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Near-term ecological forecasting for climate change action

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A substantial increase in predictive capacity is needed to anticipate and mitigate the widespread change in ecosystems and their services in the face of climate and biodiversity crises. In this era of accelerating change, we cannot rely on historical patterns or focus primarily on long-term projections that extend decades into the future. In this Perspective, we discuss the potential of near-term (daily to decadal) iterative ecological forecasting to improve decision-making on actionable time frames. We summarize the current status of ecological forecasting and focus on how to scale up, build on lessons from weather forecasting, and take advantage of recent technological advances. We also highlight the need to focus on equity, workforce development, and broad cross-disciplinary and non-academic partnerships.

The dual climate and biodiversity crises[1] jeopardize our ability to manage and conserve natural resources and sustain socio-economic systems. Impacts are already being felt across all levels of society, from individuals to nations[2–4], and many of the world's ecosystems are at risk of collapse[5]. Indeed, when considering the most severe risks facing society over the next 10 years, the World Economic Forum ranked environmental changes as the top four most severe risks and they comprise six of the top ten[6]. In the face of accelerating change and increasingly frequent extreme climate events, responses to these crises cannot continue to be focused primarily on projections that extend decades into the future. Similarly, historical patterns (for example, species ranges, fire/drought/flood frequency) can no longer be relied on as the primary basis for environmental decision-making[7]. Steady-state solutions do not work in a world dominated by non-equilibrium transient conditions; society is in uncharted territory. Moving forwards requires new approaches to research, management and decision-making.

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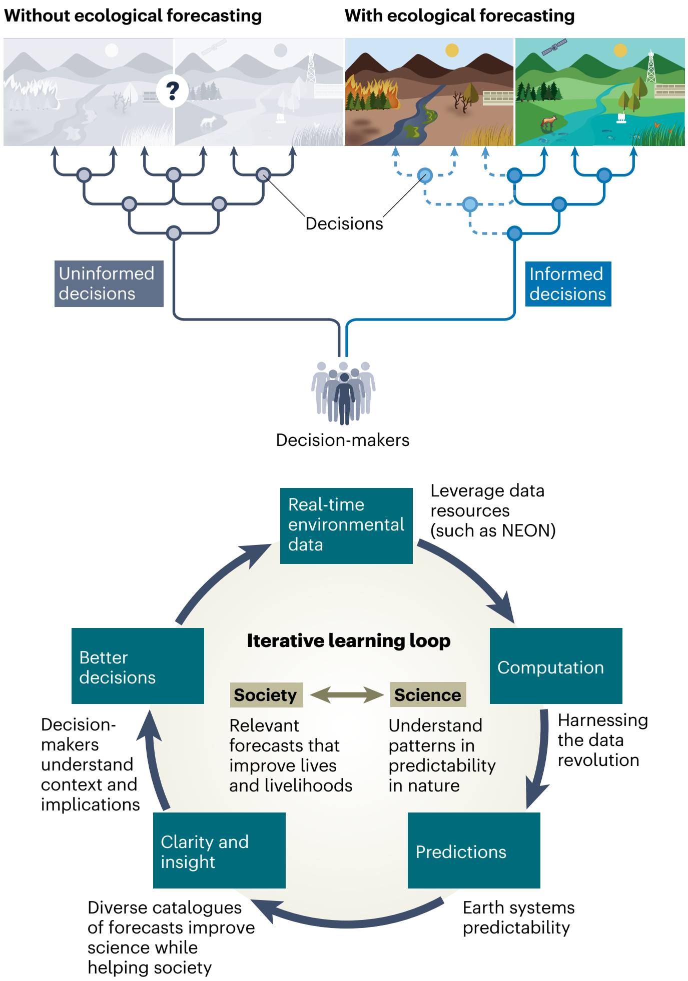

Fig. 1 | Near-term iterative ecological forecasting. Top: ecological forecasting provides quantitative predictions of how different management scenarios impact the environment on decision-relevant timescales. Bottom: iterative ecological forecasting involves continually updating predictions in light of new data. By establishing an iterative learning loop, ecological forecasting provides a win–win strategy: answering grand challenge questions about ecological predictability while improving environmental decisions. NEON, National Ecological Observatory Network.

