WILEY ECOLOGICAL APPLICATIONS

# Increased adoption of best practices in ecological forecasting enables comparisons of forecastability

| | |
|---|---|
| Journal: | *Ecological Applications* |
| Manuscript ID | EAP21-0269.R1 |
| Wiley - Manuscript type: | Articles |
| Date Submitted by the Author: | 13-Jul-2021 |
| Complete List of Authors: | Lewis, Abigail; Virginia Tech, Biological Sciences<br>Woelmer, Whitney; Virginia Tech, Biological Sciences<br>Wander, Heather; Virginia Tech, Biological Sciences<br>Howard, Dexter; Virginia Tech, Biological Sciences<br>Smith, John ; Virginia Tech, Statistics<br>McClure, Ryan; Virginia Tech, Biological Sciences<br>Lofton, Mary; Virginia Tech, Biological Sciences<br>Hammond, Nicholas; Virginia Tech, Geosciences<br>Corrigan, Rachel; Virginia Tech, Forest Resources and Environmental Conservation<br>Thomas, R. Quinn; Virginia Tech, Forest Resources and Environmental Conservation<br>Carey, Cayelan; Virginia Tech, Biological Sciences |
| Substantive Area: | Statistics and Modeling < Theory < Substantive Area |
| Organism: | |
| Habitat: | |
| Geographic Area: | Global < Geographic Area |
| Key words/phrases: | Data assimilation, Decision support, Ecological predictability, Forecast automation, Forecast horizon, Forecast uncertainty, Iterative forecasting, Near-term forecast, Null model, Open science, Uncertainty partitioning, Forecast evaluation |
| Abstract: | Near-term iterative forecasting is a powerful tool for ecological decision support and has the potential to transform our understanding of ecological predictability. However, to this point, there has been no cross-ecosystem analysis of near-term ecological forecasts, making it difficult to synthesize diverse research efforts and prioritize future developments for this emerging field. In this study, we analyzed 178 near-term (≤10-year forecast horizon) ecological forecasting papers to understand the development and current state of near-term ecological forecasting literature and compare forecast accuracy across scales and variables. Our results indicate that near-term ecological forecasting is widespread and growing: forecasts have been produced for sites on all seven continents and the rate of forecast publication is increasing over time. As forecast production has accelerated, a number of best practices have |

been proposed and application of these best practices is increasing. In particular, data publication, forecast archiving, and workflow automation have all increased significantly over time. However, adoption of proposed best practices remains low overall: for example, despite the fact that uncertainty is often cited as an essential component of an ecological forecast, only 45% of papers included uncertainty in their forecast outputs. As the use of these proposed best practices increases, near-term ecological forecasting has the potential to make significant contributions to our understanding of forecastability across scales and variables. In this study, we found that forecastability (defined here as realized forecast accuracy) decreased in predictable patterns over 1–7 day forecast horizons. Variables that were closely related (i.e., chlorophyll and phytoplankton) displayed very similar trends in forecastability, while more distantly related variables (i.e., pollen and evapotranspiration) exhibited significantly different patterns. Increasing use of proposed best practices in ecological forecasting will allow us to examine the forecastability of additional variables and timescales in the future, providing a robust analysis of the fundamental predictability of ecological variables.

**Running head:** Best practices and forecastability

**Title:** Increased adoption of best practices in ecological forecasting enables comparisons of forecastability

**Authors:** Abigail S. L. Lewis[1a], Whitney M. Woelmer[1b], Heather L. Wander[1c], Dexter W. Howard[1d], John W. Smith[2e], Ryan P. McClure[1f], Mary E. Lofton[1g], Nicholas W. Hammond[3h], Rachel S. Corrigan[4i], R. Quinn Thomas[4j], Cayelan C. Carey[1k]

[1]Department of Biological Sciences, Virginia Tech, Blacksburg, Virginia, USA

[2]Department of Statistics, Virginia Tech, Blacksburg, Virginia, USA

[3]Department of Geosciences, Virginia Tech, Blacksburg, Virginia, USA

[4]Department of Forest Resources and Environmental Conservation, Virginia Tech, Blacksburg, Virginia, US

---

[a] Corresponding author. Address: Department of Biological Sciences, Derring Hall Room 2025, 926 West Campus Drive, Mail Code 0406, Blacksburg, VA 24061, USA. Phone: +1-540-231-0788. Fax: +1-540-231-9307. Email: aslewis@vt.edu, ORCID ID: 0000-0001-9933-4542

[b] Email: wwoelmer@vt.edu, ORCID ID: 0000-0001-5147-3877

[c] Email: hwander@vt.edu, ORCID ID: 0000-0002-3762-6045

[d] Email: dwh1998@vt.edu, ORCID ID: 0000-0002-6118-2149

[e] Email: wsjohn2@vt.edu, ORCID ID: 0000-0002-1564-3290

[f] Email: ryan333@vt.edu, ORCID ID: 0000-0001-6370-3852

[g] Email: melofton@vt.edu, ORCID ID: 0000-0003-3270-1330

[h] Email: hammondnw@vt.edu, ORCID ID: 0000-0003-2975-8280

[i] Email: rachelc1@vt.edu, ORCID ID: 0000-0001-6101-8085

[j] Email: rqthomas@vt.edu, ORCID ID: 0000-0003-1282-7825

[k] Email: cayelan@vt.edu, ORCID ID: 0000-0001-8835-4476

**Open data statement**

Data, metadata, and analysis code are provided as a published data package in the Environmental Data Initiative (EDI) repository (Lewis et al. 2021).

Submitted as a Research Article to *Ecological Applications*

Declarations of interest: none

ABSTRACT

Near-term iterative forecasting is a powerful tool for ecological decision support and has the potential to transform our understanding of ecological predictability. However, to this point, there has been no cross-ecosystem analysis of near-term ecological forecasts, making it difficult to synthesize diverse research efforts and prioritize future developments for this emerging field. In this study, we analyzed 178 near-term (≤10-year forecast horizon) ecological forecasting papers to understand the development and current state of near-term ecological forecasting literature and compare forecast accuracy across scales and variables. Our results indicate that near-term ecological forecasting is widespread and growing: forecasts have been produced for sites on all seven continents and the rate of forecast publication is increasing over time. As forecast production has accelerated, a number of best practices have been proposed and application of these best practices is increasing. In particular, data publication, forecast archiving, and workflow automation have all increased significantly over time. However, adoption of proposed best practices remains low overall: for example, despite the fact that uncertainty is often cited as an essential component of an ecological forecast, only 45% of papers included uncertainty in their forecast outputs. As the use of these proposed best practices increases, near-term ecological forecasting has the potential to make significant contributions to our understanding of forecastability across scales and variables. In this study, we found that forecastability (defined here as realized forecast accuracy) decreased in predictable patterns over 1–7 day forecast horizons. Variables that were closely related (i.e., chlorophyll and phytoplankton) displayed very similar trends in forecastability, while more distantly related variables (i.e., pollen and evapotranspiration) exhibited significantly different patterns. Increasing use of proposed best practices in ecological forecasting will allow us to examine the

forecastability of additional variables and timescales in the future, providing a robust analysis of the fundamental predictability of ecological variables.

KEY WORDS

Data assimilation, decision support, ecological predictability, forecast automation, forecast horizon, forecast evaluation, forecast uncertainty, iterative forecasting, near-term forecast, null model, open science, uncertainty partitioning

## INTRODUCTION

Nearly 90 years ago, Hodgson (1932) published what was arguably the first near-term ecological forecast, using demographic trends to predict herring age structure one year into the future. Hodgson concluded by stating "... we hope that before long these prognostications will be issued with the same confidence as those which are broadcast daily by the Meteorological Office, and, once they are received with confidence by the trade, they should be of considerable financial value" (p. 118). During the past 90 years, advances in data availability, computational power, and statistical methodologies have enabled a substantial increase in the development and application of near-term ecological forecasts (Luo et al. 2011, Petrovskii and Petrovskaya 2012, Hampton et al. 2013, LaDeau et al. 2017). Near-term ecological forecasting has become an increasingly powerful tool for ecological decision support (Dietze 2017a, Henden et al. 2020, Carey et al. 2021) and has the potential to provide new insights into fundamental questions about ecological functioning and predictability (Petchey et al. 2015, Dietze 2017b, Dietze et al. 2018). However, to this point, there has been no systematic analysis of the development or current state of near-term ecological forecasting literature, making it difficult to synthesize diverse research efforts and prioritize future developments for this emerging field.

Throughout the development of near-term ecological forecasting, there have been numerous calls for the adoption of standardized best practices (e.g., Clark et al. 2001, Pielke and Conant 2003, Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021). Developing and adhering to best practices advances the contributions of forecasting to both basic and applied research, as it allows for comparisons of forecast accuracy across forecast horizons (the amount of time into the future for which predictions are made) and increases the reliability of forecast products as decision support tools (Armstrong 2001). Recent interest in establishing best practices for ecological forecasting follows similar efforts in meteorology and economics, disciplines in which forecasting is well-established (Armstrong 2001, Hyndman and Athanasopoulos 2018).

