially for the freshwater realm, which is currently not adequately considered in BMIPs.

Beyond these broader questions of process understanding and decision support, benchmark data are needed with historical observations at sufficient spatial and temporal scales to validate model predictive performance within BMIPs and allow detection and attribution of past biodiversity changes[24,93]. Explicit evaluation of the model accuracy against historic observations will be key to providing legitimacy and confidence in model projections and for attributing historical biodiversity changes to different anthropogenic drivers and relevant eco-evolutionary processes[93,94]. Biodiversity data are typically sparse and biased, as many species-rich developing countries are underrepresented in global information databases[97,98]. Time series of historical biodiversity changes are even scarcer[99]. An important aspect for establishing BMIPs will thus be to identify appropriate datasets that are representative for the targeted species, ecosystems and action planning under consideration and to design monitoring schemes to aid biodiversity assessments[100]. Additionally, improved data and scenarios on drivers are needed that go beyond climate and land cover to also include information on land use, pollution and overexploitation. Harmonizing modelling protocols across impact sectors as advocated by ISIMIP[29] can facilitate integration of additional drivers and explicit feedback between biodiversity and anthropogenic drivers[101]. Active participation of BMIP representatives, such as in the CMIP community consultation[39,40], can also help to ensure that the climate and Earth system models, or at least a subset of them, produce the variables necessary for running biodiversity models[19].

Although biodiversity modelling and BMIPs are lagging behind climate modelling, this gap can be filled quickly if sufficient resources and coordination are mobilized. Over recent decades, computational power has increased tremendously, modelling methods are continuously being improved, and models are increasingly open access.