Near-term iterative ecological forecasting has the potential to anticipate ecological change at the scale and speed needed by society[8] (Fig. 1). Such forecasts provide predictions and scenario-based projections about the future state of ecosystems and their benefits to people, with fully specified uncertainties that are continually updated as new observations become available[9]. In contrast to long-term projections, near-term forecasts (on daily to decadal timescales) are more closely aligned with the timescales that are most relevant to environmental management, and thus allow society to anticipate challenges and improve decisions on actionable timeframes[10]. Actionable forecasts present decision-makers with a range of predictions (and in some cases projections under different decision alternatives or climate extremes) with clear statements of forecast confidence and uncertainty that can be propagated into decision analyses.

Climate change is happening now. As such, near-term iterative ecological forecasting is becoming more and more important for climate adaptation and mitigation. While many ecological forecasts have focused on projections to 2100 and beyond[3,11–14], the impacts of climate change on ecosystems and their services are increasingly urgent policy and management problems in the present. Recent advances in ecological forecasting are beginning to address this need. For example, forecasts are being used in semi-arid systems to predict the impacts of real-time climate extremes on the likely success of ecological restoration efforts[15,16] and the quantity and quality of grass that will be available for livestock to graze on[17–19]. In marine systems, predictions about the impacts of climate variability on species migrations are fuelling real-time multispecies forecasts of fisheries bycatch risk[20,21]. Ecological forecasts are starting to be used by freshwater managers to predict the impacts of climate change on a wide range of real-time water quality issues, including harmful algal blooms and anoxia[22,23]. On the climate mitigation side, biogeochemical forecasts (for example, predictions of soil carbon storage and trace gas emissions that account for climate variability and alternative management scenarios) are already being used by industry as part of nature-based solutions[24]. More broadly, the ability to forecast ecosystem responses to heatwaves, wildfires, droughts, land-use change, biological invasions and disease outbreaks will help us better understand and manage non-equilibrium conditions[25,26] and their climate and biodiversity feedbacks.

While the development and application of near-term iterative ecological forecasts have grown rapidly in recent years, achieving the predictive capacity needed by decision-makers will require a substantial increase in the number of operationalized forecasts. Here we aim to summarize the current state of ecological forecasting research, how it is responding to societal needs (for example, climate change) and grand challenge scientific questions and where it is going, with a central focus on how to scale up ecological forecasting far beyond what is currently possible.

Global demand for ecological forecasts

While much past work on near-term ecological forecasting has focused on local- to regional-scale environmental issues, meaningfully contributing to international environmental goals and initiatives will require ecological forecasting to scale up to global issues. One place to start is forecasting the flows of mass and energy through terrestrial and marine ecosystems, as they are already present in most of the Earth system models that are part of the Coupled Model Intercomparison Project (CMIP), which in turn forms the basis for IPCC reports and projections[27]. Next-generation Earth System models already include a wide range of ecological processes (for example, vegetation demography, microbial biogeochemistry, disturbance) and ecosystems (lakes, rivers and wetlands; urban; agricultural), as well as a more explicit representation of biodiversity[28,29], but these global models have primarily been applied to project long-term climate responses. So far, they have been underused at shorter timescales where (if they are properly initialized and propagate uncertainty[30]) there are opportunities to inform climate adaptation, mitigation, carbon monitoring and the UN Sustainable Development Goals (for example hunger, disease, water quality, sustainability, climate action and terrestrial and marine biodiversity). For example, ecological forecasts could be incorporated into the UN's Early Warnings for All climate adaptation initiative[31], which focuses on global equity in forecasting, risk management, communication and preparedness activities from a weather and water perspective.

While long-term ecosystem forecasting is informing the UNFCCC through the IPCC process, biodiversity forecasting is just beginning to play a role in the UN Convention on Biological Diversity and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). For example, only one global scenario modelling effort has been integrated into IPBES so far and it was not a major focus of the assessment[32]. That said, the Group on Earth Observation's Biodiversity Observation Network (GEO BON) has proposed a global biodiversity observing system (GBiOS), which includes the goal of increasing the capacity to forecast biodiversity change and the loss of ecological and evolutionary resilience[33]. GEO BON has also launched a new working group (EcoCode) with the aims of synthesizing biodiversity modelling tools, developing shared platforms and creating a biodiversity model intercomparison platform. These are exciting and promising steps in the right direction. Even with initiatives like these, large-scale biodiversity forecasting will remain challenging because of the number of species involved and because the drivers can be both more complex and less well measured than those of ecosystem fluxes[13,34]. However, there is a good understanding of how climate change impacts biodiversity in general (for example, most systems are expected to shift polewards or upslope, with many communities being compressed, eliminated or reorganized in new combinations) and this should be leveraged in scenario analyses and risk assessments related to climate change-based loss and damages[13,35,36]. In addition, there are many areas where biodiversity forecasts can be developed to address specific international environmental goals. This need for forecasts is not limited to IPBES, but also extends to international efforts around sustainable use and biodiversity (Sustainable Development Goals 12, 14 and 15), threatened and endangered species (such as CITES (Convention on International Trade in Endangered Species) and the IUCN (International Union for Conservation of Nature)), international waters (for example, fisheries, whaling), neutral territories (such as Antarctica and CCAMLR (Commission for the Conservation of Antarctic Marine Living Resources)) and disease (for example, the World Health Organization). Overall, UN programmes and agencies have a unique opportunity to play a central leadership role in advancing ecological forecasting and its application in management decisions.

