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INNOVATIVE VIEWPOINTS

Bridging the divide between ecological forecasts and environmental decision making

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Abstract. The rate of human-induced environmental change continues to accelerate, stimulating the need for rapid and science-based decision making. The recent availability of cyberinfrastructure, open-source data and novel techniques has increased opportunities to use ecological forecasts to predict environmental change. But to effectively inform environmental decision making, forecasts should not only be reliable, but should also be designed to address the needs of decision makers with their assumptions, uncertainties, and results clearly communicated. To help researchers better integrate forecasting into decision making, we outline ten practical guidelines to help navigate the interdisciplinary and collaborative nature of forecasting in social–ecological systems. Some guidelines focus on improving forecasting skills, including how to build better models, account for uncertainties and use technologies to improve their utility, while others are developed to facilitate the integration of forecasts with decision making, including how to form effective partnerships and how to design forecasts relevant to the specific decision being addressed. We hope these guidelines help researchers make forecasts more accurate, precise, transparent, and most pressingly, useful for informing environmental decisions.

Key words: co-production; decision support; forecast horizon; iterative; Open science; prediction; reproducibility; scenario analysis; science communication; team-building; uncertainty; validation.

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Introduction

The Anthropocene is characterized by an accelerated rate of human-induced environmental change, forcing decision makers to respond quickly to unprecedented circumstances (Foley et al. 2005). Ecological forecasting, the process of predicting changes in ecosystem components and environmental conditions with specified uncertainties, can help decision makers operate on shorter time scales and respond to environmental issues even in uncertain conditions (Clark et al. 2001, Dietze 2017*a*). In particular, ecological forecasting can play an essential role in informing responses to a variety of key environmental issues, including zoonotic and vector-borne diseases, insect outbreaks, invasive species, biodiversity decline, and natural disturbances (e.g., droughts, fires and floods; Dietze et al. 2018). As climate change and other human-mediated impacts will likely continue to exacerbate these environmental issues, the need for ecological forecasting will only grow.

Nowadays, the increased availability of cyberinfrastructure, open-source data, and novel techniques provides greater opportunities to create forecasts than in previous decades. However, forecasts that effectively inform environmental decisions require more than new technologies and a diverse forecasting toolbox; they must also be informed by an understanding of the specific environmental challenges decision makers (e.g., managers, landowners, politicians, community members) are seeking to address and the considerations and constraints of potential decisions (e.g., policies, mandates, management options). As the urgency for science-based decision grows, the ecological forecasting community needs to start addressing these challenges now.

Here, we outline ten brief guidelines to help researchers integrate ecological forecasting into environmental decision making. We developed these guidelines as part of a working group on forecasting for decision making, drawing on our experiences across academia, government, and industry. We are scientists, most from affluent countries, and acknowledge that this common background limits our perspective. But our guidelines come from a variety of career trajectories and should provide practical advice to researchers on how to produce ecological forecasts that are more applicable to decision makers.

The ten guidelines outlined are designed for researchers who have some familiarity with ecological forecasting but are less versed in integrating models into decision making. We recognize that engagement in decision making is not a binary state, but a stepwise process associated with a range of participatory actions (Fig. 1). Thus, our guidelines are designed to account for researchers' different levels of engagement, with some guidelines intended to improve forecasting skills (e.g., guidelines 4 and 5; Fig. 1a), and others intended to facilitate the inclusion of decision makers and decision-relevant issues into the forecasting process (e.g., guidelines 2 and 3; Fig. 1c, d). Our guidelines also vary in novelty and theme: Some pertain to novel forecasting topics (e.g., developing updatable forecasts with cyberinfrastructure) and others focus on established ideas about integrating science into decision making (e.g., building effective dialogue with different audiences). We hope these guidelines encourage researchers to make their forecasts more accurate, reliable, transparent, and most importantly, useful to environmental decision making.