While proposed best practices for near-term ecological forecasting differ among papers, a number of common themes related to forecast development, assessment, archiving, and decision support can be identified (Box 1; Appendix S1). As ecological forecasting has developed over the past several decades, we expect that adherence to these proposed best practices is increasing. However, without a comprehensive review of published ecological forecasts, it is difficult to assess which of the proposed best practices have been adopted and which should be prioritized for further advancement of the field (e.g., see Payne et al. 2017 for marine ecological forecasting). Ideally, best practices should evolve using a community-driven approach to enable buy-in and robustness to many applications (following Hanson et al. 2016); consequently, the list of proposed best practices in Box 1 is not exhaustive, and some of the practices may not be appropriate for every forecasting application. However, these practices provide a framework to begin analyzing the state of the field.

Adoption of these proposed best practices in near-term ecological forecasting may be particularly important to improving our understanding of forecastability across scales and variables. As the number of published near-term ecological forecasts has increased over the past several decades (Luo et al. 2011, Dietze et al. 2018), we now have an unprecedented opportunity to compare across studies and analyze the relative forecastability (defined here as realized forecast accuracy) of environmental variables at varying forecast horizons. Understanding ecological predictability is a fundamental goal in ecology (e.g., Gleason 1926, Clements 1936, Sutherland et al. 2013, Godfray and May 2014, Houlahan et al. 2017, and references therein) and provides valuable information regarding the nature of ecological processes (Petchey et al. 2015). Ecological forecasting can be a particularly powerful test of predictability, as forecasting requires predicting beyond the range of observed data (Dietze et al. 2018). Thus, comparisons of forecastability complement and extend existing theoretical and modeling-based work that has predicted how various factors (e.g., forecast horizon, computational irreducibility) influence the relative predictability of ecological variables (Beckage et al. 2011, Petchey et al. 2015).

In this study, we performed a systematic analysis of near-term ecological forecasting papers to examine the use of our proposed best practices over time (Box 1). To illustrate how proposed best practices can enable insights into fundamental ecological understanding, we then compared forecast accuracy across scales and variables. We discuss the implications of our findings for further development and adoption of best practices within the near-term ecological forecasting research community.



## METHODS

We systematically reviewed literature on near-term ecological forecasting to determine how proposed best practices have been implemented over time and compare forecastability across ecosystems. First, we searched the Web of Science™ Core Collection [v.5.34] database (Clarivate Analytics, Philadelphia, USA) and reviewed abstracts to identify papers that reported near-term ecological forecasts (described in *Literature search* below). Two reviewers then independently read and analyzed each selected paper using a standardized matrix of criteria (*Matrix analysis*) and recorded forecast accuracy when reported. Once collated, we analyzed the full dataset to understand the development and current state of ecological forecasting (*Dataset description* and *Assessment of forecasting best practice adoption*). Finally, we analyzed forecast evaluation data to assess how forecast performance varied with forecast horizon for ecological variables with sufficient data (*Comparing forecast accuracy across ecosystem and models*).

**Literature search**

Creating an all-encompassing search query to identify near-term ecological forecasts presented three challenges: first, the term "near-term" was neither universally defined nor used in all papers that report near-term forecasts; second, there was no one search term that can match all papers describing ecological variables; and third, many papers used the word "forecast" when talking about implications of their research, despite not actually reporting forecasting results in the paper. To address these challenges, we began by querying the Web of Science Core Collection [v.5.34] for "forecast*" in the title, abstract, or keywords of papers published in 301 ecological journals, then manually screened abstracts of all resulting papers. We conducted the Web of Science search on 18 May 2020 and limited the search to articles and proceedings papers (hereafter, 'papers') published in English. This yielded 2711 results (Fig. 1).

We screened the abstracts of all 2711 papers and selected those that met three criteria:

1. Papers had to include at least one forecast, which we defined as a prediction of future conditions from the perspective of the model; forecasts could be developed retroactively (i.e., "hindcasts") but could only use driver data that were available before the forecast date (e.g., forecasted or time-lagged driver variables).
2. The forecast had to be near-term, which we defined as predicting ≤10 years into the future (following Dietze et al. 2018).
3. The forecast had to be ecological, which we defined as predicting a biogeochemical, population, or community response variable. This definition therefore excluded physical

(e.g., streamflow or water temperature) and meteorological forecasts. Forecasts of human disease were only included if there was an animal vector.

If the abstract indicated that the paper met all three criteria, it was moved to the second round of screening. Here, a second reviewer read the full paper to ensure that at least one forecast in the paper met all three criteria.

By the end of this screening process, we identified 142 near-term ecological forecasting papers out of the 2711 Web of Science results (Fig. 1a, 1b). The initial Web of Science search did well at identifying studies with ecological focal variables, as 74% of the initial search results were marked as 'ecological' during our review process. However, only 36% of papers from this search actually included forecasts (predicting future conditions from the perspective of the forecast model). Furthermore, of the ecological forecasts identified in this search (n = 669), only 21% met our near-term criteria by including forecast horizons that were ≤10 years; the majority of forecasts predicted ecological changes over multidecadal timescales (Fig. 1b).

Because ecological forecasts may be published in journals that are not categorized as “ecological” by Web of Science, we then searched all papers that were cited by the 142 near-term ecological forecast papers we identified, as well as all papers that cited these studies. From the citing and cited papers, we selected those that were published in English and included “forecast*” in the title, abstract, or keywords, then screened the abstracts using our three criteria described above. Finally, a second reviewer read all papers that passed the abstract screening to confirm that at least one forecast in the paper met all three criteria. Searching the papers that cite and are cited by the near-term ecological forecasting papers from our initial search yielded proportionally more ecological forecasting papers than the initial Web of Science search. Of the 472 search results, 112 (24%) of these papers were identified as near-term ecological forecasts after two rounds of review (Fig. 1a, 1c). Furthermore, this search highlighted predominantly near-term forecasts; 73% of the ecological forecasts identified in this search included forecast horizons that were ≤10 years (Fig. 1c). After combining our initial search with the citing and cited papers, 254 papers were included in our dataset for matrix review (Fig. 1a).

**Matrix analysis**

We analyzed each of the 254 papers using a standardized matrix of questions (Appendix S2). This matrix was co-developed over several months of iteration and discussion by all authors within an Ecological Forecasting graduate seminar at Virginia Tech (January–May 2020). The final matrix used for this study included 58 fields of information about the forecast paper's model(s), evaluation, cyberinfrastructure, archiving, and decision support (Lewis et al. 2021).

During the graduate seminar, we read and analyzed 10 papers as a group, ensuring that all reviewers understood how to interpret and answer questions in a consistent manner. Prior to the start of this analysis, reviewers also screened several papers independently and checked their responses with another reviewer, helping to ensure consistency between reviewers. For the matrix analysis described in this paper, all 254 papers were read and analyzed independently by two reviewers, and reviewers then compared any differing answers to reach consensus on a final set of responses for each paper.

During the matrix analysis, 76 papers were determined to not meet our criteria of being near-term ecological forecasts, despite having passed the initial rounds of screening. These papers typically used one or more data sources that became available after the forecast issue date, which was difficult to identify without reading the entire text, including all supplementary information, in detail. These papers were excluded from the analysis, leaving 178 papers in the final dataset (Fig. 1a).

**Dataset description**

To characterize the current state of near-term ecological forecasting, we began by analyzing the distribution of forecasts presented in the 178 papers across geographical locations, variables, and time scales, as described below.

We classified the spatial scale of each forecast into five categories: point (localized to one discrete site, such as pollen forecasts for a city or algal forecasts for a lake), multipoint (several distinct forecast locations, such as three different lakes), regional (localized to a broad geographic region, such as coral bleaching forecasts that span a sea), national (spanning all of one nation, such as nationwide production of an agricultural crop), or global (such as coral bleaching stress in world oceans), and we calculated the percentage of forecasting papers within each of these categories. We recorded latitude and longitude of the forecast site(s) for point or multipoint forecasts or of the approximate centroid of the site for regional and national forecasts.

Forecast variables were divided into two categories: organismal (population and community; e.g., white-tailed deer populations) and biogeochemical (e.g., evapotranspiration), and each paper was classified within one of 11 ecosystem types: forest, grassland, freshwater, marine, desert, tundra, atmosphere, agricultural, urban, global, other, where "other" included any ecosystem types that could not be classified within one of the other 10 categories (e.g., plant phenology across the entire United States). We recorded the number of years of data used to create each forecasting paper (summed across model development, training, evaluation, etc.) and calculated the percentage of papers that used long-term datasets in their analysis, using the definition of long-term as any dataset with more than 10 years of data (Lindenmayer et al. 2012).