Efforts to reduce this gap in forecast development and use can be facilitated by combining what is known about how biodiversity responds in general with the available data from targeted systems and using iterative evaluation to refine models and prioritize data needs[13]. This iterative improvement will be most rapid when direct connections with management create learning feedback loops to improve outcomes. While the IPBES effort to explore plausible futures for biodiversity and ecosystem services used a large number of models driven by land-use change and climate change scenarios from integrated assessment models[37,38], a gap remains between such long-range projections and near-term forecasts driven by policy-relevant management scenarios[39]. Scenario-based projections evaluating conservation and management options are particularly important for IPBES and other international conservation efforts because of the critical impacts of human choices on biodiversity preservation, as well as its resulting benefits to people.

One general area where ecological forecasting has the potential to actively inform international decision-making for climate adaptation and mitigation is predicting discrete events (for example, drought, wildfire and other disturbances, disease and pest outbreaks, coastal flooding, coral bleaching) and the time-lagged ecological consequences of event-driven change (such as biological invasions, land-use change, post-disturbance regeneration and restoration). Although ecologists have devoted substantial attention to some of these problems, such as trying to predict which species are likely to be invasive[40–42] or understanding how ecosystems respond to drought[43–45], others are relatively underexplored, such as developing real-time forecasts of forest pests[46], forecasting the potential impacts of different ecosystem management strategies (for example, restoration, burning, grazing, herbicides, dam releases to rivers)[15,16] or combining forecasts of multiple ecological variables to evaluate competing management objectives (for example, lake organic carbon storage versus methane production)[22]. Across this broad range of applications, taking a forecasting approach not only makes our science more robust and repeatable, but can force us to rethink old assumptions (both scientific and management-related) and open up new avenues for exploration and innovation[47].

Putting ecological forecasting into practice at the international level does not have to be limited to large-scale UN efforts. Numerous conservation organizations, non-governmental organizations (NGOs) and natural-resource industries (such as agriculture, forestry and fisheries) that operate at an international scale would benefit from forecasts to assist with climate adaptation, the management of threatened, invasive, commercially important or bycatch species, ecosystem restoration, sustainability certification or natural climate solutions. Similarly, as COVID-19 made apparent, emerging infectious diseases are increasingly global in impact and frequently zoonotic in origin. A related emerging idea is forecast-based action, which proactively ties event-driven emergency management plans, including the release of emergency funds, to forecast-based thresholds (for example, climate extremes), rather than acting reactively to disaster events[48]. Forecast-based action approaches have been adopted by international humanitarian organizations (such as the Red Cross) and by the UN itself to reduce the impacts of natural disasters, including many that are exacerbated by climate change and ecological in nature (such as plant drought stress). However, forecast-based action has not yet been adopted by international conservation organizations or applied explicitly to the problem of climate adaptation.

Finally, there are unique global opportunities to help build out ecological forecasting endeavours. Many ecological forecasts already rely heavily on datasets that are international in scope, such as meteorological forecasts, remote sensing data and large-scale community databases (for example, the Global Biodiversity Information Facility, FLUXNET, GLEON), which creates natural pathways for the spatial scaling of forecasts and for further international cooperation on monitoring and data sharing (for example, Group on Earth Observations). Similarly, efforts to build an ecological forecasting community, which includes community coordination on training, tools, standards and synthesis, have primarily been grass-roots operations (see the 'State of ecological forecasting'), but such efforts are themselves increasingly international in scope. This international growth in focus and investment has not been distributed equally, however. Data volumes, investments in research and development, and existing ecological forecasts are all substantially biased towards the global north (with the important exception of satellite imagery), while the impacts of the dual biodiversity and climate crises are biased towards the global south[49,50]. Investments in ecological forecasting (development, training, data collection and so on) are critically needed to deliberately address historic and current inequities, both within and across nations, and to support efforts led by Indigenous peoples.