1) Build diverse teams that are flexible, cohesive, and supportive

A modeler alone can develop a simple forecast. Yet, a forecast that is both robust and ecologically meaningful usually requires a team of researchers with common interests contributing knowledge from a variety of disciplines. Different parts of the forecasting process benefit from different types of experts: Modelers design and implement forecasting models; data architects manage data;

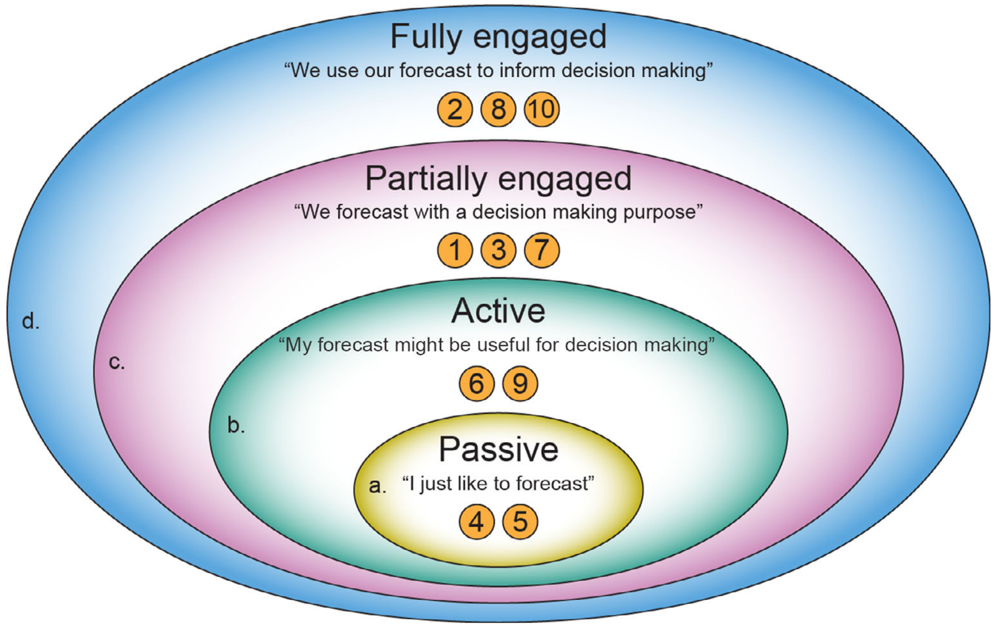

Fig. 1. A researcher's engagement with using ecological forecasts to inform decision making. The level of engagement is additive, such that maximum commitment to using forecasts to inform decision making depends on fulfilling all ten guidelines (numbered in orange circles). The nested configuration of engagement, represented by the concentric oval shapes, includes: (a) Researchers with little interest in becoming involved with decision making and just focused on forecasting—the Passive researchers (yellow); (b) those who believe in the potential utility of their research and thus believe in making the forecast accessible—the Active researchers (green); (c) those interested in collectively building decision-relevant forecasts—the Partially engaged researchers (pink); and (d) the forecasting teams with a strong commitment to building relationships with decision makers—the Fully committed researchers (blue). While we encourage all researchers to strive to engage "early" and "strongly," we recognize that being fully-committed is not feasible for everyone. Therefore, some guidelines require minimal effort and thus are designed to help researchers contribute to using their forecasts to inform decision making, while others are designed for those researchers who have more interest, time, and resources to fully commit to engaging in the decision making process.

computer programmers create user-friendly platforms; domain experts ensure environmental forecasts build upon problem-specific knowledge, theory, and understanding; social scientists create better coupled socio-ecological forecasts and provide insight into the policy process (e.g., timing of the policy cycle); and interdisciplinary boundary spanners facilitate communication and integration across disciplines (Goodrich et al. 2020).