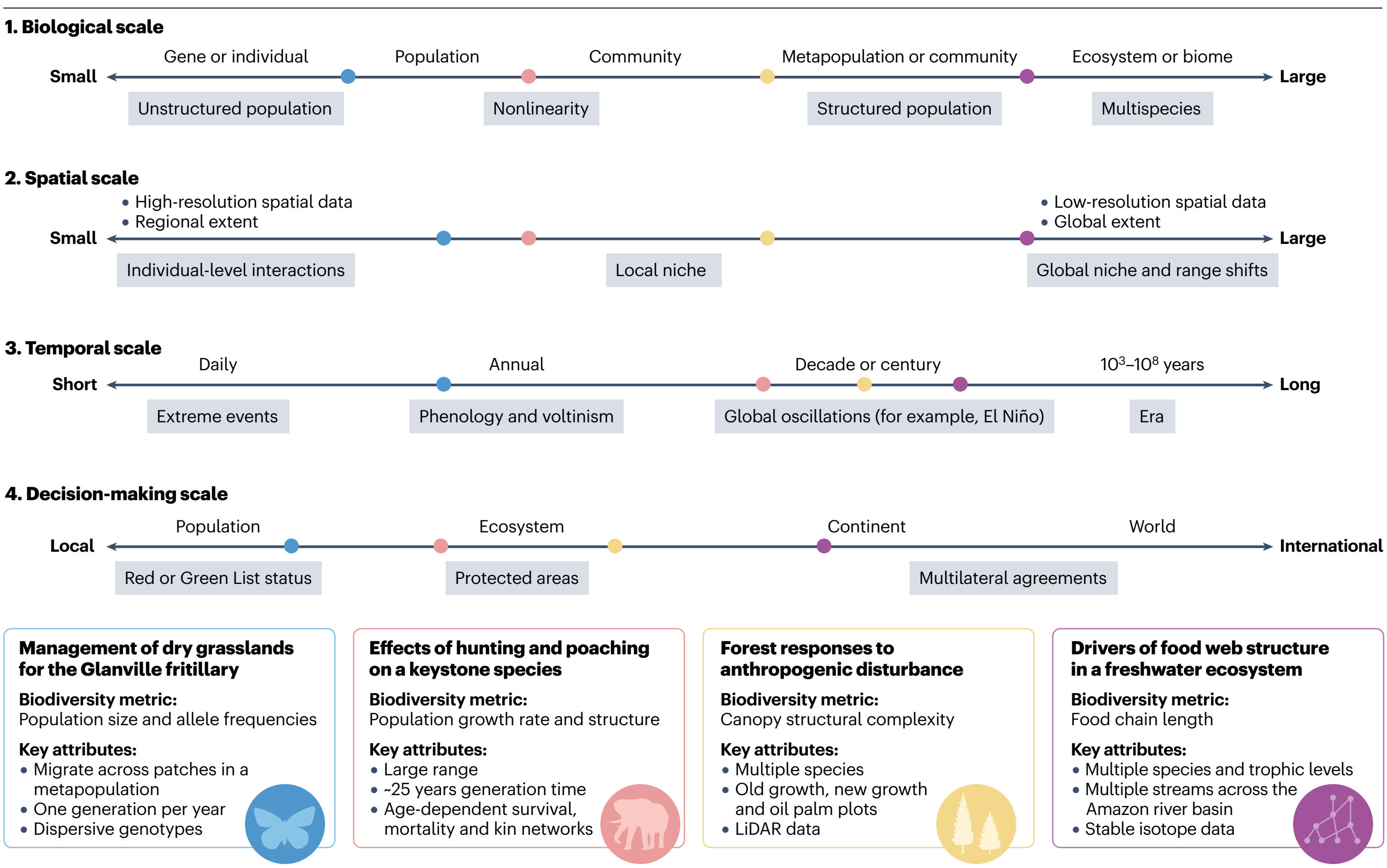

Fig. 3 | Scale dependence in biodiversity modelling. Scale dependence arises along multiple dimensions of the biodiversity modelling pipeline related to the biological, spatial and temporal scales and the scale of decision-making. For each scale dimension, the levels from small to large scale are listed above the line, and observable patterns and processes are listed below the line. Importantly, scale dependencies interact and can constrain both the modelling methodologies and inferences for decision-making. This interplay of scale dependence is further shown with four examples (bottom panel) in which the inferred scale across the different scale dimensions is illustrated with dots corresponding to the colour of each case study. Although each of these examples aims to model an aspect of biodiversity (from a population to a community), key attributes of the focal study system and scale dependencies result in different scales for decision-making. References for examples (boxes in the bottom row, from left to right): ref. 115; ref. 116; ref. 117; ref. 118. LiDAR, light detection and ranging.

Also, availability of monitoring data and mobilization of historical data such as museum records is constantly improving[102]. New technologies for automated, sensor-based or DNA-based monitoring are appearing and, when paired with artificial intelligence, have the potential to reduce shortfalls in our biodiversity knowledge[103,104]. Artificial intelligence and deep learning techniques could also improve parameterization, emulation or downscaling of complex models, as shown by newer developments in climate science[105,106]. Building on lessons learned from climate science and other impact sectors, wider implementation of BMIPs could enhance the reliability and robustness of biodiversity projections and effectively support policy and action planning.

Outlook

Drawing on the success of climate model intercomparison projects, BMIPs offer a powerful instrument and standardized framework to assess model performance, quantify uncertainty and produce transparent projections to support science and policy (Box 1). BMIPs are high-level, coordinated experiments that (1) reveal the strengths and weaknesses of prevailing modelling approaches, (2) guide research needs and model developments, (3) allow quantification of uncertainty in biodiversity trends based on comparison of different modelling approaches and (4) provide defensible and transparent results and projections to support policy and action planning at national to international level. Among these outcomes, the first two can accelerate progress in the wider field of biodiversity modelling and can provide guidance for selecting the most appropriate model approaches for case-specific applications in conservation and restoration (Fig. 3). The last two outcomes can directly contribute to the knowledge base required to achieve the GBF targets and goals. We suggest that substantial progress in both arenas is possible but will need a strong commitment to international coordination and collaboration, funding and knowledge sharing (Box 3).

We advocate for a broader use of BMIPs to support the GBF and the National Biodiversity Strategies and Action Plans, in which they could have a central role in evaluating and guiding biodiversity strategies through both goal-seeking and policy-screening scenarios[8,89]. Unlike in climate science, international policy commitments such as the GBF cannot yet rely on a broad suite of trusted biodiversity models to ascertain the effectiveness of certain actions. Instead, they are forced to rely on monitored indicators that are inherently retrospective rather than proactive. In target-seeking scenarios (sensu IPBES[10]), which assess whether planned actions are sufficient to meet specified biodiversity targets, BMIPs would allow evaluation of ambition (such as a reduction in average extinction risk), whereas in policy-screening contexts, which compare the biodiversity outcomes of alternative policy or management options, BMIPs would enable systematic comparison of alternative pathways to reach a given target. Embedding such questions within a BMIP framework provides a means to quantify uncertainties, standardize outputs and connect results to monitored indicators, ultimately strengthening the credibility of model projections in a policy context. As a critical next step, we recommend that the biodiversity community develop a priority list of model projections most relevant to GBF goals and targets and systematically evaluate how the full range of EBVs respond to different drivers and policy interventions. By embedding BMIPs more firmly in the GBF process, the scientific community can provide policymakers with transparent and robust evidence to identify the most effective policy and management options and place global biodiversity on a path to recovery.

Current BMIPs exhibit several important gaps, including a lack of species and population-level, process-based models needed to assess extinction risk, genetic diversity and associated time lags relevant to several GBF targets. For example, most existing BMIPs focus on changes in species distributions or community and ecosystem-level metrics, which are insufficient to capture population-level patterns and processes such as the recovery of local populations and genetic diversity within and between populations (Target 4). Additionally, time lags are ubiquitous in ecological systems, meaning that the effects of conservation or management actions on population size, extinction risk or genetic diversity might only become observable decades after implementation and might not be detectable in short-term monitoring data[107]. Process-based models that explicitly consider transient dynamics can fill this void, evaluate whether nations are projected to be on track to achieving their national targets and define interim targets[108]. Yet, to support this action planning and reporting, uncertainty should be reported transparently to ensure the accurate communication of confidence in model estimates and projections. Lessons from climate science demonstrate that MIPs are vital to assess and improve policymaker confidence in model estimates[13,109]. National to regional BMIPs should be designed across all realms, including freshwater, marine and terrestrial, to produce the EBVs relevant to GBF targets and national action planning.