Scientific acceleration and grand challenge questions

The cyclic nature of iterative forecasting aims to establish a learning loop in which predictions can be meaningfully compared with new observations and the models then updated to improve future predictions (Fig. 1). This approach is central to the idea of adaptive management, which emphasizes the importance of evaluating and learning from the outcomes of previous decisions to inform future decisions[51]. Similarly, results from numerous disciplines have demonstrated that a learning loop is essential to improve forecasting skill[52,53]. As such, the ecological forecasting cycle can be a win–win—simultaneously improving decision-making while accelerating scientific understanding. This is possible because well-executed ecological forecasts are specific and quantitative (and thus falsifiable). Forecasts provide continuous real-time feedback, which facilitates rapid testing of the ecological hypotheses embedded in the forecasting models. In many cases the same forecasts can be used to address both decision-focused and basic science questions, helping to align the needs of these two fields of the ecological research community. For example, the Forecasting Lake And Reservoir Ecosystems system is used by drinking-water reservoir managers to improve water quality in the face of non-stationary climate variability, while scientists are using the same forecasts to improve understanding of freshwater ecosystem dynamics[22,54,55]. More broadly, comparative analyses across forecasts for different systems have the potential to answer grand challenge questions about the predictability of nature[56–58]: how far into the future can different aspects of nature be

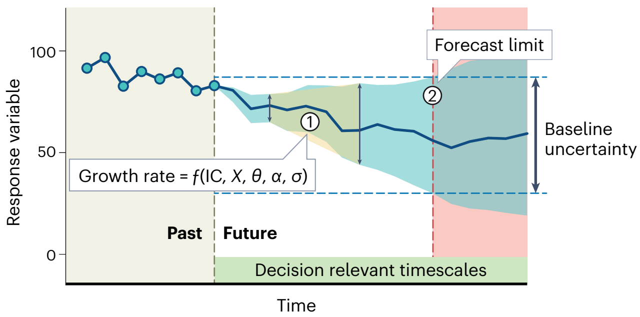

Fig. 2 | Ecological predictability. The predictability of a forecast is measured by (1) the rate at which forecast uncertainty (blue shaded area) grows into the future and (2) the limit at which the forecast performs no better than a historical baseline. The growth in uncertainty is controlled by uncertainty in (and sensitivity to) the initial conditions (IC), exogenous drivers (X), parameter uncertainty (θ), parameter variability (α) and model structural (process) errors (σ). Credit: Kristina Davis.

successfully predicted? Why do some ecological systems respond to climate change more predictably than others? When are ecological forecasts limited by the quality of other forecasts (for example, weather) that are commonly used as model inputs? Is ecological understanding transferable across systems? What do the answers to these questions tell us about the overarching rules and patterns in ecology?

Existing theory about ecological predictability has focused on two key metrics (Fig. 2): (1) the rate at which forecast uncertainty grows with time; and (2) the limit at which forecast accuracy is no better than chance[59]. Our previous work showed that the uncertainty growth rate is a function of uncertainties in five key inputs and the sensitivity of the forecast to each of these inputs[56]. Atmospheric scientists used this type of uncertainty decomposition in the 1960s to determine that weather forecast uncertainty was dominated by uncertainty in the initial conditions[60], a theoretical advance that has guided large-scale investments (US$ billions per year) in weather monitoring, modelling and data assimilation that aim to constrain the initial condition uncertainty in each new forecast. These investments have driven decades of continual improvements in the skill, understanding and utility of weather forecasts[61]. Ecological forecasting is now poised to make a similar leap in foundational understanding. While some ecological forecasts are (like weather) highly sensitive to initial conditions, others are dominated by sensitivity to the uncertainty in external drivers (for example, climate change), model structural (process) uncertainty, data limitations in constraining model parameters and the inherent variability of biological systems[30,56,62–65]. Understanding which sources of uncertainty dominate which ecological forecasts is critical to deploying effective monitoring, modelling and model–data integration efforts. Furthermore, unlocking the grand challenge of understanding the patterns of predictability in nature will require a comparative approach across the diversity of ecological systems to quantify which ecological forecasts are limited by which uncertainties[56]. Ultimately, being able to anticipate which ecological systems will be predictable, and what information will be needed to constrain new predictions, will drive improvements in our ability to make decision-relevant forecasts and decision-makers' abilities to make better and more confident decisions.