With appropriate funding and coordination, multi-disciplinary collaborations can be built into networks such as the Turning Risk Into Action for the Mountain Pine Beetle Epidemic network (TRIA network; http://tria-net.srv.ualberta.ca/resteam/). This network involves different research specialists (e.g., genomicists, ecologists, socio-ecologists) who work together to predict mountain pine beetle dynamics and their social impacts (James and Huber 2019). Adopting an interdisciplinary approach is not only beneficial for large partnerships as small collaborations can also benefit from involving multiple academic disciplines. For example, Molnár et al. (2020) combined knowledge from climate scientists, polar bear experts, and ecological modelers to generate better predictions for how climate change associated sea ice declines will affect polar bear persistence across their circumpolar range. Similarly, Hughes et al. (2017) collaborated with ecologists, mathematicians, and doctors to design disease models to understand potential effect of antimicrobial de-escalation on infection prevalence as well as its consequences for patients.

Beyond including different academic disciplines within a research team, diverse teams should also strive to include individuals who contribute different ways of knowing and diverse world views (Norström et al. 2020). Teams that include Traditional Knowledge Holders (e.g., Indigenous People) will gain expertise on environmental and social factors largely overlooked by the scientific community (Johnson et al. 2016) and teams that include underrepresented groups will likely produce novel and inclusive forecasts (Hofstra et al. 2020). The Western Boreal Initiative is one recent example of a collaboration that relies on braiding (i.e., weaving, combining) of Dene Nation Traditional Knowledge and Western science to build models of landscape change and conservation planning (Environment and Climate Change Canada 2021).

While we encourage researchers to build diverse teams, we also recognize that it can be a challenging task. For example, in our working group we strived to balance gender and career-stage, and prioritized researchers with experience in both ecological forecasting and informing environmental decision making in Canada. Yet, our team is not representative of most minority groups nor does it include different ways of knowing.

Fortunately, there are steps we can all take to help address these diversity imbalances. First, we need to identify the diversity gap that exists and allocate time, energy, and resources to correct it. Teams can be expanded after the onset of a forecasting process so even if teams are lacking in representation at first, this can still be addressed by extending invitations throughout the course of a project. Beyond simply providing an invitation, however, team environments need to be built to accommodate diverse opinions, perspectives, and backgrounds and thus should be flexible, encouraging, designed to counter implicit biases, and supportive of mentorship networks (Hansen et al. 2018). To help create teams that foster knowledge co-production specifically, researchers should ensure projects are based in frameworks designed to support co-production (e.g., "Two-Eyed Seeing"; Reid et al. 2021). Finally, researchers can refer to other practical guidelines designed to help address specific diversity imbalances such as remedying gender imbalances (Tulloch 2020), improving the representation of minority groups (Duc Bo Massey et al. 2021), and including a broader range of values and viewpoints (Green et al. 2015). While building diverse teams requires more effort than many of our other proposed guidelines (Fig. 1), the result can not only produce more innovative research but also help reduce diversity attrition in the ecological research community (Stokols et al. 2008, Hansen et al. 2018).

2) Involve decision makers, stakeholders, and rights-holders throughout the forecasting process

Forecasts that inform decisions are generally most useful when designed in conjunction with decision makers (those with decision power, e.g., a government official), stakeholders (those with interest, e.g., resource users with economic interest), and rights-holders (those with rights, e.g., communities with rights to the land). The TRIA network and the Western Boreal Initiative are both examples of how partnerships between multiple groups including government, industry, not-for-profit organizations, and First Nations communities can be established and maintained to inform and shape research agendas. For all forecasting projects, partners should be case-specific, whereby both large- and local-scale interests are represented to ensure the maintenance of local livelihoods and sustainability (Berkes 2007). For example, in Bristol Bay, Alaska, a tight feedback between models, local data, and commercial fisheries has secured Sockeye Salmon sustainability for decades, benefiting the ecological system and the regional market that supports the livelihoods of over 8000 local fishers (Hilborn et al. 2003, McKinley Research Group LLC 2021).

Establishing early involvement with various groups helps to set forecasting priorities, ensures forecasts that are relevant to targeted environmental issues, and increases forecasts' accessibility (Clark et al. 2001). Moreover, forming relationships early-on helps to build trust and familiarity with each other's languages, communication styles and ways of knowing, allowing for better collaborations. Maintaining relationships throughout the forecasting process helps ensure forecasts are sensitive to evolving objectives, needs, and priorities. This maintenance can be achieved if involved parties are committed to continuously sharing updates throughout the length of the partnership. For example, the TRIA network hosted annual meetings where researchers presented their work and decision makers discussed their needs, which facilitated ongoing communication and data sharing.