Establishing BMIPs will require greater investment in modelling centres, coordination of activities and model development. To support

Box 3 | Establishing and sustaining biodiversity model intercomparison projects

In this Box, we discuss the primary needs to establish and sustain biodiversity model intercomparison projects (BMIPs).

Formalization of BMIPs across realms
Establish coordinated and standardized BMIPs across realms to enhance comparability, transparency, uncertainty quantification and policy relevance of biodiversity models and projections.

Global coordinating body
Develop a global coordinating body to oversee BMIP initiatives, analogous to the World Climate Research Programme for climate models. Define clear governance structures, funding strategies, consultation mechanisms and data-sharing policies to ensure the long-term sustainability of BMIPs.

National coordinating committees
Establish national steering committees to align BMIP efforts with national biodiversity policies and strategies and ensure that BMIP results are directly applicable to national goals and targets.

International collaboration and engagement
Strengthen collaboration among scientists, research institutions, policymakers and diverse stakeholders to increase BMIP relevance and ensure that national results will scale up to meet international goals.

Building modelling and data infrastructure
Establish necessary infrastructure to facilitate access to modelling platforms and data servers, and ensure computing resources for large-scale model simulations.

Standardized protocols and experimental design
Create common protocols for model inputs, scenarios and outputs to ensure comparability. Define clear experimental set-ups, including historical runs and future projections, to assess model performance and enhance transparency.

Common benchmark data
Develop shared, high-quality biodiversity and ecosystem benchmark datasets across realms to validate models and assess predictive performance. Ensure continuous monitoring and data mobilization to update datasets and fill data gaps.

Integration of mechanistic modelling
Assess the potential for mechanistic modelling approaches to enhance BMIPs, particularly for capturing ecological and evolutionary dynamics and improving biodiversity projections under global change scenarios.

Model scaling
Assess model complexity needs across different scale dimensions, including spatial, temporal and taxonomic scales. Design adequate approaches to scale between national, regional and global models.

Capacity building and knowledge sharing
Establish platforms for knowledge sharing, including best practice guidelines and participatory modelling frameworks. Develop training programmes to build modelling expertise and technical skills.

Inclusive and equitable participation
Ensure diverse representation in modelling initiatives, including participation by researchers from data-poor regions. Promote equitable access to resources and opportunities to enable participation from diverse countries and researchers. Facilitate capacity building through toolbox development, data accessibility and training modules.

IPBES global assessments, national policy and action planning, clear governance structures are essential for the timely production and dissemination of results. Initiatives such as FishMIP and ISIMIP are led by a group of science coordinators, mostly on voluntary basis, who oversee activities and communication with other sectors and with CMIP. These projects operate as open and inclusive networks of modellers and stakeholders. In a related effort, the Ecological Forecasting Initiative, which focuses on near-term to decadal projections, has developed a mature assessment procedure and associated cyberinfrastructure for model comparison and evaluation[11]. These examples offer valuable blueprints for the development of BMIPs. However, although community-driven networks can successfully catalyse BMIPs, the WCRP's role in coordinating CMIP underscores the need for a dedicated global body to support biodiversity modelling efforts[89]. Given the complexity of projecting and protecting biodiversity across national boundaries and among numerous scientists and disciplines, establishing such a structure will be critical.

Ensuring equitable access to models and modelling expertise will be a key prerequisite for the establishment of national and regional BMIPs. Ideally, not only the model outputs but the model frameworks themselves should be made available in easy-to-use toolboxes for other teams along with best practice guidance for their usage[8,9,110], as demonstrated in 'BON in a Box'[111], a platform that consolidates validated tools and pipelines to help scientists and policymakers to translate monitoring data into biodiversity indicators. Modelling centres should support capacity-building initiatives to reduce regional inequities in human capital, technology and data access that are prerequisites to the development of local to national scale models[10]. The model frameworks and toolboxes need to be (1) flexible enough to include the key biological processes that are relevant for a given geographical range, at spatial and temporal scales and for a given system[86]; (2) transferable enough to be parameterized for different types of ecosystems and organisms; (3) scalable enough to model the same processes or EBVs[65] to be integrated differently depending on the spatio-temporal scales under study; and (4) interoperational because modelling outputs on one EBV should be comparable or translatable into other EBVs (such as abundance into biomass) to meet the needs of model intercomparisons or action planning. Standard documentation will further enhance legitimacy and reproducibility[72,112,113]. Participatory modelling could be an interesting framework to turn global or regional models into reusable and useful tools aligned with local needs and actors. CMIP has facilitated the development of communities translating larger-scale projections into fine-scale climate information for impact studies[114], and we anticipate similar progressions for BMIPs.