**Assessment of forecasting best practice adoption**

We synthesized proposed best practices for ecological forecasting from four recent papers—Harris et al. (2018), Hobday et al. (2019), Carey et al. (2021), and White et al. (2019), then selected all practices that were mentioned in at least two of these papers (Appendix S1). To analyze how adherence to the nine selected best practices has changed over time, we performed binary logistic regressions assessing how adoption of each best practice (binary yes/no) varied with publication year. Hodgson (1932) was excluded from this best practice analysis as a temporal outlier, leaving a dataset of papers published between 1980 and 2020. We used the following criteria in the matrix analysis to assess which proposed best practices (Box 1) were included in each forecasting paper:

*Forecast Requirements*

1. "Include uncertainty": uncertainty was included in forecast outputs
2. "Report forecast accuracy": any form of forecast evaluation was reported (this includes figures that compare forecasts and observations, as well as any evaluation metric)

*Decision Support*

3. "Identify an end user": A specific end user was mentioned
4. "Make iterative forecasts": Forecasts were made repeatedly, incorporating new data over time. For this practice, we included all types of data assimilation, including those that only updated the initial conditions of the forecast. As a separate analysis, we also

determined whether the use of data assimilation methods that updated the parameters of the model (not just initial conditions) have increased over time

5. "Automate forecasting workflows": at least one source of new driver and/or observation data was made available to the model in real time (<24 hours from collection) without any manual effort when the forecasting system was working as intended

*Research*

6. "Make data available": Data availability was specified
7. "Archive forecasts": Text specified that forecasts were archived and available
8. "Use null model comparisons": Forecasts were compared to a null model (e.g., a persistence or climatology null model)
9. "Compare modeling approaches": At least two modeling approaches that have different model structures (not including null models) were compared

All analyses were performed using R version 4.0.3 (R Core Team 2020).



**Comparison of forecast performance across scales and variables**

To compare forecast performance across forecast variables, sites, and scales, it was necessary to identify an evaluation metric that is not dependent on the units or range of the forecast variable. For reasons discussed below, we chose $R^2$ as our metric of forecast performance in this analysis. Petchey et al. (2015) recommend using the length of time until a forecast performs no better than a relevant threshold value as one way of comparing between papers. However, this type of analysis would require that a threshold value be determined equitably for each forecast variable, which would be challenging across the numerous variables in our dataset. Performance of null models offers one objective way of determining these threshold values, but null models were not commonly reported in this dataset. Another means of comparing forecast performance would be to directly compare forecast accuracy using a standardized statistical score. Commonly used forecast evaluation metrics include root mean squared error (RMSE), mean absolute error (MAE), the coefficient of determination ($R^2$), and bias (Petchey et al. 2015, Dietze 2017a). To fully assess probabilistic forecasts, the continuous ranked probability score (CRPS) and ignorance can also be used (Roulston and Smith 2002, Gneiting et al. 2005). Among these, only $R^2$ allows comparisons between forecasts that have different native units or forecasts for the same variable in very different ranges. Furthermore, more papers reported Pearson's r or $R^2$ (n = 56, 42%) than any other forecast performance metric in this dataset: for comparison, only 34% included RMSE and 20% included MAE. While the fact that $R^2$ is typically bias-corrected makes it an imperfect metric of forecast performance, it remains widely reported and uniquely suited to inter-study comparisons.

We recorded all $R^2$ and Pearson's r data reported in papers in the dataset. Pearson's r values were squared to yield $R^2$ (following Rousso et al. 2020). We selected all forecast variables that had at least three papers and three forecast horizons represented, and we plotted forecast performance (in $R^2$) as a function of forecast horizon for these variables. To allow comparability between variables, we limited the analysis to forecast horizons between one and seven days, which were reported for all variables selected. Because some papers reported $R^2$ individually for each plot, site, or year and others reported one overall evaluation per model, we averaged all $R^2$ across sites and years for forecasts that used the same model within each paper.

We used indicator variable analysis (Draper and Smith 1998) to compare the slope of $R^2$ values over 1–7 day horizons among forecast variables by performing a 50% quantile regression that predicted $R^2$ based upon indicator ("dummy") predictors for all forecast variables, as well as terms for the interaction between all forecast variables and forecast horizon. Quantile regression was used rather than standard linear regression to account for heteroscedasticity and non-normal data distribution. The regression was performed using the package "quantreg" in R (Koenker et al. 2021). Indicator analysis compares the slope and intercept of the first indicator ("reference" indicator) to all subsequent indicators (Draper and Smith 1998). In this case, chlorophyll was used as the reference indicator to enable comparisons between phytoplankton and chlorophyll, two closely related forecast variables. We analyzed which terms were significant in the model to determine how patterns in forecast performance over time differed among forecast variables: significance was determined using the "wild" bootstrapping method to account for heteroskedasticity (Feng et al. 2011).



RESULTS

**Dataset description**

The number of ecological forecasts published each year has increased substantially over time: more papers were published in the last seven years of the dataset (2014–2020) than in the first 82 years (1932–2013; Fig. 2). Forecast sites for these papers were located on all seven continents (Fig 3a). The majority of forecast sites were located in the northern hemisphere (n = 211, 91%), especially the United States, China, and Western Europe (Fig. 3a). The geographic scale of the forecasts was most often either point (n = 66, 37%), or regional (n = 66, 37%; Fig. 3b).

More ecological forecasts predicted organismal (population and community) variables than biogeochemical variables. Very few papers included forecasts for both biogeochemical and organismal focal variables (organismal: n = 146, 82%; biogeochemical: n = 43, 24%; both: n =

11, 6%; Fig. 3c). The majority of papers predicted ecological processes in either marine (n = 49, 28%), freshwater (n = 41, 23%), or agricultural (n = 34, 19%) ecosystems (Fig. 3). In particular, many papers predicted fish taxa (n = 25), phytoplankton taxa (n = 20), chlorophyll (n = 14), evapotranspiration (n = 14), pollen (n = 10), and crop yield (n = 9).

Papers in this dataset included forecasts at a wide range of forecast horizons and were developed using diverse time steps, forecast horizons, and datasets. Among the forecasts surveyed in this analysis, 75% of papers predicted within one year into the future (n = 130; Fig. 4). In particular, many papers either predicted 2–7 days into the future on a daily time step (n = 39, 23% of all papers) or one year into the future on a yearly time step (n = 30, 17%; Fig. 4). The median temporal duration of data used to create a forecasting paper (summed over model development, training, evaluation, etc.) was 15 years (min. = 17 days, mean = 19.2 years, max. = 145 years; Fig. 5), and 60% of papers (n = 107) used more than 10 years of data in the forecast paper.

The 178 papers included in this analysis were published in 114 unique journals and conference proceedings (103 journals, 11 conferences). The journal with the greatest number of papers represented in the dataset was *Ecological Applications*, which published a total of 14 near-term ecological forecasting papers.

**Adoption of proposed best practices is low but increasing over time**

Overall rates of best practice use are low but may be increasing. On average, papers used three of the proposed nine best practices (median and mode = 3, mean = 2.83), but there was considerable variation: seven papers did not use any of the best practices, and one paper used eight of the best practices. The percentage of papers that demonstrated a given best practice did not exceed 50% for any practice except “Report forecast accuracy” (Fig. 6). All but one (“Use null model comparisons”) of our proposed best practices have been increasingly adopted over time. However, the increase in adoption with time was only statistically significant ($p < 0.05$) for three practices: “Automate forecasting workflows,” “Archive forecasts,” and “Make data available” (Fig. 6; Table 1).

Of the *Forecast Requirement* best practices, “Include uncertainty” was demonstrated in 45% of papers and “Report forecast accuracy” was demonstrated in 75% of papers. Both of the *Forecast Requirement* best practices show a positive trend in adoption, though neither had a statistically significant relationship with publication year (Fig. 6; Table 1). When uncertainty was included in forecasts ($n = 80$), the most commonly included uncertainty sources were observation uncertainty (48%), process uncertainty (40%), and parameter uncertainty (35%). Driver uncertainty was included in 23% of papers that report uncertainty, and initial condition uncertainty was included in 18%. Of the 80 papers that reported uncertainty, 55% did not specify a data-driven origin of this uncertainty (e.g., ensemble model parameters, forecasted meteorological driver data) in the text. Only three papers partitioned uncertainty sources (Caughlin et al. 2019, Geremia et al. 2014, Dietze 2017b), and all of these papers were published in or after 2014. All three papers quantified the influence of process, initial condition, and parameter uncertainty, and one partitioned driver uncertainty. Process uncertainty dominated total uncertainty for two papers (Geremia et al. 2014, Dietze 2017b), while initial condition uncertainty dominated in the third paper (Caughlin et al. 2019). Over 70% of forecasts that did not report forecast evaluation in the text ($n = 44$) predicted at forecast horizons of at least one year; in comparison, 47% predicted at forecast horizons of at least one year in the dataset as a whole. As noted in the Methods, the most commonly reported metric of forecast performance was $R^2$.

Overall, 20% of papers identified a specific end user, 39% of papers made iterative forecasts, and 11% of papers included automated forecasting workflows. All three of these proposed best practices ("Identify an end user", "Make iterative forecasts", "Automate forecasting workflows") in the *Decision Support* tier showed positive relationships with publication year, but only "Automate forecasting workflows" significantly increased over time (Fig. 6, Table 1). Of the papers that mentioned a specific end user (n = 35), 31% mentioned that the end user aided in forecast development and 46% mentioned that forecasts were in use by the end user. Data assimilation for iterative forecasts most often updated initial conditions but not parameters of the model (67% of the 69 iterative forecasts only updated initial conditions). However, data assimilation methods that updated the parameters of the model (not just initial conditions) have increased significantly over time (Table 1).