Establishing and maintaining relationships with decision makers, stakeholders, and rights-holders may require greater investment in time and resources if those involved have incompatible interests and views, and/or differences in culture and language that make communication difficult. Some incompatibilities can be resolved through decision making tools, such as structured decision making (Gregory and Long 2009), or by following frameworks designed to accommodate multiple perspectives. For example, Norström et al. (2020) recommended that projects engaging multiple groups be pluralistic (recognizing there are multiple ways of knowing) and interactive (allowing for ongoing learning, active engagement, and frequent interactions among actors) to promote meaningful co-productive practices. Research initiatives may also benefit from including boundary spanners, individuals who can mediate interactions between partners to reconcile interests, foster common understanding, build trust, and enhance the co-production of actionable knowledge (Goodrich et al. 2020).

In general when working with multiple different partners, researchers need to recognize the limitations of quantitative scientific knowledge and the validity of other perspectives (e.g., Reid et al. 2021). Fostering these relationships requires building an ethical space "for knowledge systems to interact with mutual respect, kindness, [and] generosity" (The Indigenous Circle of Experts 2018), elevating the voices of historically underrepresented groups in science and governance (e.g., Indigenous Peoples), and consciously working to halt the perpetuation of harm and structural racism (Chaudhury and Colla 2020, Miriti 2020, Wong et al. 2020). Even if researchers are not engaged in partnerships when designing and implementing their forecasts, it is important to realize that the forecast may still inform a decision that directly impacts people's lives and therefore should always be built with the awareness of their potential consequences.

3) Design decision-relevant forecasts

Forecasts are useful to decision makers when they are decision-relevant. Relevance arises from understanding the current and future environmental priorities of decision makers, stakeholders, and rights-holders and by knowing the potential strategies being considered by these groups to manage an environmental issue. This understanding can be gained through formal partnerships, such as the Haida Gwaii Strategic Land Use Agreement (British Columbia, Canada), which brought together researchers, government officials, and First Nation representatives to model the effects of current and alternative management practices on timber supply (Government of British Columbia n.d.). Alternatively, if partnerships (guideline 2) are not possible, researchers can still identify the priorities and strategies of different groups by referencing content produced by them, such as reports, policies, or data provided on online portals (e.g., Open Government Portal Canada). While designing models in partnerships with other groups may limit the scope and usage of the model, designing models to be nimble can help ensure they are adaptable to other forecasting challenges (e.g., SpaDES; Chubaty and McIntire 2021).

Ultimately, to be decision-relevant, researchers should know the context of the decision-of-interest, its temporal and spatial scales, and the alternative targets and/or decision options being considered. First, the context of the decision can guide which model structures, drivers, and parameters to incorporate to best capture the environmental effects and the management options. For example, forecasts in fisheries for harvest management may explicitly incorporate climatic variability as well as fishing quotas (e.g., Shelton and Mangel 2011) to capture important environmental influences and the effects of human regulation. Next, accounting for the temporal and spatial scales of a decision ensures forecasts are relevant to the time horizons and spatial extent (e.g., jurisdictions) of interest to decision makers. Forecasts mismatched with the scales of decisions will likely be unusable, such as using forecasts built on 100-yr climate projections for seasonal decision making. Finally, incorporating different targets or strategies as alternative plausible futures into forecasts can help evaluate which decision option performs best under uncertainty (Schindler and Hilborn 2015). Decision options included in forecasts may be general goals (e.g., maintain fisheries sustainability and biodiversity) and may include specific management targets (e.g., catch and size limits). This approach can lead to a best "static" decision, where the strategy performing best under many plausible futures is selected, or preferably lead to "adaptive" approaches, where the optimal strategies might switch given an updated forecast (Maier et al. 2016). Remember, even in situations with high uncertainty, a forecast can often predict whether a management action will have a negative or positive impact, still providing sufficient information for decision makers to act on (Adams et al. 2020). Hollowed et al. (2020) provided an excellent example of how decision-relevant forecasts can be implemented in a marine social–ecological system impacted by climate change, where iterative engagement with managers and fishery-dependent communities continues to ensure that forecasts are built upon policy-relevant scenarios and realistic decision options.