In summary, critical gaps and opportunities remain for biodiversity model intercomparisons. By drawing on lessons from climate science and the success story of CMIP and by building on forerunners such as FishMIP and BES-SIM, the development of comprehensive and standardized BMIPs can substantially enhance predictive understanding of biodiversity change and inform effective policy. We advocate for increased international coordination and collaboration, integration of mechanistic modelling and augmented funding to bridge the existing gaps (Box 3). Future research should focus on developing robust benchmarks and improving data availability in order to facilitate more reliable projections. Addressing these challenges will be essential for achieving the GBF targets and goals. As biodiversity faces unprecedented threats, collaborative efforts and informed policy-making are imperative to preserve biodiversity, ecosystems and human well-being. We invite stakeholders and researchers alike to prioritize these actions, ensuring that the scientific community, society and policymakers are well equipped to address the urgent biodiversity crisis.

Published online: 06 February 2026

References

1. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. *Global Assessment Report on Biodiversity and Ecosystem Services* (IPBES, 2019).
2. Scheffers, B. R. et al. The broad footprint of climate change from genes to biomes to people. *Science* **354**, aaf7671 (2016).
3. Urban, M. C. Climate change extinctions. *Science* **386**, 1123–1128 (2024).
4. Convention on Biological Diversity. *Kunming-Montreal Global Biodiversity Framework. Decision CBD/COP/DEC/15/4* (CBD, 2022).
5. Urban, M. C. Projecting biological impacts from climate change like a climate scientist. *WIREs Clim. Change* **10**, e585 (2019).
6. Purvis, A. Bending the curve of biodiversity loss requires a 'satnav' for nature. *Philos. Trans. R. Soc. B* **380**, 20230210 (2025).
7. Grimm, V., Johnston, A. S. A., Thulke, H.-H., Forbes, V. E. & Thorbek, P. Three questions to ask before using model outputs for decision support. *Nat. Commun.* **11**, 4959 (2020).
8. Urban, M. C. et al. Coding for life: designing a platform for projecting and protecting global biodiversity. *BioScience* **72**, 91–104 (2022).
9. Zurell, D. et al. Spatially explicit models for decision-making in animal conservation and restoration. *Ecography* **4**, e05787 (2022).
10. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. *The Methodological Assessment Report on Scenarios and Models of Biodiversity and Ecosystem Services* (IPBES, 2016).
11. Dietze, M. et al. Near-term ecological forecasting for climate change action. *Nat. Clim. Change* **14**, 1236–1244 (2024).
12. Touzé-Peiffer, L., Barberousse, A. & Le Treut, H. The Coupled Model Intercomparison Project: history, uses, and structural effects on climate research. *WIREs Clim. Change* **11**, e648 (2020).
13. IPCC. *Climate Change 2021: The Physical Science Basis* (Cambridge Univ. Press, 2021).
14. Griffies, S. M. et al. OMIP contribution to CMIP6: experimental and diagnostic protocol for the physical component of the Ocean Model Intercomparison Project. *Geosci. Model Dev.* **9**, 3231–3296 (2016).
15. Notz, D. et al. The CMIP6 Sea-Ice Model Intercomparison Project (SIMIP): understanding sea ice through climate-model simulations. *Geosci. Model Dev.* **9**, 3427–3446 (2016).
16. Rosenzweig, C. et al. The Agricultural Model Intercomparison and Improvement Project (AgMIP): protocols and pilot studies. *Agric. For. Meteorol.* **170**, 166–182 (2013).
17. Hantson, S. et al. The status and challenge of global fire modelling. *Biogeosciences* **13**, 3359–3375 (2016).
18. Durack, P. J. et al. The Coupled Model Intercomparison Project (CMIP): reviewing project history, evolution, infrastructure and implementation. *EGUsphere* https://doi.org/10.5194/egusphere-2024-3729 (2025).
19. Novaglio, C. et al. The past and future of the Fisheries and Marine Ecosystem Model Intercomparison Project. *Earth's Future* **12**, e2023EF004398 (2024).
20. Frieler, K. et al. Assessing the impacts of 1.5 °C global warming – simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). *Geosci. Model Dev.* **10**, 4321–4345 (2017).
21. Tittensor, D. P. et al. A protocol for the intercomparison of marine fishery and ecosystem models: Fish-MIP v1.0. *Geosci. Model Dev.* **11**, 1421–1442 (2018).
22. Tittensor, D. P. et al. Next-generation ensemble projections reveal higher climate risks for marine ecosystems. *Nat. Clim. Change* **11**, 973–981 (2021).
23. Lotze, H. K. et al. Global ensemble projections reveal trophic amplification of ocean biomass declines with climate change. *Proc. Natl Acad. Sci. USA* **116**, 12907–12912 (2019).
24. Blanchard, J. L. et al. Detecting, attributing, and projecting global marine ecosystem and fisheries change: FishMIP 2.0. *Earth's Future* **12**, e2023EF004402 (2024).
25. Ortega-Cisneros, K. et al. An integrated global-to-regional scale workflow for simulating climate change impacts on marine ecosystems. *Earth's Future* **13**, e2024EF004826 (2025).
26. Eddy, T. D. et al. Global and regional marine ecosystem models reveal key uncertainties in climate change projections. *Earth's Future* **13**, e2024EF005537 (2025).
27. Kim, H. et al. A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios. *Geosci. Model Dev.* **11**, 4537–4562 (2018).
28. Pereira, H. M. et al. Global trends and scenarios for terrestrial biodiversity and ecosystem services from 1900 to 2050. *Science* **384**, 458–465 (2024).
29. Frieler, K. et al. Scenario setup and forcing data for impact model evaluation and impact attribution within the third round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a). *Geosci. Model Dev.* **17**, 1–51 (2024).
30. Hof, C. et al. Bioenergy cropland expansion may offset positive effects of climate change mitigation for global vertebrate diversity. *Proc. Natl Acad. Sci. USA* **115**, 13294–13299 (2018).
31. Mahnken, M. et al. Accuracy, realism and general applicability of European forest models. *Glob. Change Biol.* **28**, 6921–6943 (2022).
32. Fordham, D. A. et al. How complex should models be? Comparing correlative and mechanistic range dynamics models. *Glob. Change Biol.* **24**, 1357–1370 (2018).