Learning from meteorology while addressing unique challenges

Ecological forecasting has much to learn from other forecasting communities that are deeply embedded in decision-making. For example, decades of progress in meteorology demonstrate that reliable predictions are possible for complex natural systems if iterative approaches are adopted[61,66,67]. Meteorology also illustrates the potential for both the open provisioning of public goods (such as climate data, weather forecasts, severe weather alerts) and private-sector innovation (for example, broadcast meteorology, weather apps, artificial intelligence-augmented forecasts)[68]. Furthermore, weather forecasts are more than just the outputs from numerical models. Multiple times a day, at meteorological centres around the world, weather models are iteratively updated with new data from a globally connected network of satellite and ground sensors, and new predictions are generated from the updated models. These numerical predictions are then interpreted and adjusted by human forecasters and algorithms to produce the forecasts society depends on[69]. Ecological forecasting should build on this framework by continually updating forecasts as new data become available to provide decision-makers with the best available scientific insight, accelerate scientific discovery and improve understanding of ecological predictability more broadly[61,70].

Ecological forecasting should also draw inspiration from the early days of numerical weather prediction, when forecast skill was low. Weather forecasters had a choice between stepping back from forecasting until the mechanics of the atmosphere were better understood or stepping forwards into an iterative forecast cycle of learning by doing[66]. By stepping forwards, they achieved a critical win–win of relentless improvements in theory, skill and utility to society[9]. Ecology is now at a similar crossroads. Society is facing climate and biodiversity crises, but finally has the observations, models, theory and prototype iterative forecasts to improve decisions, both big and small[8].

Compared with other forecasting fields, however, ecological forecasting presents unique challenges. Whereas a weather model has 10–20 state variables that follow the same physical equations throughout the atmosphere, there are millions of species on the planet and individual organisms vary (both within and between species) in the primary drivers of their dynamics and their responses to those drivers. Organisms are heterogeneous across space, time and phylogeny in how they respond to changes in climate and human activities, and those responses are continually adapting and evolving across a cascade of different timescales. Even if there is only interest in forecasting emergent ecosystem processes (such as carbon, water, and nutrient cycling), biodiversity causes the parameters in the equations, and sometimes the equations themselves, to continuously change across space and time. However, this variability is not unconstrained, nor wholly unpredictable. As the data necessary to make forecasts are only available for a fraction of the world's species, comparative analyses of predictability and forecast transferability (for example, how parameters and equations change across space, time and taxa) are critical to the advancement of ecological forecasting. Beyond being important to theory, sharing information across forecasts of different systems (through hierarchical models of across-species parameter variability, for example) lowers the amount of data necessary to make predictions, allowing the scope of ecological forecasting to be extended. This can be particularly important for rare and novel (for example, invasive) taxa.

The inherent complexity of biodiversity introduces further challenges in ecological forecasting related to both monitoring requirements and the infrastructure for producing forecasts. Weather forecasting represents a single large forecasting problem that nations have addressed by constructing large centres with dedicated staff, models and both physical infrastructure and cyberinfrastructure. Ecological forecasts represent a spectrum of forecasting challenges that vary in size (a single global forecast to many local forecasts), approach (process-based, statistical, machine learning), system (terrestrial, freshwater, marine) and biological scale (physiological, organismal, population, community, ecosystem/biogeochemistry). The diversity of forecasts has resulted in numerous unique data processing and forecasting workflows that require non-trivial costs and expertise to build and maintain[22,71–74]. That said, these challenges also represent opportunities to use forecasts to optimize and iteratively adapt monitoring programmes, to develop new sensor technologies and to better integrate ecological monitoring and infrastructure[75–77]. The expansion of ecological forecasting has delivered progress and opportunities to leverage economies of scale through reusable community standards[78], workflows, models and cyberinfrastructure[49,71] and to reduce the costs, time and learning curve involved in launching and maintaining forecasts. These advances will not be limited to near-term forecasts, but will simultaneously increase the capacity for, and confidence in, ecological forecasting on climate timescales.