Making forecasts decision-relevant does not guarantee that forecasts will be used for decision making. Opportunities for informing decisions come and go and learning about the timing of the decision making process can help understand opportunity windows. By designing forecasts that complement the context, scales, and decision options, forecasts are available for whenever opportunities arise and, in the meantime, can be used to shape the decision making agenda.

4) Identify uncertainties and account for those deemed most important

Uncertainty persists even in the most realistic, well-parameterized models (Schindler and Hilborn 2015) and if ignored can instill decision makers and researchers with a false confidence in the forecast's skill. Instead, identifying and accounting for uncertainties can lead to appropriate risk-benefit policy assessments, and inform future data collection and monitoring needs, resulting in better future forecasts. However, not all uncertainties are equivalent in magnitude or are of equal interest to decision makers. Therefore, besides prioritizing uncertainties related to current decision making considerations (guideline 3), researchers should also attempt to identify and account for the uncertainties that have the strongest effects on the forecasted outcome.

Identifying uncertainties requires identifying both their location in the model (e.g., initial conditions, covariates, parameters, structure) and their qualities (e.g., degree, type). For example, uncertainties arise either due to a lack of human knowledge (i.e., epistemic uncertainty) and thus are reducible, or arise due to natural variation (i.e., aleatory uncertainty) and thus are irreducible. Uncertainty analysis and sensitivity analysis can identify which uncertainties have the largest effect on a forecast (Bodner et al. 2021), and value of information analysis (Schlaifer and Raiffa 1961) can determine when collecting additional information is worth the cost (Canessa et al. 2015). By identifying uncertainties and their relative contributions, researchers can help decision makers understand uncertainty sources and how best to reduce them.

Accounting for uncertainties involves quantifying the uncertainties in different inputs and alternate models, propagating them into the forecast, and partitioning their impact on overall forecast uncertainty (Dietze 2017*a*). By accounting for important uncertainties, decision makers can better understand the risks when evaluating a forecast. In cases of high uncertainty, sometimes just doing better than chance is sufficient as the decision sciences provide frameworks for making decisions under uncertainty and translating uncertainty into risk (Winkler 2010, Gregory et al. 2012). Yet, researchers should not forget about the "unknown unknowns," which if ignored can end up greatly misguiding management actions (Milner-Gulland and Shea 2017). While it is infeasible to fully identify and account for all uncertainties, by prioritizing important ones, and seeking to address those that are reducible, decision making will be increasingly informed by more reliable forecasts.

5) Create models with forecasting in mind

While in-depth reviews on best forecasting/predicting practices can be found in Mouquet et al. (2015), Dietze (2017*a*), and Bodner et al. (2020), here we highlight two often overlooked but important considerations for creating accurate and reliable forecasts: (1) only include forecastable covariates within models and (2) prioritize forecasting evaluation techniques over traditional methods when evaluating models.

First, the covariates that go into a forecast must be forecastable. If the covariates of a given model cannot be projected into the future for the period-of-interest, an alternative model with forecastable inputs needs to be developed, even if it has lower performance. For example, ungulate distribution models often include the normalized difference vegetation index (NDVI), an index measuring the "greenness" of live vegetation, as a covariate. As forecasts of NDVI are not as readily available, the leaf area index may be preferable as it is not only readily available from historical remote sensing, but is also part of the output of most Earth System Model climate projections and some seasonal forecasts. In the future, we should hopefully have more forecasted covariates, providing more input options for forecasting models.