33. Briscoe, N. J. et al. Can dynamic occupancy models improve predictions of species' range dynamics? A test using Swiss birds. *Glob. Change Biol.* **27**, 4269–4282 (2021).
34. Buckley, L. B. et al. Can mechanism inform species' distribution models? *Ecol. Lett.* **13**, 1041–1054 (2010).
35. Farmer, G. T. & Cook, J. *Climate Change Science: A Modern Synthesis, Vol. 1 The Physical Climate* (Springer, 2013).
36. Eyring, V. et al. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* **9**, 1937–1958 (2016).
37. Tebaldi, C. & Knutti, R. The use of the multi-model ensemble in probabilistic climate projections. *Philos. Trans. R. Soc. A* **365**, 2053–2075 (2007).
38. Guillemot, H. in *A Critical Assessment of the Intergovernmental Panel on Climate Change* (eds De Pryck, K. & Hulme, M.) 126–136 (Cambridge Univ. Press, 2022).
39. Ruane, A. C. et al. The Vulnerability, Impacts, Adaptation and Climate Services Advisory Board (VIACS AB v1.0) contribution to CMIP6. *Geosci. Model Dev.* **9**, 3493–3515 (2016).
40. Ruane, A. C. et al. CMIP7 data request: impacts and adaptation priorities and opportunities. *EGUsphere* https://doi.org/10.5194/egusphere-2025-3408 (2025).
41. CMIP Panel. MIP best practice guidance. *Zenodo* https://doi.org/10.5281/zenodo.10572155 (2024).
42. Dormann, C. F. et al. Correlation and process in species distribution models: bridging a dichotomy. *J. Biogeogr.* **39**, 2119–2131 (2012).
43. Cabral, J. S., Valente, L. & Hartig, F. Mechanistic simulation models in macroecology and biogeography: state-of-art and prospects. *Ecography* **40**, 267–280 (2017).
44. Levins, R. The strategy of model building in population ecology. *Am. Sci.* **54**, 421–431 (1966).
45. Botkin, D. B., Janak, J. F. & Wallis, J. R. Some ecological consequences of a computer model of forest growth. *J. Ecol.* **60**, 849 (1972).
46. Bugmann, H. & Seidl, R. The evolution, complexity and diversity of models of long-term forest dynamics. *J. Ecol.* **110**, 2288–2307 (2022).
47. Bugmann, H. A review of forest gap models. *Clim. Change* **51**, 259–305 (2001).
48. Porter, W. P., Mitchell, J. W., Beckman, W. A. & DeWitt, C. B. Behavioral implications of mechanistic ecology: thermal and behavioral modeling of desert ectotherms and their microenvironment. *Oecologia* **13**, 1–54 (1973).
49. Briscoe, N. J. et al. Mechanistic forecasts of species responses to climate change: the promise of biophysical ecology. *Glob. Change Biol.* **29**, 1451–1470 (2023).
50. Booth, T. H. Why understanding the pioneering and continuing contributions of BIOCLIM to species distribution modelling is important. *Austral Ecol.* **43**, 852–860 (2018).
51. Watters, G. M. et al. Physical forcing and the dynamics of the pelagic ecosystem in the eastern tropical Pacific: simulations with ENSO-scale and global-warming climate drivers. *Can. J. Fish. Aquat. Sci.* **60**, 1161–1175 (2003).
52. Pastor, J. & Post, W. M. Response of northern forests to CO_2-induced climate change. *Nature* **334**, 55–58 (1988).
53. Busby, J. R. in *Greenhouse: Planning for Climate Change* (ed. Pearman, G. I.) 387–398 (CSIRO, 1988).
54. McDonald, K. A. & Brown, J. H. Using montane mammals to model extinctions due to global change. *Conserv. Biol.* **6**, 409–415 (1992).
55. Carey, P. D. Disperse: a cellular automaton for predicting the distribution of species in a changed climate. *Glob. Ecol. Biogeogr. Lett.* **5**, 217 (1996).
56. Jager, H. I., Van Winkle, W. & Holcomb, B. D. Would hydrologic climate changes in Sierra Nevada streams influence trout persistence? *Trans. Am. Fish. Soc.* **128**, 222–240 (1999).
57. Shuter, B. J. & Post, J. R. Climate, population viability, and the zoogeography of temperate fishes. *Trans. Am. Fish. Soc.* **119**, 314–336 (1990).
58. Schwartz, M. W. Modelling effects of habitat fragmentation on the ability of trees to respond to climatic warming. *Biodivers. Conserv.* **2**, 51–61 (1993).
59. Hinch, S. G. et al. Potential effects of climate change on marine growth and survival of Fraser River sockeye salmon. *Can. J. Fish. Aquat. Sci.* **52**, 2651–2659 (1995).
60. Kearney, M., Porter, W. P., Williams, C., Ritchie, S. & Hoffmann, A. A. Integrating biophysical models and evolutionary theory to predict climatic impacts on species' ranges: the dengue mosquito *Aedes aegypti* in Australia. *Funct. Ecol.* **23**, 528–538 (2009).
61. Botkin, D. B. et al. Forecasting the effects of global warming on biodiversity. *BioScience* **57**, 227–236 (2007).
62. Levin, S. A. Ecosystems and the biosphere as complex adaptive systems. *Ecosystems* **1**, 431–436 (1998).
63. Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. Impacts of climate change on the future of biodiversity. *Ecol. Lett.* **15**, 365–377 (2012).
64. Nadeau, C. P. & Urban, M. C. Eco-evolution on the edge during climate change. *Ecography* **42**, E3276–E3284 (2019).
65. Pereira, H. M. et al. Essential biodiversity variables. *Science* **339**, 277–278 (2013).
66. Foden, W. B. et al. Identifying the world's most climate change vulnerable species: a systematic trait-based assessment of all birds, amphibians and corals. *PLoS ONE* **8**, e65427 (2013).
67. Foden, W. B. et al. Climate change vulnerability assessment of species. *WIREs Clim. Change* **10**, e551 (2019).
68. Pacifici, M. et al. Assessing species vulnerability to climate change. *Nat. Clim. Change* **5**, 215–224 (2015).
69. Akçakaya, H. R. Viability analyses with habitat-based metapopulation models. *Popul. Ecol.* **42**, 45–53 (2000).
70. Akçakaya, H. R., Butchart, S. H. M., Mace, G. M., Stuart, S. N. & Hilton-Taylor, C. Use and misuse of the IUCN red list criteria in projecting climate change impacts on biodiversity. *Glob. Change Biol.* **12**, 2037–2043 (2006).