Ecological forecasting is also generating opportunities to improve forecasting across disciplines. The challenges of forecasting ecological systems mean that researchers need to revisit theoretical assumptions around predictability[56] and the data assimilation tools used to integrate new observations into forecasts[30] while acknowledging that a wider range of uncertainties must also now be accounted for (Fig. 2). Hybrid approaches that combine traditional process-based models and data assimilation with newer machine learning methods are advancing rapidly in both Earth system and ecological forecasting[79–83]. Ecological forecasters are important consumers of forecasts (atmosphere, oceans and so on), translating these physical forecasts into information about Earth's life support systems, on which humanity depends. The biosphere also generates feedbacks to other parts of the Earth system, such that improvements in ecological forecasting will improve Earth system predictions of the boundary conditions used in both weather and climate models[29,84,85].

State of the ecological forecasting community

Dramatic improvements in ecological forecasting are now emerging that were unimaginable even a decade ago. Advances in sensor technologies, satellites and genomics provide access to unprecedented volumes of environmental data that are born-digital and increasingly near real time. The urgency of climate change has driven shifts towards large-scale networked science, which in turn has made data access more standardized and equitable—both in terms of top-down international observatories[86] (such as NEON, Australia's Terrestrial Ecosystem Research Network (TERN), the South African Environmental Observation Network (SAEON) and the International Long Term Ecological Research network (ILTER)) and bottom-up globally distributed experiments with standardized protocols (NutNet[87,88], DroughtNet[89], Cellulose Decomposition Experiment (CELLDEX)[90] and so on). At the same time, there have been rapid advances in computational methods and cyberinfrastructure, including revolutions in artificial intelligence and machine learning[91,92], workflow containerization[93], distributed cloud computing and cloud-native data storage. Collectively, these advances have fuelled the recent growth of ecological forecasting and herald opportunities for further increases in scope and reach.

To leverage these technical advances, ecological forecasting needs to build coherent communities of practice to support its growth as a discipline[94]. Successful ecological forecasts represent a convergence of expertise across a range of ecological subdisciplines, the social and decision sciences, physical environmental sciences, computational and data sciences and statistics[8]. However, each discipline operates under different norms and approaches, as do the different sectors (academia, agencies, industry, NGOs and so on) involved in forecast research, development and operationalization. Overcoming the resulting barriers will require: educational efforts designed to broaden disciplinary backgrounds and train researchers in interdisciplinary collaboration[95,96], transdisciplinary organizations and teams with the time and commitment to develop shared interests and vocabularies[97] and funding mechanisms to support social science and non-academic partner collaborations[98]. Expanding the ecological forecasting community in a way that includes everyone influenced by climate change will also require actively addressing issues of equity—including who has access to ecological forecasting tools and data streams, who can interpret and use them for decision-making[99] and whose perspectives and priorities are incorporated into their development and dissemination[100].

This sort of community building has accelerated recently through efforts such as the Ecological Forecasting Initiative (EFI), an international grass roots consortium aimed at fostering a community of practice around ecological forecasting[8]. EFI has engaged thousands of academic, agency, NGO and industry scientists and partners through a broad mix of international chapters and conferences, working groups, webinars, articles, videos, standards[78], policy briefs, training opportunities (including minority-serving institution student mentoring and faculty partnerships) and contributions to government reports[16,67,98,101,102]. Since 2021, EFI's Research Coordination Network has hosted an ongoing NEON Forecasting Challenge[72,103,104] with the goal of predicting data before it is collected. Over 200 teams (including 11 university courses and 2 minority-serving institution mentoring programmes) have participated and the Challenge has developed new educational resources and community cyberinfrastructure[105,106], as well as comparative analyses that help tackle grand challenge questions[103,104]. EFI's progress is indicative of a new and growing discipline in which the number and diversity of forecasts, forecasters, decision scientists and end users could be rapidly scaled up to help address the climate and biodiversity crises.

A path forwards

Responding to pressing global environmental challenges in an era of climate change will require substantial local and global development to scale up the ecological forecasting enterprise. Rapid progress has been made, particularly over the past 5 years as efforts to bring together the community have accelerated. Meeting this challenge requires an intentional and inclusive approach to build the human dimensions of our forecasting capability.