Second, even if forecastable covariates are available, this does not guarantee that the model that fits best against historical data will make the best predictions. Besides having forecastable covariates, researchers should evaluate models and variables using appropriate forecasting evaluation methods. The underlying issue is that forecast uncertainties for different covariates are generally larger than hindcast observation errors, causing traditional metrics such as AIC and probability values (*P*-values) to systematically select for overly complex forecast models (Dietze 2017*b*). Moreover, as different uncertainties can propagate forward at different rates, the "best" model structure and covariates may change depending on forecast lead time (Lofton et al. n.d.). Therefore, to account for this additional uncertainty when evaluating forecasting models, adopting alternative model selection metrics, such as predictive loss (Gelfand and Ghosh 1998) or predictive validation (Power 1993), is recommended. When evaluating at the variable-level, instead of focusing on significant *P*-values to provide a baseline of each variable potential value, focus on effect sizes, which convey a variable's effect on a forecast. Even if variables are statistically significant, they might not be kept if forecasts of that variable are uncertain, as they may increase the uncertainty in the model without improving the prediction. By adopting these forecasting practices, forecasts are immediately improved allowing researchers to focus on the other pressing challenges of forecasting (Fig. 1).

6) Build updatable models and iterate them when feasible

Given the accelerating pace of environmental change, it is increasingly important for forecasts to be iteratively updated as new information becomes available and the goals of decision makers change (Dietze et al. 2018). Thus, the forecasting community needs flexible and updatable models. It is advantageous if models can be updated by other users without further input from the original developers (see guideline 9), and even better still if models can be automated to produce forecasts as new information becomes available.

At the most basic-level, researchers should build updatable forecasting models using version control (e.g., GitHub; Perez-Riverol et al. 2016) and include a recommended protocol for continual validation as well as updating (see Zwart et al. (2020) on how to create reproducible forecasting protocols). As many forecasts use increasingly complex methods and data, forecasting tools (e.g., models, modeling platforms, databases, dashboards) should also be scalable and leverage existing models as well as cyberinfrastructure. When first designing a forecasting system, surveying existing tools can help determine if any are reusable for a given purpose. Connecting to community cyberinfrastructure can help lower the barriers to entry when setting up new forecast pipelines (and long-term maintenance costs) and reduce time lags between model-data integration and fast-paced decision makers (Fer et al. 2021).

Once models are set up to be easily updatable, the next step is determining when the model should be updated. The basic answer is to update a model when useful information becomes available, particularly information that reduces important uncertainties (guideline 5). In general, researchers should update the model outputs when drivers are updated; state variables when new observations are generated (e.g., through data assimilation; Lewis et al. 2006, Dietze 2017*a*); and the model structure as more is learned about the built-in processes, including the discovery of new ones (but making sure to apply a fairly strong correction during iterative model selection to avoid a very high false positive rate). By leveraging open access portals (e.g., Nature Map Explorer, NEON, Sentinel Online), forecasts can be automatically updated and made publicly available once new data become available on the platform. Importantly, planning ensures updates are done regularly and reliably, ideally through a standardized continuous integration and deployment (CI/CD) pipeline (White et al. 2019). While the effort required to make forecasting models updatable may seem burdensome, taking these steps will reduce costs for the future, increasing forecast utility, value, and longevity.

7) Realize that ecological forecasts influence and are influenced by social systems

Despite researchers often addressing environmental issues in isolation, environmental and social factors are highly interdependent. For instance, fire suppression in natural systems may unintendedly increase forest flammability to future wildfires and impair human health and safety (Steel et al. 2015). To account for such social–ecological interdependencies in ecological forecasts, models can be built to include social–ecological drivers, interactions, and feedback (e.g., Cooper and Dearing 2019).

Forecasting in social–ecological systems also requires that researchers account for increased uncertainties that arise due to social components. The uncertainties prioritized in the modeling framework will depend on which uncertainties are deemed most relevant to the specific context. For example, the Alaska Climate Integrated Modeling framework, which forecasts the ecological impact of climate change on the Bering Sea species and fisheries, quantifies the contribution of management and fishing scenarios uncertainties as these are both regulated by decision makers and are expected to influence coastal sustainability (Hollowed et al. 2020). When modeling diseases such as COVID-19, forecasts may focus instead on accounting for the uncertainties surrounding people's perception of risk (e.g., willingness to social distance, wear masks) as it has been shown to have a large influence on outbreak dynamics (Duong et al. 2021).