Overall, there was a wide range in the percentage of papers that used *Research* tier best practices. “Make data available” was demonstrated in 25% of papers, “Archive forecasts” was demonstrated in 8% of papers, “Use null model comparisons” was demonstrated in 12% of papers, and “Compare modeling approaches” was demonstrated in 47% of papers. Two of the five *Research* tier practices have increased significantly over time (“Make data available” and “Archive forecasts”; Table 1). “Use null model comparisons” was the only practice that has decreased in adoption over time (Fig. 6). For papers that described forecast archiving (n = 15), the most common repository for archived forecasts was Zenodo (used in 20% of papers that archive forecasts); other papers used websites or other archives specific to the forecasting project. Only two of the seven papers that mentioned archiving forecasts on a website had links that were still functional as of 14 Jun 2021. Of the papers that used null models in this study (n = 21), 62% used persistence null models and 48% used climatology null models. Two papers used both persistence and climatology null models. Of the papers that compared multiple modeling approaches (n = 84), a median of 3 different approaches were included (not including null models; mean = 5.4, max. = 49).

**Declines in forecast performance over increasing forecast horizons differ between variables**

Forecast accuracy data ($R^2$) from at least three papers on 1–7 day forecast horizons were available for four forecast variables: chlorophyll, phytoplankton taxa, pollen, and evapotranspiration (ET). Forecast performance decreased with increasing forecast horizon for all forecast variables (Fig. 7, Table 2). The slope and intercept of forecast accuracy over increasing forecast horizons differed between variables, as revealed in our indicator analysis: the intercepts for pollen and ET were significantly lower than for chlorophyll, the reference indicator. In comparison to chlorophyll, forecast accuracy for pollen and ET decreased significantly more slowly over time. Unsurprisingly, the intercept and slope of phytoplankton were not significantly different from the intercept and slope of chlorophyll, the reference indicator (Fig. 7, Table 2).

DISCUSSION

Our systematic analysis of 178 near-term ecological forecasting papers demonstrates that the field of near-term ecological forecasting is widespread and growing: forecasts have been produced on all seven continents, and the rate of forecast publication is increasing over time. Although the overall implementation of proposed best practices is low, best practice use is increasing. In particular, the use of automated forecasting workflows, making data available, and archiving forecasts are all increasing significantly over time. We used this dataset of published studies to compare forecast accuracy across scales and variables, and we found that forecast accuracy decreased in consistent patterns over 1–7 day forecast horizons. Variables that were closely related (i.e., chlorophyll and phytoplankton) displayed very similar trends in predictability over increasing forecast horizons, while more distantly related variables (i.e., pollen, evapotranspiration) exhibited significantly different patterns.

**Near-term ecological forecasting: state of the field**

As publication of near-term ecological forecasts continues to accelerate, evaluating the state of the field now can provide critical insight to help prioritize areas of improvement moving forward. Below, we discuss aspects of near-term ecological forecasting that are well-developed, those that are improving over time, and areas that may need improvement based upon the results of this analysis.

*Well-developed practices in near-term ecological forecasting: high rates of forecast assessment and model comparison*

Only one out of the nine proposed best practices was demonstrated in more than half of the papers in this analysis: report forecast accuracy. In this study, high rates of forecast assessment and reporting allowed us to compare forecast performance across scales and variables. While $R^2$ was the most commonly reported forecast evaluation metric and served as an effective accuracy score for this preliminary analysis, it would be preferable to use a metric of forecast performance that is not bias-corrected. Other scale-independent metrics of forecast performance include percentage errors (e.g., mean absolute percentage error; MAPE) or scaled errors (e.g., mean absolute scaled error; MASE; Hyndman and Athanasopoulos 2018). Percentage errors are not universally applicable because they penalize a lack of precision more heavily in a range closer to zero (in the units of the forecast), which is not valid for a number of forecast variables (e.g., temperature in units of Fahrenheit or Celsius, net ecosystem exchange of carbon dioxide; Hyndman and Athanasopoulos 2018). Scaled errors may present the most effective means of comparing forecasts with different ranges and units, however, they require choosing a relevant null model (Hyndman and Athanasopoulos 2018), which is currently not common in near-term ecological forecasting literature (Fig. 6).

Of the papers that did not assess and report any metric of forecast accuracy, many (77%) predicted at forecast horizons greater than or equal to one year, suggesting that part of the reason these papers did not assess forecast accuracy may be the long time lag before data would be available for forecast evaluation. In cases when the forecast horizon is too far into the future to evaluate results, researchers could consider making and evaluating additional forecasts at short horizons to provide at least an intermediate evaluation of their forecasting system (Harris et al. 2018). Assessing hindcasts may also provide a means of evaluating the forecasting system, given sufficient historical data.

Notably, many papers that included forecast assessment also compared multiple modeling approaches; 47% of papers in the dataset included model comparisons, despite the fact that this is a *Research* tier practice and may not be relevant to all applications. These high rates of model comparison may facilitate future analyses that determine relevant model structures for a variety of ecological applications (e.g., see Rousso et al. 2020).

*Developments in near-term ecological forecasting: increasing automation and use of open science practices*

Over time, near-term ecological forecasting is becoming increasingly automated, creating forecast products that enable real-time decision support (Dietze et al. 2018). Forecast automation can be beneficial to decision support because it decreases the amount of manual effort required to create each forecast once the automated system is set up and thereby increases the sustainability of iterative forecasting workflows (White et al. 2019, Hobday et al. 2019, Carey et al. 2021). However, it is important to note that automated forecasting workflows may still require significant human effort to maintain cyberinfrastructure over time (Carey et al. 2021). While the increase in use of iterative forecasts over time was not statistically significant, the percentage of papers that use iterative workflows to update model parameters rather than just the initial conditions of the forecast has increased significantly (Table 1). Updating model parameters as new data are incorporated allows the forecasting system to learn over time and potentially make more accurate predictions in the future (Luo et al. 2011, Niu et al. 2014, Zwart et al. 2019).

Another area of promise is in the adoption of open scientific practices: both data publication and forecast archiving have increased significantly over the past 40 years. These advances likely reflect a broader movement for open scientific practices that has gained momentum over the past decade in response to intersecting needs for greater reproducible science, knowledge dissemination, and collaboration (e.g., Reichman et al. 2011, Fecher and Friesike 2013, Beardsley 2014, Wilkinson et al. 2016, Munafò et al. 2017, Powers and Hampton 2019). Further increases in the use of open scientific practices have the potential to increase the reproducibility of published forecasting literature while fostering collaboration and accelerating the development of the field.

*Priorities for the future development of near-term ecological forecasting: uncertainty, end user engagement, and null models*

One of the most notable gaps identified in this analysis is the lack of specified uncertainty in published forecasts. Meaningful representations of uncertainty are considered so critical to forecast interpretation and evaluation that many definitions of ecological forecasts include uncertainty as an essential component (e.g., Clark et al. 2001, Luo et al. 2011, Harris et al. 2018, Dietze et al. 2018, Carey et al. 2021). However, only 45% of papers included uncertainty in their forecasts. Lack of forecast uncertainty can be problematic in decision support because when uncertainty is not specified in a forecast output, forecast users create their own, often inaccurate, expectations of forecast uncertainty (Morss et al. 2008, Joslyn and Savelli 2010).

Moving beyond specifying uncertainty to partitioning uncertainty into its component parts (e.g., initial condition, driver, parameter, and process uncertainty) provides information to help forecast developers prioritize improvements to their forecasting system and allows researchers to understand the constraints to predictability for a given ecological variable (Dietze 2017b). It is well established that forecasting meteorological conditions is a fundamentally chaotic problem, dominated by initial condition uncertainty (Kalnay 2003). Due to stabilizing feedbacks in ecological systems (e.g., carrying capacity, functional redundancy), other components of uncertainty are hypothesized to dominate ecological forecasts (Dietze 2017b). This hypothesis is partially supported by our dataset: initial condition uncertainty was the dominant source of forecast uncertainty in only one of three papers that partitioned uncertainty in this analysis. However, because uncertainty partitioning is a relatively new development in ecological forecasting, the small number of studies that partition uncertainty currently prevents us from making conclusions about the limiting factors for predictability across variables and forecast horizons.

While not all of the near-term ecological forecasts described in our dataset were designed for decision support, approximately 20% of papers mentioned a specific end user for their forecasts. Of these, nearly half specify that the forecasting system was in use by the specified end user (e.g., drinking water management organization, coral reef conservation agency, etc.). Designing forecasts for end users involves a variety of ethical considerations, including equity for end users, communication of forecast accuracy, and stakeholder education (Hobday et al. 2019). However, it was rare for a paper to include any explicit mention of ethical considerations made in designing the forecast (5% of papers overall; 25% of forecasts that are in use by an end user). Given the power of forecasts to inform decision support, education on how to navigate engagement with end users, and particularly any ethical considerations that must be made, may be useful in improving the utility of forecasts for stakeholder use.

In this study, we found that the use of null model comparisons remains low and has not increased in adoption over time, despite the importance of this practice for contextualizing forecast skill (Harris et al. 2018, Dietze et al. 2018, White et al. 2019). For meteorological forecasting, comparing forecasts to a climatological null model has proved useful as a means of analyzing the limit of predictive skill and the comparative performance of weather forecasts across spatial and temporal scales (Buizza and Leutbecher 2015). Parallel advances in ecological forecasting may be enabled through increased use of null model comparisons in the future (Petchey et al. 2015, Hyndman and Athanasopoulos 2018).

