So you want to forecast: navigating multiple pathways into ecological forecasting

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Abstract

In the face of increasing ecological variability, and with the emergence of new monitoring networks and computing capacity, many people find themselves wondering if they can predict the future states of ecosystems. In response, there has been a rapid expansion of ecological forecasting within research, education, management, and applied spheres. Researchers come to the practice of ecological forecasting via different pathways, and the applications of forecasting are diverse. While some studies have outlined "best" practices for building forecasting systems, a growing field also needs to be inclusive of multiple practices and be flexible to multiple social configurations. The goal of this Perspective is to discuss the balance between lowering the barrier of entry for forecasting and being realistic about the limitations and risk of forecasting. We provide an overview of two forecasting paradigms that can serve as a starting point for ecologists and others entering the field of ecological forecasting from different backgrounds. These paradigms have been constructed from a review of forecasting perspectives and approaches used by practitioners, and they offer multiple entry points and pathways. The paradigms are: (1) a Motivation Pathways Model, to help evaluate at the outset the benefits and risks of different forecasting approaches; and (2) "Forecast Card" Questions, designed following the approaches used in Algorithm Accountability and Data Justice. These tools can help aspiring and current forecasters reflect on their own positionality, map out their plan, build networks, and prioritize resources they need as they explore new forecasting endeavors.

Introduction

From armchair coders to professional scientists, more and more people are exploring new technologies for predicting the future (Bach, 2019; Lewis et al. 2022). The availability of large datasets and machine learning has lowered the bar of entry for all kinds of forecasting, and ease of slick data visualizations has broadened the appeal. For example, at the outset of the COVID-19 pandemic, epidemic forecasts were produced at an unprecedented rate (Cramer et al. 2022); the drawback to this proliferation was that most of these forecasts were inaccurate and counterproductive at best (Ioannidis et al. 2022). The tradeoff between the benefits of opening up a scientific practice and the potential for its unintentional misuse is a delicate balance: science should be inclusive while minimizing the risks of unintended consequences.

Ecological forecasting is a field that has had rapidly broadening accessibility (Woelmer et al. 2021). Generally, ecological forecasts have been defined as predictions about future ecosystem states with specified uncertainty (Luo et al. 2011, Petchey et al. 2015), though there are multiple ways to frame the concept (Hobday et al. 2020). In this Perspective, we address the tension between opening the field of ecological forecasting versus rigid standardizing of its practices. Part of the motivation is to emphasize that there is not a 'right' pathway for entering into ecological forecasting. We lay out a model for multiple pathways into ecological forecasting, balancing what we see as a need to remove barriers with a need to be deliberate about intentions and goals.

Positionality - We comprise scientists from two ecological forecasting centers based in the US: the Tandy Center for Ocean Forecasting at the Bigelow Laboratory for Ocean Sciences and the Virginia Tech Center for Ecosystem Forecasting. Our work spans terrestrial to aquatic environments, and includes work in both educational and applied contexts with a range of communities, participants, and decision makers. The perspectives here represent what we have learned from our own cumulative experiences. Recognizing the position of institutional privilege from which we are writing, our hope in mapping out multiple pathways into ecological forecasting is to broaden accessibility to the field.

Review

Ecological forecasting has a long history in some applications, such as fisheries management (Ottenstad 1960), but is comparatively new for other systems. Following revolutions in big data and algorithms (e.g., LaDeau et al. 2017, Farley et al. 2018), and calls for ecology to be more quantitative and predictive, ecological forecasting has been proliferating and diversifying (Payne et al. 2017, Lewis et al. 2022). Because of the recognized risk of unintended consequences (Hobday et al. 2019), there has been a move toward standardization and "best practices" (Harris et al. 2018, Bodner et al. 2021, Lewis et al. 2022), as well as co-production (Record et al. 2022).

The recent proliferation of ecological forecasting provides an opportunity for reflecting on the growth and inclusivity of the community of ecological forecasters. Researchers enter the field of ecological forecasting from different pathways and backgrounds and with different motivations. For many decision-support applications, a careful co-production approach might be appropriate (e.g., Carey et al. 2022). However, “best practices” can be a barrier to entry, and co-production protocols can lead to gate-keeping and exclusivity, sometimes excluding groups who are already marginalized. In response to this challenge, we begin this Perspective with four case studies informed by our own forecasting centers to help illustrate the range of pathways into forecasting.