71. Elith, J. & Leathwick, J. R. Species distribution models: ecological explanation and prediction across space and time. *Annu. Rev. Ecol. Evol. Syst.* **40**, 677–697 (2009).
72. Zurell, D. et al. A standard protocol for reporting species distribution models. *Ecography* **43**, 1261–1277 (2020).
73. Guisan, A., Thuiller, W. & Zimmermann, N. E. *Habitat Suitability and Distribution Models: With Applications in R* (Cambridge Univ. Press, 2017).
74. Kattge, J. et al. TRY – a global database of plant traits. *Glob. Change Biol.* **17**, 2905–2935 (2011).
75. Enquist, B. J., Condit, R., Peet, R. K., Schildhauer, M. & Thiers, B. M. Cyberinfrastructure for an integrated botanical information network to investigate the ecological impacts of global climate change on plant biodiversity. Preprint at *PeerJ Preprints* https://doi.org/10.7287/peerj.preprints.2615v2 (2016).
76. Salguero-Gómez, R. et al. COMADRE: a global data base of animal demography. *J. Anim. Ecol.* **85**, 371–384 (2016).
77. Wüest, R. O. et al. Macroecology in the age of big data — where to go from here? *J. Biogeogr.* **47**, 1–12 (2020).
78. Tobias, J. A. et al. AVONET: morphological, ecological and geographical data for all birds. *Ecol. Lett.* **25**, 581–597 (2022).
79. Elith, J. et al. Novel methods improve prediction of species' distribution from occurrence data. *Ecography* **29**, 129–151 (2006).
80. Cheaib, A. et al. Climate change impacts on tree ranges: model intercomparison facilitates understanding and quantification of uncertainty. *Ecol. Lett.* **15**, 533–544 (2012).
81. Bahlburg, D., Thorpe, S. E., Meyer, B., Berger, U. & Murphy, E. J. An intercomparison of models predicting growth of Antarctic krill (*Euphausia superba*): the importance of recognizing model specificity. *PLoS ONE* **18**, e0286036 (2023).
82. Zurell, D. et al. Benchmarking novel approaches for modelling species range dynamics. *Glob. Change Biol.* **22**, 2651–2664 (2016).
83. Ruane, A. C. et al. Carbon–temperature–water change analysis for peanut production under climate change: a prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP). *Glob. Change Biol.* **20**, 394–407 (2014).
84. Daigneault, A. et al. How the future of the global forest sink depends on timber demand, forest management, and carbon policies. *Glob. Environ. Change* **76**, 102582 (2022).
85. Briscoe, N. J. et al. Forecasting species range dynamics with process-explicit models: matching methods to applications. *Ecol. Lett.* **22**, 1940–1956 (2019).
86. Urban, M. C. et al. Improving the forecast for biodiversity under climate change. *Science* **353**, aad8466 (2016).
87. Merow, C., Bois, S. T., Allen, J. M., Xie, Y. & Silander, J. A. Climate change both facilitates and inhibits invasive plant ranges in New England. *Proc. Natl Acad. Sci. USA* **114**, E3276–E3284 (2017).
88. Briscoe, N. J., Kearney, M. R., Taylor, C. A. & Wintle, B. A. Unpacking the mechanisms captured by a correlative species distribution model to improve predictions of climate refugia. *Glob. Change Biol.* **22**, 2425–2439 (2016).
89. Zurell, D. et al. Predicting the way forward for the global biodiversity framework. *Proc. Natl Acad. Sci. USA* **122**, e2501695122 (2025).
90. Yates, K. L. et al. Outstanding challenges in the transferability of ecological models. *Trends Ecol. Evol.* **33**, 790–802 (2018).
91. Bouchet, P. J. et al. Better model transfers require knowledge of mechanisms. *Trends Ecol. Evol.* **34**, 489–490 (2019).
92. Petchey, O. L. et al. The ecological forecast horizon, and examples of its uses and determinants. *Ecol. Lett.* **18**, 597–611 (2015).
93. Gonzalez, A., Chase, J. M. & O'Connor, M. I. A framework for the detection and attribution of biodiversity change. *Philos. Trans. R. Soc. B* **378**, 20220182 (2023).
94. Malchow, A.-K., Hartig, F., Reeg, J., Kéry, M. & Zurell, D. Demography–environment relationships improve mechanistic understanding of range dynamics under climate change. *Philos. Trans. R. Soc. B* **378**, 20220194 (2023).
95. McGowan, P. J. K. et al. Understanding and achieving species elements in the Kunming–Montreal Global Biodiversity Framework. *BioScience* **74**, 614–623 (2024).
96. Bell-James, J. & Watson, J. E. M. Ambitions in national plans do not yet match bold international protection and restoration commitments. *Nat. Ecol. Evol.* **9**, 417–424 (2025).
97. Meyer, C., Kreft, H., Guralnick, R. & Jetz, W. Global priorities for an effective information basis of biodiversity distributions. *Nat. Commun.* **6**, 8221 (2015).
98. Meyer, C., Weigelt, P. & Kreft, H. Multidimensional biases, gaps and uncertainties in global plant occurrence information. *Ecol. Lett.* **19**, 992–1006 (2016).
99. Dornelas, M. et al. BioTIME: a database of biodiversity time series for the Anthropocene. *Glob. Ecol. Biogeogr.* **27**, 760–786 (2018).
100. Gonzalez, A. et al. A global biodiversity observing system to unite monitoring and guide action. *Nat. Ecol. Evol.* **7**, 1947–1952 (2023).
101. Cabral, J. S. et al. The road to integrate climate change projections with regional land-use–biodiversity models. *People Nat.* **6**, 1716–1741 (2024).
102. Navarro, L. M. et al. Integrating historical sources for long-term ecological knowledge and biodiversity conservation. *Nat. Rev. Biodivers.* **1**, 657–670 (2025).
103. Hartig, F. et al. Novel community data in ecology-properties and prospects. *Trends Ecol. Evol.* **39**, 280–293 (2024).
104. Pollock, L. J. et al. Harnessing artificial intelligence to fill global shortfalls in biodiversity knowledge. *Nat. Rev. Biodivers.* **1**, 166–182 (2025).
105. Reichstein, M. et al. Deep learning and process understanding for data-driven Earth system science. *Nature* **566**, 195–204 (2019).
106. Ling, F. et al. Diffusion model-based probabilistic downscaling for 180-year East Asian climate reconstruction. *npj Clim. Atmos. Sci.* **7**, 131 (2024).