**Published forecasts provide insight into forecastability across scales and variables**

Analyzing forecastability across variables, we found that aquatic chlorophyll and phytoplankton taxa were more predictable than pollen and evapotranspiration at the shortest forecast horizons (chlorophyll: 1–5 days; phytoplankton: 1–7 days). However, the predictability of chlorophyll and phytoplankton decayed faster over increasing forecast horizons than that of evapotranspiration and pollen. Similar patterns in forecast performance for chlorophyll and phytoplankton likely result from the fact that these two ecological variables are closely related. Greater predictability of chlorophyll and phytoplankton than evapotranspiration and pollen at short forecast horizons likely indicates a greater degree of autocorrelation in these processes (Reynolds 2006), but predictability quickly decays over time due to bloom dynamics (e.g., Rigosi et al. 2011, Recknagel et al. 2016). The consistency of these patterns across 3–10 different papers for each forecast variable suggests that the relationship between forecast performance and forecast horizon could be a robust indicator of the predictability of other ecological processes.

While this is a preliminary analysis limited to four ecological variables, it is among the first comparative tests that have analyzed forecastability across scales and variables, building on two previously published studies. Ward et al. (2014) analyzed the ability of multiple time-series models to predict 2379 vertebrate population datasets. They found that increased forecast performance (measured using MASE) was correlated with long lifespans and large body size for fish and high trophic level for birds over 1–5 year forecast horizons. Additionally, Rousso et al. (2020) performed a systematic review of cyanobacterial bloom forecasting literature and analyzed the relationship between forecast performance ($R^2$) and forecast horizon for three types of models: artificial neural networks, decision trees, and genetic programming. They found that forecast performance decreased over 1–30 day forecast horizons, and forecasts created using greater amounts of historical data had superior forecast performance. Altogether, these first analyses of the forecastability of ecological variables highlight the growing applicability of forecasting to inform our understanding of ecological predictability.

Accelerating forecast publication and increased adoption of proposed best practices will increase the statistical strength of future analyses to detect trends in forecast performance over increasing forecast horizons, including possible non-linear patterns. In particular, increased assessment and reporting of forecast accuracy ensures that published papers can be included in a meta-analysis of predictability; increased data publication allows reevaluation of forecasts; increased forecast archiving addresses publication biases in forecast results; increased use of null models allows researchers to analyze how the maximum length of time until a forecast performs no better than the null differs among variables; and increased quantification of uncertainty allows researchers to compare how uncertainty sources differ across scales and variables.



**Literature search process: observations and limitations**

While the rates of adoption of these proposed best practices (Box 1) are low overall, they are not necessarily unexpected. Different forecasting applications likely require different best practices; in this analysis, we have divided our selected best practices among three categories: *Forecast Requirements*, *Decision Support*, and *Research*. However, this is a coarse delineation, and the last two tiers are not mutually exclusive: *Decision Support* practices can also be important for ecological understanding and vice versa. Ecological forecasting is an emerging discipline and many of these methods are still in development; notably, our list of proposed best practices was derived from papers that were all published within the last four years of the dataset (Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021; Appendix S1). Ideally, best practices should evolve using a community-driven approach to enable buy-in and robustness to many applications (following Hanson et al. 2016). Armstrong (2001) proposed as many as 139 principles for forecasting at large, all of which could be relevant to ecological forecasting applications. If one had to wait to publish a forecast until it satisfied all potential best practices, it is likely that no forecasting papers would ever be published. Increasing the number of published ecological forecasts benefits the field of ecological forecasting even if forecasts do not follow all proposed best practices because the research community gains increasingly more information about the forecastability of ecological variables and the tools and techniques needed to make effective forecasts (Dietze et al. 2018). Still, as near-term ecological forecasting continues to grow, assessing the rate of best practice adoption now allows researchers to identify and prioritize areas for growth and education, simultaneously advancing the basic and applied value of ecological forecasting.

Results from our literature search process highlight the decentralized nature of near-term ecological forecasting and the challenges associated with systematically reviewing this literature. The 178 near-term ecological forecasting papers in this analysis came from 114 unique journals and conference proceedings, and no one journal published more than 15 near-term ecological forecasts papers in this analysis. Decentralized forecast publications may present a barrier to those interested in this literature, particularly because there is no one search term that comprehensively surveys the current near-term ecological forecasting literature. Many papers do not explicitly use the terms “near-term” or “ecological” when describing forecasts for a particular application, and only 5% of the results from our initial search for the term “forecast*” in ecology-related journal articles were identified as near-term ecological forecasts after two rounds of review (Fig. 1). By systematically reviewing and synthesizing near-term ecological forecasting literature published to date, we aim to begin addressing this gap.

Importantly, this comprehensive analysis of near-term ecological forecasting literature is limited to published forecast results. Operational forecasting systems that have not been described in peer-reviewed literature were not included (e.g., the U.S. National Oceanic and Atmospheric Administration, NOAA, has multiple operational forecasting systems for harmful algal blooms, fisheries, and coral reef bleaching that are available via websites). We anticipate that this exclusion may affect results in at least three ways: first, because unpublished operational forecasting systems are often used for decision support, the percentage of forecasting systems that connect to a specific end user is likely underrepresented in published literature. Second, both the need to refine forecasting models prior to paper submission and reviewer requests for forecast revisions may make it difficult to publish genuine forecasts. Because of this, most papers in this study are likely hindcasts or forecast reanalyses. Third, because of publication biases (Dickersin 1990, Mlinarić et al. 2017), we anticipate that average forecast performance is artificially inflated in published literature relative to unpublished operational forecasts. As coordination within the near-term ecological forecasting discipline increases, surveying and comparing operational forecasts may become increasingly possible over time.



**Future needs in near-term ecological forecasting**

Looking to the future, advancing the field of near-term ecological forecasting will involve a suite of technological, organizational, and educational advances. First, the low level of adoption of the proposed best practices suggests that increased coordination within the ecological forecasting research community for developing common forecasting standards (e.g., Dietze et al. 2021), best practices, and vocabulary will advance near-term ecological forecasting. Second, we find that incorporation of uncertainty and use of null models are critical gaps in ecological forecasting literature where education may be needed. The creation of additional educational resources will enable more forecasts to be created and facilitate the adoption of best practices in ecological forecasting. Third, our analysis strongly suggests that long-term data are an important resource for near-term ecological forecast development and assessment. In our dataset, 60% of published near-term ecological forecasting studies used >10 years of ecological data when developing, calibrating, and assessing their forecasts (Fig. 5). Long-term support for data collection will likely be necessary to advance the field. Finally, our analysis indicates that near-term ecological forecasting may be disproportionately centered in the northern hemisphere, particularly the United States of America, Western Europe, and China. This result follows the disproportionate representation of these geographic regions across all sciences (UNESCO 2015). Lack of forecast locations in other countries, particularly in the southern hemisphere, is a detriment to the field as a whole, as the full diversity of ecological systems is not represented in ecological forecasting research to date.

While there are a variety of challenges and opportunities facing the development of near-term ecological forecasting, the literature indicates that the field has grown significantly over the past 90 years. Near-term ecological forecasting is now widespread and the rate of forecast publication continues to increase over time. Moving forward, near-term ecological forecasting is well-positioned to transform ecological management and provide critical insight into the predictability of ecological variables.

ACKNOWLEDGMENTS

We thank members of the Ecological Forecasting Initiative (EFI), particularly the Theory working group and the EFI Research Coordination Network (RCN) Steering Committee, for productive discussions throughout the process of writing this paper, and we thank two anonymous reviewers for their helpful revisions. We are also grateful for the assistance of Arpita Das in helping compile $R^2$ values and the Virginia Tech libraries in planning this review and accessing the papers in the analysis. This project was supported by U.S. National Science Foundation (NSF) grants 1737424, 1926050, 1926388, 1933016, and 1933102, as well as NSF Graduate Research Fellowships to ASL and WMW (DGE-1651272).

Authorship contributions: This paper originated in an Ecological Forecasting graduate seminar at Virginia Tech led by CCC and RQT; all authors participated in the seminar and co-developed the matrix used for this analysis. Conceptualization of the project was led by ASL, CCC, JS, RPM, RQT, and WMW. ASL, CCC, MEL, and WMW led the development of methods for the project. All authors contributed to abstract screening and paper review. Data analysis was led by ASL, with input from CCC, HLW, and WMW. ASL, CCC, DWH, HLW, MEL, RPM, and WMW contributed to initial development of the manuscript, which was written by ASL. All authors edited and approved the final manuscript.



REFERENCES

Armstrong, J. S. 2001. Principles of forecasting: a handbook for researchers and practitioners. Springer Science & Business Media, New York.

Beardsley, T. M. 2014. Are you ready for open data? BioScience 64:855–855.

Beckage, B., L. J. Gross, and S. Kauffman. 2011. The limits to prediction in ecological systems.

Ecosphere 2:art125.

Buizza, R., and M. Leutbecher. 2015. The forecast skill horizon. Quarterly Journal of the Royal Meteorological Society 141:3366–3382.