To account for human behavior in ecological forecasting, social components can be either directly incorporated into ecological forecasting models or can be used to contextualize ecological forecasts. When social components are included in models, their influence on inputs, parameters or processes can be explored through techniques such as scenario analyses (Maier et al. 2016). If the data are available, sub-models of human behavioral change could be incorporated into forecasting models to more explicitly account for human behavior. While collecting this type of data can be challenging, the ongoing growth of publicly available data on human mobility and social networks provides novel opportunities to build these models in new ways (e.g., Ilin et al. 2021). When social components cannot be explicitly built into forecasting models, social information can still be used to interpret and contextualize outputs of ecological forecasts. For example, Maina et al. (2016) used social surveys to assess the ability of coastal communities to adapt to future climate given their forecasted changes. If social components cannot be incorporated into the forecasting process at all, at a minimum, researchers should recognize the potential for these factors to affect both the accuracy and reliability of their forecasts.

8) Communicate forecasts and aspire to do so effectively

A forecast is only a "forecast" when communicated prior to the dates being predicted and is most useful to decision makers if its corresponding assumptions and uncertainties are also communicated. Communication can help a stakeholder understand forecasts and their uncertainties (e.g., van der Bles et al. 2019) as well as teach them that forecasts can still be useful even if stakeholder actions cause a forecast to be inaccurate (guideline 7). A key step toward effective communication is understanding the audience and accounting for their level of forecasting knowledge, priorities, and interests related to the forecast. Communication with diverse audiences can be facilitated by adopting common language (e.g., plain language summaries of research papers), by linking the science to direct human needs, and emphasizing the consequences of adopting different actions (e.g., McDonald et al. 2019). The use of analogies can also facilitate the understanding of more complex biological processes when communicating to the general public (e.g., disease dynamics; Archer et al. 2021). For decision makers, Grimm et al. (2020) proposed that effective communication arises from addressing three main questions: "What is the model's purpose?" "How is the model organized?" and "What evidence is there that the model works?".

When attempting to reach a broader audience, researchers should present and discuss forecasts in a more culturally relevant or practical way. For example, instead of focusing on the forecast's methodology, communicating how fish size limits are established based on the age structure of harvested fish can offer a more practical explanation of fishing limits to communities of fishers. However, more active involvement may be necessary to communicate more complex topics. For example, leading participatory workshops where simple models are developed and implemented can help participants understand model behavior and limitations. For other considerations on effective active communication and training resources, see Baron (2010) and Cooke et al. (2017).

Visualizations can also help non-modelers intuitively understand the process of forecasting and its outputs in non-verbal and non-mathematical ways. Uncertainty visualizations are particularly important for forecasts (e.g., hurricane forecasts; Ruginski et al. 2016) as they can help increase the awareness of uncertainties (e.g., https://xkcd.com/1885/; Munroe n.d.) and explain how uncertainty may limit the ability to forecast reliably (guideline 4). Visualizations such as infographics can also help convey how human behavior may impact outcomes-of-interest (e.g., swiss cheese infographic; Mackay 2020) and can be tailored to specific audiences (Norström et al. 2020). Additionally, non-traditional and inclusive visualization techniques (e.g., Tekwa 2021) can help increase communication to new audiences. Overall, effective communication translates a technical forecast into an understandable forecast, empowering individuals to incorporate measured risk when making decisions. Taking steps to better communicate forecasts will go a long way in making forecasts broadly accepted and more often used in the decision making process.