107. Moreno-Mateos, D. et al. Anthropogenic ecosystem disturbance and the recovery debt. *Nat. Commun.* **8**, 14163 (2017).
108. Watts, K. et al. Ecological time lags and the journey towards conservation success. *Nat. Ecol. Evol.* **4**, 304–311 (2020).
109. Kause, A. et al. Confidence levels and likelihood terms in IPCC reports: a survey of experts from different scientific disciplines. *Clim. Change* **173**, 2 (2022).
110. Grimm, V. Ecology needs to overcome siloed modelling. *Trends Ecol. Evol.* **38**, 1122–1124 (2023).
111. Griffith, J. et al. BON in a Box: an open and collaborative platform for biodiversity monitoring, indicator calculation, and reporting. *BioScience* https://doi.org/10.1093/biosci/biaf189 (2026).
112. Grimm, V. et al. The ODD protocol for describing agent-based and other simulation models: a second update to improve clarity, replication, and structural realism. *J. Artif. Soc. Soc. Simul.* **23**, 7 (2020).
113. Grimm, V. et al. Towards better modelling and decision support: documenting model development, testing, and analysis using TRACE. *Ecol. Model.* **280**, 129–139 (2014).
114. Giorgi, F. Thirty years of regional climate modeling: where are we and where are we going next? *J. Geophys. Res.* **124**, 5696–5723 (2019).
115. Hanski, I. et al. Ecological and genetic basis of metapopulation persistence of the Glanville fritillary butterfly in fragmented landscapes. *Nat. Commun.* **8**, 14504 (2017).
116. Jackson, J., Childs, D. Z., Mar, K. U., Htut, W. & Lummaa, V. Long-term trends in wild-capture and population dynamics point to an uncertain future for captive elephants. *Proc. R. Soc. B* **286**, 20182810 (2019).
117. Rosen, A. et al. Tracking shifts in forest structural complexity through space and time in human-modified tropical landscapes. *Ecography* **2024**, e07377 (2024).
118. Hoeinghaus, D. J., Winemiller, K. O. & Agostinho, A. A. Hydrogeomorphology and river impoundment affect food-chain length of diverse neotropical food webs. *Oikos* **117**, 984–995 (2008).
119. Valavi, R., Guillera-Arroita, G., Lahoz-Monfort, J. J. & Elith, J. Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. *Ecol. Monogr.* **92**, e01486 (2022).
120. Araújo, M. B., Pearson, R. G., Thuillers, W. & Erhard, M. Validation of species-climate impact models under climate change. *Glob. Change Biol.* **11**, 1504–1513 (2005).
121. Sofaer, H. R., Jarnevich, C. S. & Flather, C. H. Misleading prioritizations from modelling range shifts under climate change. *Glob. Ecol. Biogeogr.* **27**, 658–666 (2018).
122. Wheatley, C. J. et al. Climate change vulnerability for species—assessing the assessments. *Glob. Change Biol.* **23**, 3704–3715 (2017).