Carey, C. C., W. M. Woelmer, M. E. Lofton, R. J. Figueiredo, B. J. Bookout, R. S. Corrigan, V. Daneshmand, A. G. Hounshell, D. W. Howard, A. S. L. Lewis, R. P. McClure, H. L. Wander, N. K. Ward, and R. Q. Thomas. 2021. Advancing lake and reservoir water quality management with near-term, iterative ecological forecasting. Inland Waters. doi: 10.1080/20442041.2020.1816421

Caughlin T. T., E. I. Damschen, N. M. Haddad, D. J. Levey, C. Warneke, and L. A. Brudvig. 2019. Landscape heterogeneity is key to forecasting outcomes of plant reintroduction. Ecological Applications 29:e01850.

Clark, J. S., S. R. Carpenter, M. Barber, S. Collins, A. Dobson, J. A. Foley, D. M. Lodge, M. Pascual, R. Pielke, W. Pizer, C. Pringle, W. V. Reid, K. A. Rose, O. Sala, W. H. Schlesinger, D. H. Wall, and D. Wear. 2001. Ecological forecasts: an emerging imperative. Science 293:657–660.

Clements, F. E. 1936. Nature and structure of the climax. Journal of ecology, 24:252–284.

Dickersin, K. 1990. The existence of publication bias and risk factors for its occurrence. JAMA 263:1385–1389.

Dietze, M. C. 2017a. Ecological forecasting. Princeton University Press, Princeton.

Dietze, M. C. 2017b. Prediction in ecology: a first-principles framework. Ecological Applications 27:2048–2060.

Dietze, M. C., A. Fox, L. M. Beck-Johnson, J. L. Betancourt, M. B. Hooten, C. S. Jarnevich, T. H. Keitt, M. A. Kenney, C. M. Laney, L. G. Larsen, H. W. Loescher, C. K. Lunch, B. C.

Pijanowski, J. T. Randerson, E. K. Read, A. T. Tredennick, R. Vargas, K. C. Weathers, and E. P. White. 2018. Iterative near-term ecological forecasting: Needs, opportunities, and challenges. Proceedings of the National Academy of Sciences 115:1424–1432.

Dietze, M. C., R. Q. Thomas, J. Peters, C. Boettiger, A. N. Shiklomanov, J. Ashander. 2021. A Community Convention for Ecological Forecasting: Output Files and Metadata. EcoEvoRxiv. doi: 10.32942/osf.io/9dgtq

Draper, N. R., and H. Smith. 1998. Applied regression analysis. John Wiley & Sons.

Fecher, B., and S. Friesike. 2013. Open science: one term, five schools of thought.

Feng, X., X. He, and J. Hu. 2011. Wild bootstrap for quantile regression. Biometrika 98:995–999.

Geremia, C., P. J. White, J. A. Hoeting, R. L. Wallen, F. G. R. Watson, D. Blanton, and N. T. Hobbs. 2014. Integrating population- and individual-level information in a movement model of Yellowstone bison. Ecological Applications 24:346–362.

Gleason, H. A. 1926. The individualistic concept of the plant association. Bulletin of the Torrey botanical club 7–26.

Gneiting, T., A. E. Raftery, A. H. Westveld, and T. Goldman. 2005. Calibrated probabilistic forecasting using ensemble model output statistics and minimum CRPS estimation. Monthly Weather Review 133:1098–1118.

Godfray, H. C. J., and R. M. May. 2014. Open questions: are the dynamics of ecological communities predictable? BMC Biology 12:22.

Hampton, S. E., C. A. Strasser, J. J. Tewksbury, W. K. Gram, A. E. Budden, A. L. Batcheller, C. S. Duke, and J. H. Porter. 2013. Big data and the future of ecology. Frontiers in Ecology and the Environment 11:156–162.

Hanson, P. C., K. C. Weathers, and T. K. Kratz. 2016. Networked lake science: how the Global Lake Ecological Observatory Network (GLEON) works to understand, predict, and communicate lake ecosystem response to global change. Inland Waters 6:543–554.

Harris, D. J., S. D. Taylor, and E. P. White. 2018. Forecasting biodiversity in breeding birds using best practices. PeerJ 6:e4278.

Henden, J.-A., R. A. Ims, N. G. Yoccoz, E. J. Asbjørnsen, A. Stien, J. P. Mellard, T. Tveraa, F. Marolla, and J. U. Jepsen. 2020. End-user involvement to improve predictions and management of populations with complex dynamics and multiple drivers. Ecological Applications 30:e02120.

Hobday, A. J., J. R. Hartog, J. P. Manderson, K. E. Mills, M. J. Oliver, A. J. Pershing, and S. Siedlecki. 2019. Ethical considerations and unanticipated consequences associated with ecological forecasting for marine resources. ICES Journal of Marine Science 76:1244–1256.

Hodgson, W. C. 1932. The forecasting of the East Anglian herring fishery. Journal of Animal Ecology 1:108–118.

Houlahan, J. E., S. T. McKinney, T. M. Anderson, and B. J. McGill. 2017. The priority of prediction in ecological understanding. Oikos 126:1–7.

Hyndman, R. J., and G. Athanasopoulos. 2018. Forecasting: principles and practice. OTexts.

Joslyn, S., and S. Savelli. 2010. Communicating forecast uncertainty: public perception of weather forecast uncertainty. Meteorological Applications 17:180–195.

Kalnay, E. 2003. Atmospheric modeling, data assimilation and predictability. Cambridge University Press, New York.

Koenker, R., S. Portnoy, P. T. Ng, B. Melly, A. Zeileis, P. Grosjean, C. Moler, Y. Saad, V.

Chernozhukov, I. Fernandez-Val, and B. D. Ripley. 2021. quantreg: Quantile Regression.

LaDeau, S. L., B. A. Han, E. J. Rosi-Marshall, and K. C. Weathers. 2017. The next decade of big data in ecosystem science. Ecosystems 20:274–283.

Lewis, A. S. L., W. M. Woelmer, H. L. Wander, D. W. Howard, J. W. Smith, R. P. McClure, M. E. Lofton, N. W. Hammond, R. S. Corrigan, R. Q. Thomas, and C. C. Carey. 2021. Systematic review of near-term ecological forecasting literature published between 1932 and 2020. Environmental Data Initiative. https://doi.org/10.6073/pasta/c4bea94f100f39a6b73c7b9a577df214

Lindenmayer, D. B., G. E. Likens, A. Andersen, D. Bowman, C. M. Bull, E. Burns, C. R. Dickman, A. A. Hoffmann, D. A. Keith, M. J. Liddell, A. J. Lowe, D. J. Metcalfe, S. R. Phinn, J. Russell-Smith, N. Thurgate, and G. M. Wardle. 2012. Value of long-term ecological studies. Austral Ecology 37:745–757.

Luo, Y., K. Ogle, C. Tucker, S. Fei, C. Gao, S. LaDeau, J. S. Clark, and D. S. Schimel. 2011. Ecological forecasting and data assimilation in a data-rich era. Ecological Applications 21:1429–1442.

Mlinarić, A., M. Horvat, and V. Šupak Smolčić. 2017. Dealing with the positive publication bias: why you should really publish your negative results. Biochemia Medica 27:447–452.

Morss, R. E., J. L. Demuth, and J. K. Lazo. 2008. Communicating uncertainty in weather forecasts: a survey of the U.S. public. Weather and Forecasting 23:974–991.

Munafò, M. R., B. A. Nosek, D. V. M. Bishop, K. S. Button, C. D. Chambers, N. Percie du Sert, U. Simonsohn, E.-J. Wagenmakers, J. J. Ware, and J. P. A. Ioannidis. 2017. A manifesto for reproducible science. Nature Human Behaviour 1:1–9.

Niu, S., Y. Luo, M. C. Dietze, T. F. Keenan, Z. Shi, J. Li, and F. S. C. Iii. 2014. The role of data assimilation in predictive ecology. Ecosphere 5:art65.

Payne, M. R., , A. J. Hobday, B. R. MacKenzie, D. Tommasi, D. P. Dempsey, S. M. M. Fässler, A. C. Haynie, R. Ji, G. Liu, P. D. Lynch, D. Matei, A. K. Miesner, K. E. Mills, K. O. Strand, and E. Villarino. 2017. Lessons from the first generation of marine ecological forecasts. Frontiers in Marine Science 4:289.

Pennekamp, F., A. C. Iles, J. Garland, G. Brennan, U. Brose, U. Gaedke, U. Jacob, P. Kratina, B. Matthews, S. Munch, M. Novak, G. M. Palamara, B. C. Rall, B. Rosenbaum, A. Tabi, C. Ward, R. Williams, H. Ye, and O. L. Petchey. 2019. The intrinsic predictability of ecological time series and its potential to guide forecasting. Ecological Monographs 89:e01359.

Petchey, O. L., M. Pontarp, T. M. Massie, S. Kéfi, A. Ozgul, M. Weilenmann, G. M. Palamara, F. Altermatt, B. Matthews, J. M. Levine, D. Z. Childs, B. J. McGill, M. E. Schaepman, B. Schmid, P. Spaak, A. P. Beckerman, F. Pennekamp, and I. S. Pearse. 2015. The ecological forecast horizon, and examples of its uses and determinants. Ecology Letters 18:597–611.