Four Case Studies

Two forecasting programs from coastal Maine, USA show contrasting approaches to co-production. First, the Paralytic Shellfish Toxin (PST) forecast in coastal Maine emerged from a need expressed by managers and harvesters to help with decision making at their shellfish monitoring and harvesting sites, particularly at the weekly timescale. Through continued dialogue, members of both industry and management joined with a toxin testing lab (Bigelow Analytical Services) and our forecasting center to conceive a project to create an operational PST forecast system. A data pipeline and forecasting software were developed in consultation with managers and local growers throughout the process (Record et al. 2022). Four real-time forecast seasons have been executed to date, and the system has proven to have good skill and adoption by users. Through ongoing communication, the forecasting system continues to change based on changing needs, including coding and data visualization preferences and data ownership needs, requiring continued maintenance and adaptability.

By contrast, we launched a coastal Maine jellyfish forecast shortly after multiple jellyfish aggregations were reported in the local press. With widespread interest in the phenomenon, we were able to use reports from the public of jellyfish encounters to enable monitoring for common species, which were then used to test the feasibility of a forecasting system (Record et al. 2018). Although no one had specifically asked for this forecast, we were able to use the incoming data to spin up a reliable daily model with a forecasting horizon of a few days, and we kept the product live for five years before sunsetting it. We are not aware of any decision-support uses. However, the forecast did help maintain public interest needed to keep public reports coming in, including news coverage and a live TV broadcast, and engagement with the public led to new hypotheses. Because of the low-stakes nature of the prediction, the risk of unintended consequences was low. However, a lot of unfunded time was invested, and without a clear decision-support use, a sustained funding model never developed. With a more deliberate approach to engaging end-users early on, it’s possible that this forecast could have been sustainable. On the other hand, there is value in determining when to close the book on a project.

In some cases, it might not make sense to consider a forecast user group at all. For example, the Ecological Forecasting Initiative Research Coordination Network created the National Ecological Observatory Network (NEON) Ecological Forecasting Challenge (hereafter, Challenge) with the goal of growing the field of ecological forecasting (Thomas et al. 2023a). The Challenge is a platform for scientists to submit iterative, near-term forecasts of NEON data as a genuine test of our predictive capacities in ecology. It empowers scientists by providing training, templates, and tools to lower the barrier of entry so that a range of experience levels can produce forecasts (Olsson et al. 2024). The Challenge was not designed to inform management since most NEON sites are not actively managed. The themes, protocols, standards, and cyberinfrastructure were designed by a community of ecologists (Thomas et al. 2023a; Peters & Thomas 2021) with a focus on maximizing participation. To date, the Challenge has had over 200 teams submit over 100,000 forecasts evaluated, leading to synthesis papers on spring canopy phenology (Wheeler et al. 2024) and lake water quality (Olsson et al. 2024), among others. Many of the forecasts have been generated as part of courses and workshops (Thomas et al. 2023b). Despite the absence of a defined decision-making context, the Challenge has had educational value, upskilling the ecological community through hands-on experience in modeling, automation, and synthesis.

Finally, sometimes forecasting projects are undertaken without a specific metric of success or end point in mind. As an example, freshwater methane ebullition is considered a very challenging emission pathway to predict because of its high spatial and temporal heterogeneity (Wik et al. 2016), presenting a compelling challenge. In a drinking water reservoir in Virginia, we developed a time series model relating ebullition to sediment temperatures (McClure et al. 2020), which we were able to use to iteratively forecast methane ebullition rates at one- and two-week horizons (McClure et al. 2021). The forecasts were updated weekly with manually-collected ebullition data measured using passive traps. While this forecasting endeavor was originally started purely for fun (specifically, to see if we could pull it off), with no explicit decision making or learning objective at the outset, the forecasting project brought enjoyment to the team. Additionally, the discovery of predictable patterns laid the groundwork for future work.

These four examples illustrate a range of approaches to ecological forecasts that don't all follow best practices, such as co-production, or have defined end-users. A recent review of ecological forecasts found that only 20% of forecasts developed had identified an end-user (Lewis et al. 2022), suggesting that co-production might be a barrier. There is a tension between the need for best practices and the need to be inclusive of multiple approaches. Unintended consequences are a real possibility for deployed forecasts. Forecasts that don't account for socio-ecological dynamics can be used inappropriately and can have harmful consequences, such as increased poaching of protected species or loss of livelihoods (Hobday et al. 2019). However, a growing field would benefit from being inclusive of multiple pathways and flexible to multiple social configurations.