The translation of forecasts from research to societal impacts has required new cross-sector partnerships that span academia, governmental agencies, industry, NGOs and other interested parties to be established. Furthermore, the technical requirements for building operational ecological forecasts often exceed the capacity of governmental agencies (the traditional producers of forecasts). For example, the soil carbon monitoring being conducted by the nascent carbon credit industry (which serves as both a key input and validation of their carbon forecasts) to inform climate mitigation is already on track to surpass the data volumes in government agency soil maps. While efforts like EFI have laid the groundwork for building bridges across sectors (for example, through interagency and cross-sector workshops and trainings), in scaling up ecological forecasting there is an important need to foster even greater innovation and engagement across a broader spectrum of partners, end users and decision-makers. Key to these partnerships is the idea of co-production: groups that will use forecasts need to be engaged in the process of launching new ecological forecasts from the outset by informing and contributing to the goals, approaches and product design[107–109]. These partnerships and the associated scaling activities must acknowledge historical biases in participation and perspectives (for example, towards the global north) and actively promote equity in participation and recognition of marginalized perspectives going forwards. Such co-production is necessary to ensure that forecasts are equitable, useful, usable and credible[110].

One key part of community building is engaging groups that have been traditionally excluded from both science and decision-making. For example, scientific research funding in the United States goes disproportionately to white principal investigators[111] and racial minority groups earn a disproportionately low fraction of US Earth science doctorates[112]. At the same time, many of the world's environmental problems disproportionately impact members of marginalized groups, including Indigenous communities and the urban poor[6,113]. Furthermore, while ecological forecasting is global in scope, low- and middle-income countries are under-represented in both research and community participation despite absorbing a disproportionately large share of the world's biodiversity, carbon storage and climate impacts[49,50]. Active investment by international bodies in the building of ecological forecasting capabilities in the global south, much as the World Meteorological Organization has historically done for meteorology[114], would help to address both these inequities and international climate, biodiversity and sustainability goals. It is essential to actively ensure that our work not only broadens participation among these groups, but also helps identify and address the underlying structural issues that create and sustain their under-representation in the first place.

Increasing forecasting capacity will also require changes in training across a wide range of sectors, from boosting the number of individuals with the technical expertise to produce usable forecasts[115], to training the next generation of managers to better use forecasts[116], to using questions of prediction to increase the scientific literacy of the broader public. Training in ecological forecasting also goes beyond technical topics such as modelling and data science. It requires interdisciplinary teams that are able to integrate expert knowledge about a specific ecological process, the social context of the decisions being informed by the forecast, the decision science frameworks for making these decisions and the legal and ethical questions about what should and should not be forecast[117]. Examples of such training efforts have grown rapidly in the past 5 years, ranging from introductory ecology courses taught from a predictive perspective, to minority-serving institution mentoring in environmental data science, to dedicated upper-level forecasting courses to academic and non-academic workshops. Moving forwards, our universities and professional societies (both research and management) can help by making such training more broadly and equitably available, including opportunities for learners without the ability to travel to in-person opportunities and those facing technological challenges, such as a lack of stable internet access[100].

Community building is also key to advancing theory and technology. Comparative analyses are central to understanding patterns of predictability and transferability, and to improving forecasts by sharing information across systems and species about model structure and parameters. Syntheses beyond the NEON Challenge are currently limited by the number and diversity of forecasts available and by the forecasts that do exist not being sufficiently catalogued, archived and interoperable for synthetic analysis[56,57,78]. Achieving the economies of scale required to generate such a broad catalogue of forecasts, as well as to respond to global environmental challenges, depends on the development and adoption of community conventions surrounding shared tools and cyberinfrastructure and the development of community norms around using them. The expansion of such technologies should move beyond academia to a model where agencies and industry play a central role in their co-production and adoption.

In conclusion, ecological forecasting is at a critical point for future growth, similar to weather forecasting in the twentieth century, and cannot afford to step back. Stepping forwards requires a quantum leap in forecasting capacity, game-changing scientific breakthroughs and technological developments and a new twenty-first-century vision of data-driven environmental management. The nations of the world, along with UN bodies, major international corporations and NGOs, can help by integrating ecological forecasting into their climate adaptation and mitigation strategies. At the same time, the scientific community, spanning academia, agencies and industry, can help build capacity to respond to this urgent need. Ecological forecasting simultaneously offers a new set of tools to advance these efforts and a new frontier of discovery about how nature works. Making forecasts of nature mainstream, and developed by diverse sections of society, will generate the foresight to mitigate further degradation and enable us to proactively build a future that is climate resilient and nurturing for people and the planet.

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Forecasting ecological dynamics has societal impacts that need to be considered at all stages of forecast development and dissemination.

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