Petrovskii, S., and N. Petrovskaya. 2012. Computational ecology as an emerging science. Interface Focus 2:241–254.

Pielke, R. A., and R. T. Conant. 2003. Best practices in prediction for decision-making: lessons from the atmospheric and earth sciences. Ecology 84:1351–1358.

Powers, S. M., and S. E. Hampton. 2019. Open science, reproducibility, and transparency in ecology. Ecological Applications 29:e01822.

R Core Team. 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Recknagel, F., R. Adrian, J. Köhler, and H. Cao. 2016. Threshold quantification and short-term forecasting of Anabaena, Aphanizomenon and Microcystis in the polymictic eutrophic Lake Müggelsee (Germany) by inferential modelling using the hybrid evolutionary algorithm HEA. Hydrobiologia 778:61–74.

Reichman, O. J., M. B. Jones, and M. P. Schildhauer. 2011. Challenges and opportunities of open data in ecology. Science 331:703–705.

Reynolds, C. S. 2006. The ecology of phytoplankton. Cambridge University Press.

Rigosi, A., R. Marcé, C. Escot, and F. J. Rueda. 2011. A calibration strategy for dynamic succession models including several phytoplankton groups. Environmental Modelling & Software 26:697–710.

Roulston, M. S., and L. A. Smith. 2002. Evaluating probabilistic forecasts using information theory. Monthly Weather Review 130:1653–1660.

Rousso, B. Z., E. Bertone, R. Stewart, and D. P. Hamilton. 2020. A systematic literature review of forecasting and predictive models for cyanobacteria blooms in freshwater lakes. Water Research 182:115959.

Sutherland, W. J., R. P. Freckleton, H. C. J. Godfray, S. R. Beissinger, T. Benton, D. D. Cameron, Y. Carmel, D. A. Coomes, T. Coulson, M. C. Emmerson, R. S. Hails, G. C. Hays, D. J. Hodgson, M. J. Hutchings, D. Johnson, J. P. G. Jones, M. J. Keeling, H. Kokko, W. E. Kunin, X. Lambin, O. T. Lewis, Y. Malhi, N. Mieszkowska, E. J. Milner-Gulland, K. Norris, A. B. Phillimore, D. W. Purves, J. M. Reid, D. C. Reuman, K. Thompson, J. M. J. Travis, L. A. Turnbull, D. A. Wardle, and T. Wiegand. 2013. Identification of 100 fundamental ecological questions. Journal of Ecology 101:58–67.

Ward, E. J., E. E. Holmes, J. T. Thorson, and B. Collen. 2014. Complexity is costly: a meta-analysis of parametric and non-parametric methods for short-term population forecasting. Oikos 123:652–661.

White, E. P., G. M. Yenni, S. D. Taylor, E. M. Christensen, E. K. Bledsoe, J. L. Simonis, and S. K. M. Ernest. 2019. Developing an automated iterative near-term forecasting system for an ecological study. Methods in Ecology and Evolution 10:332–344.

Wilkinson, M. D., M. Dumontier, I. J. Aalbersberg, G. Appleton, M. Axton, A. Baak, N. Blomberg, J.-W. Boiten, L. B. da Silva Santos, P. E. Bourne, J. Bouwman, A. J. Brookes, T. Clark, M. Crosas, I. Dillo, O. Dumon, S. Edmunds, C. T. Evelo, R. Finkers, A. Gonzalez-Beltran, A. J. G. Gray, P. Groth, C. Goble, J. S. Grethe, J. Heringa, P. A. C. ’t Hoen, R. Hooft, T. Kuhn, R. Kok, J. Kok, S. J. Lusher, M. E. Martone, A. Mons, A. L. Packer, B. Persson, P. Rocca-Serra, M. Roos, R. van Schaik, S.-A. Sansone, E. Schultes, T. Sengstag, T. Slater, G. Strawn, M. A. Swertz, M. Thompson, J. van der Lei, E. van Mulligen, J. Velterop, A. Waagmeester, P. Wittenburg, K. Wolstencroft, J. Zhao, and B. Mons. 2016. The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data 3:160018.

Zwart, J. A., O. Hararuk, Y. T. Prairie, S. E. Jones, and C. T. Solomon. 2019. Improving estimates and forecasts of lake carbon dynamics using data assimilation. Limnology and Oceanography: Methods 17:97–111.

Box 1: Proposed best practices for ecological forecasting, drawn from peer-reviewed literature: Harris et al. (2018), White et al. (2019), Hobday et al. (2019), and Carey et al. (2021). *Forecast Requirements* include traits of forecasting systems that are essential to the development of a forecast. *Decision Support* practices are those that are particularly helpful if the forecast will be applied as a decision support tool. *Research* practices include characteristics of a forecasting system that are particularly suited to enabling the advancement of fundamental ecological understanding across studies. Importantly, these last two tiers are not mutually exclusive: *Decision Support* practices can also be important for ecological understanding and vice versa.

*Forecast Requirements*

1. Include uncertainty
   a. Meaningful representations of uncertainty are important to forecast interpretation and evaluation, so much so that uncertainty is identified as an essential component of many ecological forecast definitions (Clark et al. 2001, Luo et al. 2011, Harris et al. 2018, Dietze et al. 2018, Carey et al. 2021).
2. Report forecast accuracy
   a. Assessing and reporting forecast accuracy allows end users to understand the reliability of the forecasting system (Harris et al. 2018, Hobday et al. 2019) and provides the near-term ecological forecasting research community with increased insight into the tools and techniques needed to produce effective forecasts (Dietze et al. 2018). Furthermore, assessing and reporting forecast accuracy contributes to our understanding of ecological predictability by facilitating comparisons of forecast accuracy across scales and variables (Beckage et al. 2011, Petchey et al. 2015).

*Decision Support*

3. Identify an end user
    a. One of the goals of ecological forecasting is to aid in decision-making. The first step in this process is to identify a specific end user and consider their needs throughout forecast development (Dietze et al. 2018, Hobday et al. 2019, Carey et al. 2021).
4. Make iterative forecasts
    a. Iterative forecasts incorporate new data as they become available, providing updated predictions that can aid in continuous decision-making and forecast improvement (Dietze et al. 2018, Hobday et al. 2019, Carey et al. 2021).
5. Automate forecasting workflows
    a. End-to-end automation of the forecasting workflow (from data processing to forecast communication) allows for more frequent forecast outputs and more sustainable forecasting infrastructure (Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021). This practice is particularly relevant for forecasts with horizons of days to months that are rerun often to provide updated information.

*Research*

6. Make data available
    a. To ensure full forecast reproducibility and allow future research to build off of existing forecasting workflows, all data and code used to create forecasts should be findable, accessible, interoperable, and reusable (FAIR; Wilkinson et al. 2016, Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Carey et al. 2021).

7. Archive forecasts
    a. Archiving forecasts as they are created provides a means of demonstrating when forecasts were made and tracking forecast improvement over time (Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Carey et al. 2021).
8. Use null model comparisons
    a. Comparing forecasts to simple, standard baselines (e.g., persistence or climatology null models) allows researchers to compare forecastability across systems (Petchey et al. 2015) and evaluate the amount of information contained in the forecasts (Harris et al. 2018, Dietze et al. 2018, White et al. 2019).
9. Compare modeling approaches
    a. Comparing multiple modeling approaches (e.g., process-based and empirical approaches, alternative model drivers, alternative mathematical representations of mechanistic processes) can provide insight into the nature of ecological processes and develop a better understanding of the circumstances under which different modeling approaches are most effective (Harris et al. 2018, White et al. 2019).

862 Table 1: Logistic regression results for each proposed best practice based on n = 177 papers (one paper from 1932 was excluded from this analysis). Statistically significant p values are in bold. In addition to the nine proposed best practices, statistics are included for the use of iterative forecasting to update model parameters.

| | Estimate | Standard error | Z value | P value |
|---|---|---|---|---|
| Include uncertainty | | | | |
| Intercept | -7.615 | 35.157 | -0.217 | 0.83 |
| Year | 0.004 | 0.017 | 0.211 | 0.83 |
| Report forecast accuracy | | | | |
| Intercept | -59.665 | 38.486 | -1.550 | 0.12 |
| Year | 0.030 | 0.019 | 1.579 | 0.11 |
| Identify an end user | | | | |
| Intercept | -86.809 | 52.611 | -1.650 | 0.10 |
| Year | 0.042 | 0.026 | 1.624 | 0.10 |
| Make iterative forecasts | | | | |
| Intercept | -14.147 | 36.152 | -0.391 | 0.70 |
| Year | 0.007 | 0.018 | 0.379 | 0.71 |
| Make iterative forecasts (updating model parameters) | | | | |
| Intercept | -182.741 | 85.680 | -2.133 | **0.03** |
| Year | 0.090 | 0.043 | 2.111 | **0.04** |
| Automate forecasting workflows | | | | |
| Intercept | -237.502 | 100.550 | -2.362 | **0.02** |
| Year | 0.117 | 0.050 | 2.344 | **0.02** |
| Make data available | | | | |
| Intercept | -252.217 | 69.775 | -3.615 | **<0.001** |
| Year | 0.125 | 0.035 | 3.602 | **<0.001** |
| Archive forecasts | | | | |
| Intercept | -308.891 | 136.546 | -2.262 | **0.02** |
| Year | 0.152 | 0.068 | 2.247 | **0.03** |
| Use null model comparisons | | | | |
| Intercept | 33.795 | 50.388 | 0.671 | 0.50 |
| Year | -0.018 | 0.025 | -0.710 | 0.48 |
| Compare modeling approaches | | | | |
| Intercept | -41.332 | 35.718 | -1.157 | 0.25 |
| Year | 0.021 | 0.018 | 1.154 | 0.25 |