9) Share the recipe, not just the end product

Striving to be open with the methodological steps, materials, and assumptions of forecasts is essential for a multitude of reasons: It helps build the forecasting community; ensures accountability; reduces duplication of effort; encourages innovation; allows scrutiny; builds credibility; and reduces barriers to participate in forecasting by making tools easier to find, less costly, and easier to access, modify, and apply. Furthermore, in the context of decision making, open and transparent forecasts also help build trust between researchers and decision makers—an essential aspect of fruitful collaborations. Additionally, sharing forecasting "recipes" (including the data, model assumptions, and code) also benefits other applied researchers (including those in the private sector, the public sector, and nonprofits), who often act as intermediaries between the academic and policymaking world, and can more easily integrate existing research into policy-relevant forecasts when models and code are readily available. We respect that for some researchers this is not feasible due to private data and sensitive forecasts; however, for those with the capability to do so, we advocate for making all components of the forecasting process as open as feasible.

As a scientific community, we should strive to make the software pipelines that run forecasts reproducible following Open Science best practices (Roche et al. 2020). In particular, proper documentation of models, including complete meta-data following meta-data standards for data and outputs (e.g., Feng et al. 2019), should accompany raw data and well-annotated code (Balaban et al. 2021) that is shared on open access version control platforms (e.g., GitHub; Perez-Riverol et al. 2016). Containerization approaches also allow whole forecast pipelines to be easily achieved and shared (e.g., DockerHub). Whenever using open access data, it is essential to provide explicit links to the download source and information on the data-processing. Complementary to increased openness, archiving forecasts and forecast meta-data following community standards (e.g., Ecological Forecasting Initiative n.d.) can make forecasts more transparent for stakeholders and researchers, encourage the greater development of community cyberinfrastructure (guideline 6), and facilitate synthesis efforts. Finally, if the forecast leads to a published paper that is behind a paywall, making the preprint of the published article freely accessible allows for all interested parties to read about the forecast's context, study design, and methods. Achieving the highest standards of openness and transparency requires a high degree of effort but every step toward more open forecasting is a step toward producing better science and ultimately, better decision making.

10) Practice, and then practice some more

Practice makes better forecasting models and more effective teams to address decision making priorities (Fig. 1). New forecasting models are often inaccurate, but consistent practice and feedback about performance (guideline 6) can result in continually refined understanding of the system and of the processes built-in to forecasts. The weather-forecasting community is a great source of inspiration, where with continued repetition and wide accessibility to the public, modelers transformed poor performing forecasts into relatively reliable and useful ones (Shuman 1989, Dietze et al. 2018). By practicing, researchers can develop better metrics for evaluating efforts such as establishing appropriate concrete benchmarks of success (e.g., threshold of acceptable model accuracy) and can gain knowledge and skill sets tailored to specific forecasts and applicable to improving general forecasts. The worry of creating models that are not "good enough" should not prevent anyone from forecasting. So long as uncertainties and assumptions are clearly stated and are accounted for (guideline 5), progress is not hindered by failure, but instead by the unwillingness to adapt and try again.

The act of "practicing" should not only be limited to creating forecasting models but also applies to building collaborative teams. Forecasting for decision making requires consistent collaboration with diverse groups of researchers and decision makers (guidelines 1 and 2), and therefore benefits from the good management of diverse skill sets, interests, and expectations. Practicing project management, and more specifically, developing skills in active listening and compromise, and mastering tangible and intangible technologies that foster collaborations, can lead to vast improvements in the collaborative process, translating to faster and better forecasts. While it may be overwhelming to consider the many skills to hone and strategies to develop, these worries should not prevent researchers from getting together with others and creating forecasts.

Conclusion

Here, we have provided ten guidelines to help researchers build forecasts for environmental decision making. We hope that these guidelines serve as practical suggestions to help those interested in informing decision making get started or become more involved with the process (Fig. 1). As researchers, we are often acutely aware of how much we do not know and therefore get stuck at "more research is required." However, environmental changes are increasingly affecting our world and decisions are made whether or not we are involved. So, get out there, form partnerships, connect with decision makers, build forecasts, be honest about the strengths and limitations of models, and accept that this is an iterative and adaptive process with many opportunities for learning along the way.

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Data Availability

No data were collected for this study.