Analysis of Viewpoints

The case studies described above highlight how reasons for ecological forecasting can differ according to a person's objectives, available resources, social environment, and previous experience, among other factors. Together, these elements shape a person's motivational pathway to enter into an ecological forecasting endeavor. Each pathway could be associated with different end goals, measures of success, benefits, and potential disadvantages. Understanding the benefits and risks of these different pathways is important as the field of ecological forecasting expands. Here, we describe a motivational model that delineates multiple possible pathways into ecological forecasting (Figure 1).

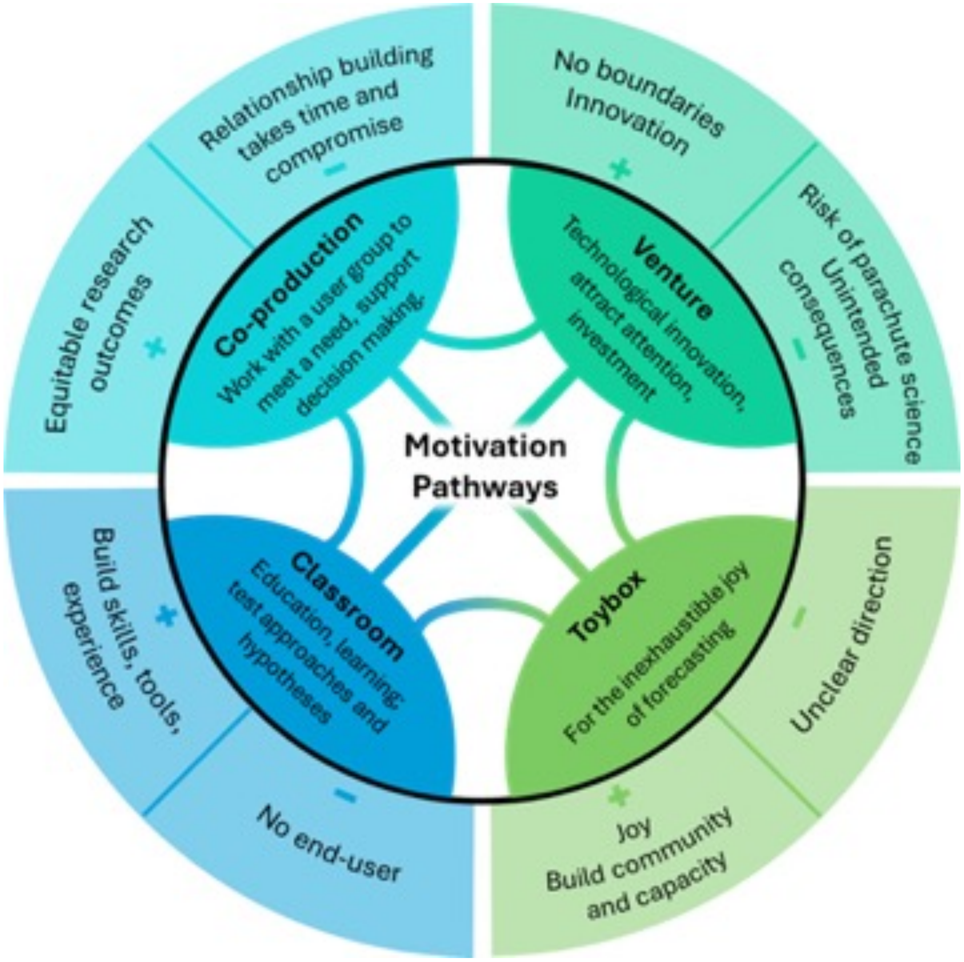

Figure 1 Motivation model for pathways into ecological forecasting, including potential benefits (+) and drawbacks (-) of each.