Acknowledgements
D.Z. and K.S. are supported by DFG Grant No. 518316503. S.J.L.G. is funded by the Novo Nordisk Challenge Programme grant number NNF20OC0060118. G.B. is funded by a Royal Society University Research Fellowship (UF160614).

Author contributions
D.Z., S.J.L.G., J.S.C, K.S., S.J.E.V. and M.C.U. researched data for the article. D.Z., A.G. and M.C.U. contributed substantially to discussion of the content. D.Z., C.H.A., G.B., N.J.B., L.B.B., G.G.-A., N.J.B.I., C.M., J.S.C., S.J.E.V. and M.C.U wrote the article. All authors reviewed and/or edited the manuscript before submission.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s44358-026-00134-4.

Peer review information *Nature Reviews Biodiversity* thanks Alice Johnston, who co-reviewed with Harriet Gold; and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Related links
BES-SIM: https://bes-sim.org/
BON in a Box: https://boninabox.geobon.org/
FishMIP: https://fishmip.org
GEO BON EcoCode: https://geobon.org/ecocode-modelling-life-on-earth/
ISIMIP: https://www.isimip.org/

[1]Institute of Biochemistry and Biology, University of Potsdam, Potsdam, Germany. [2]Institut Méditerranéen de Biodiversité et d'Ecologie, Aix Marseille University, CNRS, IRD and Avignon University, Aix-en-Provence, France. [3]School of Biological Sciences, University of Aberdeen, Aberdeen, UK. [4]School of Agriculture, Food and Ecosystem Sciences, University of Melbourne, Melbourne, Victoria, Australia. [5]Department of Biology, University of Washington, Seattle, WA, USA. [6]Department of Biology, Group on Earth Observations Biodiversity Observation Network, McGill University, Montreal, Quebec, Canada. [7]Pyrenean Institute of Ecology, CSIC, Jaca, Spain. [8]UK Centre for Ecology & Hydrology, Wallingford, UK. [9]Swiss Federal Research Institute WSL, Birmensdorf, Switzerland. [10]School of Environment, The University of Auckland, Auckland, New Zealand. [11]National Institute of Water & Atmospheric Research, Hamilton, New Zealand. [12]Coastal Marine Ecosystems Research Centre (CMERC), Central Queensland University, Gladstone Marina, Queensland, Australia. [13]Department of Ecology and Evolutionary Biology, University of Connecticut, Storrs, CT, USA. [14]Center of Biological Risk, University of Connecticut, Storrs, CT, USA. [15]Biodiversity Modelling and Environmental Change, School of Biosciences, University of Birmingham, Birmingham, UK. [16]Ecological Modelling, Bonner Institute for Organismal Biology — Department of Plant Biodiversity, University of Bonn, Bonn, Germany. [17]Instituto de Biología Subtropical, Consejo Nacional de Investigaciones Científicas y Técnicas, Universidad Nacional de Misiones, Puerto Iguazú, Argentina. [18]Department of Geography, San Diego State University, San Diego, CA, USA.