Co-production pathway - There has recently been an emphasis in environmental science toward knowledge co-production as a response to problems like parachute science and the colonial underpinnings of conservation and ecology (Liboiron 2021, Silver et al. 2022). A forecast developed using co-production involves its intended end-users and other affected communities as partners from the start (Record et al. 2023) (e.g., the PST forecast described above). A forecaster can work with a community, partner, or decision-maker to conceive an idea or respond to an idea from a partner. Different communities bring unique insights about a dataset, explain how predictions will be used, and provide feedback on the best method of communication. With the end-user involved, an iterative process can be used for deployment of the forecast, where feedback is provided to tailor the forecast to needs, akin to the "forecasting for decision making" paradigm (Bodner et al. 2021). There are challenges involved in relationship building and partnership, such as time commitment, trust building, and the process of understanding complex social configurations. Sometimes, forecasting goals need to be abandoned based on the perspectives of partners. A successful forecasting program taking this pathway can inform decision making fairly while lowering the chances of unintended consequences.

Venture pathway - One perspective on the current environmental crises is that solutions must come from rapid technological innovations that are supported by a high-risk-high-reward approach to science (Goldstein et al. 2020). A venture forecast follows this model, in which there is a hope of gain after initial investments in ideas. What defines gain depends upon the forecaster's aspirations, but examples include public awareness, demonstration of the forecaster's skill and value, or monetary return. Whatever the expected gain, the forecaster must make the initial investment to form the question, design the end product, acquire the required data, develop the computational resources, and characterize the forecast uncertainty. Akin to the tech startup model, venture forecasting requires up-front investment. The risks include lost investment (e.g., the jellyfish forecast described above), unintended consequences, or at worst harmful effects, as accountability often comes only after a technology is released and scrutinized (Garfinkel et al. 2017). On the other hand, bringing a fully developed forecast to a user can, if it aligns perfectly with a need, be an efficient pathway to deployment. As scientists affiliated with forecasting centers, we are cautious with this pathway, but there are cases where a need can be met more efficiently through a venture approach. A successful venture forecast will achieve a rapid advance, or possibly demonstrate that a particular approach or product is a deadend that can be dropped.

Classroom pathway - Not every forecast is meant to guide a decision maker or make it to market. Classroom forecasts are those designed for learning, either for experienced forecasters to learn more about a particular forecasting problem, for new forecasters to learn foundational methods (Moore et al. 2022, Ernest et al. 2023, Wilson et al. 2023), or for a broader community to develop and test new tools, models, and cyberinfrastructure (e.g., the NEON Forecasting Challenge described above). For classroom forecasts, guiding design principles can include highlighting a particular forecasting technique, such as using an ensemble Kalman filter for data assimilation (e.g., Lofton et al. 2024), or forecasting across a diversity of ecosystems to learn more about forecast performance across gradients (Thomas et al. 2023b, Wheeler et al. 2024). Rather than being assessed on predictive skill, the success of classroom forecasts can be assessed through progress toward learning objectives (Moore et al. 2022, Woelmer et al. 2023, Lofton et al. 2024) or the advancement of ecological theory (Lewis et al. 2023). While classroom forecasts enable researchers to build skills and can inform science, they typically don't have specific identified end-users or will consider end-users as hypotheticals. Thus, classroom forecasts often don't provide forecasters with experience in establishing end-user relationships or building operational forecasts and forecast teams.

Toybox pathway - Finally, we acknowledge that forecasting is fun, outside of any other specific objectives and metrics. People have been trying to make ecological forecasts for at least thousands of years (Wood 1894), so it might be part of human nature. Toybox forecasts are developed for the pure joy and challenge of developing predictions that lie outside of specific learning objectives, time investments, or end-users (e.g., the methane ebullition forecast described above). These forecasts can derive serendipitously or intentionally. As a result, toybox forecasts might stimulate a new community of forecasters, or the forecast might receive confused looks and fizzle out into the ethos of unappreciated scientific creativity. A successful toybox forecast will have brought enjoyment to the forecaster and possibly helped to build community among forecasters.

The idea of reflecting on motivation was inspired in part by the field of Algorithmic Accountability (Mitchell et al. 2019, Pushkama et al. 2022), in which an algorithm designer confronts themself with a series of questions in order to be transparent about the purpose, design, and possible uses or misuses of the algorithm in question. For example, “Data Cards” (Pushkarna et al. 2022) and “Model Cards” (Mitchell et al. 2019) provide lists of self-reflective questions to ask and document at the outset of projects. We propose a similar process of reflection for ecological forecasts, for which data and models are central. Following in this vein, we suggest a “Forecast Cards” exercise answering a series of questions to help situate a project within a motivational pathway (Table 1).

The answers to these questions can help determine the pathway and set up action items and milestones. Additionally, as with “Model Cards” and “Data Cards”, keeping a documented “Forecast Card” for a project will serve as a reference point that can help with transparency and accountability as the project develops. They are also good reference points to return to, for example, when composing disclaimers that accompany forecasts.

Discussion

The motivational pathways model that we propose is inclusive of many types of forecasting projects we have encountered through our centers and collaborations, and it allows space for different entry points into the field. The model is not exhaustive–we hope to see different pathways beyond these examples. Still, thinking carefully about motivation at the outset of a forecasting endeavor can help avoid some of the unintended consequences of forecasting. Importantly, no single pathway is inherently superior, nor do they necessarily lead to one another in a predetermined way. It’s also possible to move from one pathway to another, even multiple times. Some might require more care or investment than others, but each has something valuable to offer.

The “best” pathway for a person or forecasting project should be determined through careful consideration of the aims, personal or community interest, and financial, technical, and personnel resources available. A “Forecast Cards” approach, similar to that used in Algorithmic Accountability, can help provide scaffolding and keep forecasters accountable to their choices.

Table 1 “Forecast Card” questions to ask and document at the outset of a project, following the approach of “Model Cards” and “Data Cards” used in Algorithm Accountability. Answers could be very different depending on the motivational pathway.

Questions	Considerations
How will the forecasts be used?	What decisions will be made differently as a result of a forecast? Walk through scenarios of both intended uses in an ideal scenario and potential unintended uses. Think through who different potential users are and how they might experience benefits or losses.
Who do I plan on working with?	Who will contribute their knowledge to the forecasting system and how will collaboration be structured? Partners or users might change over time, and that different types of knowledge might be needed. Reflect also who is excluded from the list and why.
What are the roles, expertises, and contributions?	Roles might include ecologist, data scientist, decision maker, community member or other. Expertise might include scientific knowledge, decision-making knowledge, local knowledge, or other. How do these collaborators fit together, and how does each contribute?
Who is supporting the forecast?	Where is the support for time and resources coming from? What is the duration and reliability of support? What is the positionality or agenda of the funding entity?
What would be considered a success, and what are the risks involved?	Success could be short-term or long-term. It could include scientific publications, education outcomes, developing common cyberinfrastructure, community building, or, of course, the joy of forecasting. Risks can be social, political, environmental, or a combination.
What are the ethical considerations?	Notions of justice and fairness can vary, depending on location, cultural context, and other factors. What power dynamics are at play and how might those dynamics might be affected? How will ecosystems be impacted?

New Directions

The future of ecological forecasting is difficult to predict. We have seen unintended consequences as the field expands and forecasts are spun up. However, prescribing a rigid standard while a field is still developing can cause gatekeeping and stifle creativity: there has to be space to learn by failing. A good start to balancing these tensions, we believe, is an honest and deliberate process of self-reflection.

The motivational pathways model can also be turned around to face outward as a lens on the community of people involved. When viewed from this direction, one can see a variety of roles and types of knowledge that can be involved in the forecasting process, ranging from local ecological knowledge to decision making knowledge to algorithmic knowledge, and others. The forecasting community needs to welcome people into the network who fill these different roles, bring different types of knowledge, and carry different motivations.

More broadly, we see a benefit to the ecological forecasting community in recognizing different pathways. In our forecasting centers, we strive to make space for people to work along different pathways. Similarly, those funding forecasting work should consider projects that approach forecasting beyond a single pathway.

Conclusion

So, you want to forecast. It's tempting to think of forecast development as a quantitative or engineering task, but, like much of science, forecasting is a social act. The circumstances of forecasting can be as varied as social and environmental circumstances are. Our aims in highlighting different motivational pathways into ecological forecasting are to balance an inclusive approach that lowers barriers of entry with a more rigid or standardized approach that helps forecasters forecast responsibly. Excitement about forecasting should be encouraged. However, it's important to acknowledge your motivation so that your forecast is viewed through the appropriate lens. The tools provided here–a model of motivational pathways and a series of Forecasting Card questions–can be useful guides for helping new and long-term ecological forecasters navigate this emerging discipline.

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