866

Table 2: Indicator variable analysis results comparing the slope of $R^2$ values over 1–7 day horizons among forecast variables. Chlorophyll was treated as the reference variable for the analysis. Statistically significant p values are in bold.

| | Estimate | SE | t | P value |
|---|---|---|---|---|
| Chlorophyll (reference; n = 68 data points from 8 papers) | | | | |
| Intercept | 0.98 | 0.025 | 39.53 | **<0.001** |
| Horizon | -0.08 | 0.012 | -6.78 | **<0.001** |
| Phytoplankton (n = 33 data points from 8 papers) | | | | |
| Intercept | 0.04 | 0.055 | 0.71 | 0.48 |
| Horizon | 0.02 | 0.016 | 1.06 | 0.29 |
| Pollen (n = 110 data points from 3 papers) | | | | |
| Intercept | -0.29 | 0.043 | -6.62 | **<0.001** |
| Horizon | 0.05 | 0.014 | 3.94 | **<0.001** |
| Evapotranspiration (n = 113 data points from 10 papers) | | | | |
| Intercept | -0.26 | 0.059 | -4.40 | **<0.001** |
| Horizon | 0.05 | 0.015 | 3.46 | **<0.001** |

FIGURE LEGENDS

Figure 1: Systematic literature analysis methods. a: Flow chart of literature review process. b and c: Venn diagrams illustrating the number of studies that met each of our three criteria after two rounds of review (abstract and paper reviews) for our original Web of Science search (b) and a search of citing and cited papers (c).

Figure 2: Number of near-term ecological forecasts published per year. Five papers from the final year (2020) are not plotted because data for this year are incomplete: only papers indexed on Web of Science by the date of our search (18 May 2020) were included in this study.

Figure 3: Description of ecological forecasting papers identified in this study. a: Map of all forecasts: regional and national studies are shown in large transparent points near the center of the forecast region, while point and multipoint forecasts are shown in small opaque points. b: Bar chart illustrating the spatial extent of the forecast for each paper—point, multipoint (several distinct points), regional (a broad region that does not follow national bounds), national, or global (for details about how spatial extent was determined, see Lewis et al. 2021). c: Bar chart illustrating the class—organismal (population or community) or biogeochemical—of the forecast variable for each paper. Fill colors illustrate ecosystem type. Forecasts that could not be matched to one of our nine ecosystem types have been labeled "other."

Figure 4: Relationship between time step and forecast horizon of forecasting papers. Colors and numbers within each square indicate the number of papers corresponding to that combination of time step and forecast horizon (darker colors indicate more common combinations). White areas

indicate combinations of time step and horizon that were not represented in the dataset. Papers that did not have a defined horizon (e.g., predicting end of summer harvest) or that did not specify time step/horizon were omitted (n = 10).

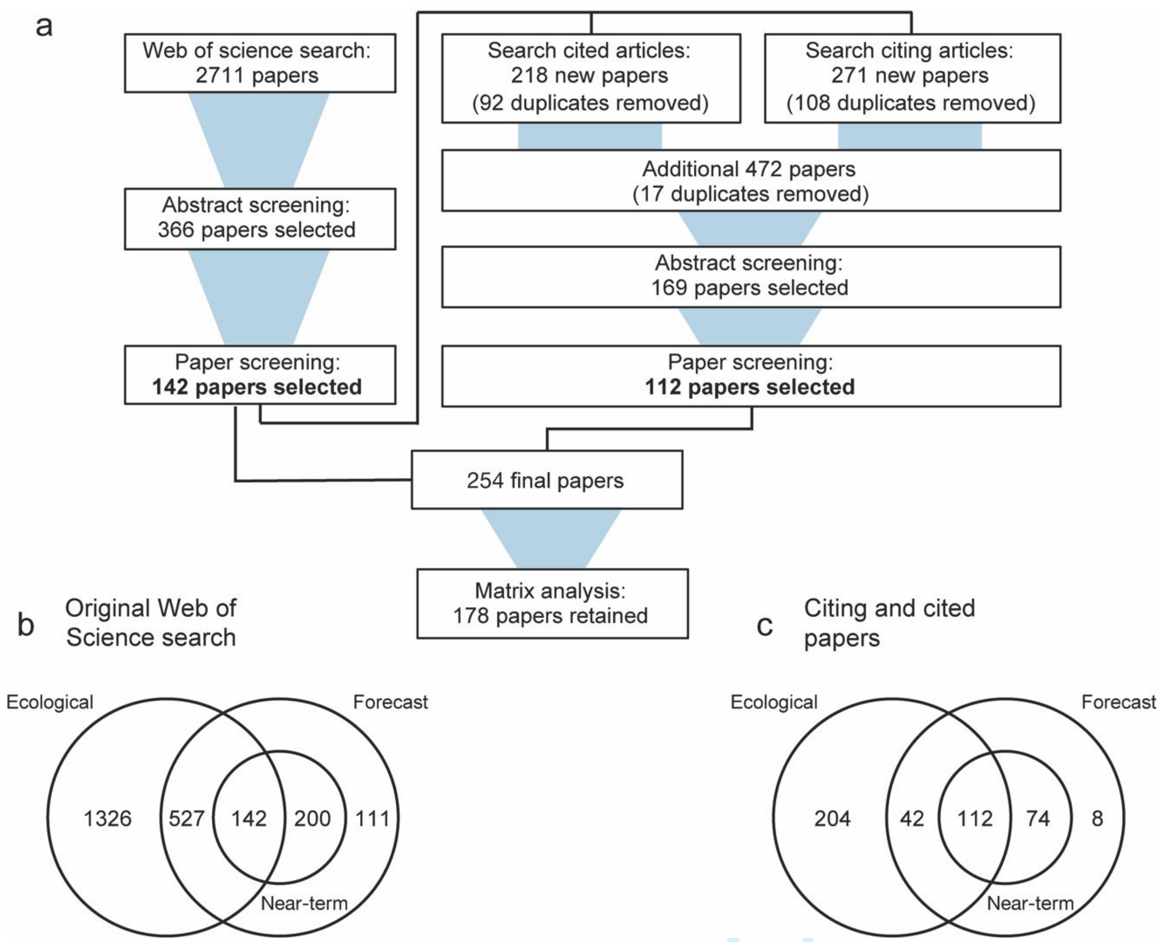
Figure 5: Histogram illustrating the total number of years of data used to develop each forecasting paper, summed across model development, training, evaluation, etc. Vertical lines represent the median (left) and mean (right) number of years used.



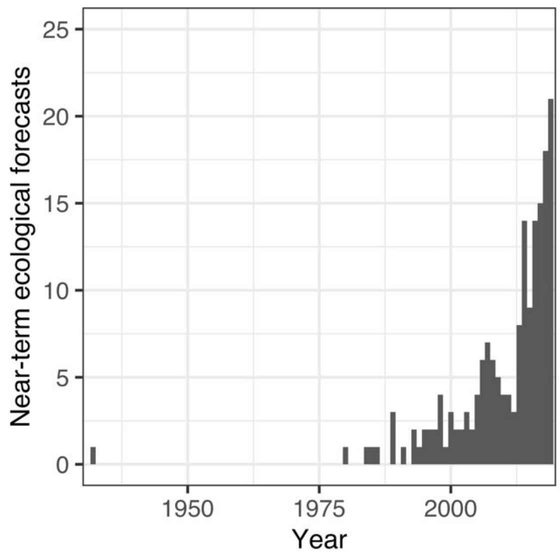
Figure 6: Best practice adoption over time. Points demarcate whether or not an individual paper demonstrated the best practice (1 = observed, 0 = not observed), and lines represent logistic regression results. Significance of the year term in the regression is indicated using asterisks: * indicates $p < 0.05$, *** indicates $p < 0.001$. One paper from 1932 was excluded from this analysis.

Figure 7: Relationship between forecast performance and forecast horizon (Horiz) for four forecast variables: chlorophyll (Chl), phytoplankton (Phyto), pollen, and evapotranspiration (ET). Different papers are indicated by points of different colors and shapes. Within a paper, forecasts using the same model were averaged (across sites, years, etc.). Rightmost panel: model predictions from the quantile regression indicator analysis.

Figure 1


a
Web of science search:
2711 papers
Abstract screening:
366 papers selected
Paper screening:
142 papers selected
Search cited articles:
218 new papers
(92 duplicates removed)
Search citing articles:
271 new papers
(108 duplicates removed)
Additional 472 papers
(17 duplicates removed)
Abstract screening:
169 papers selected
Paper screening:
112 papers selected
254 final papers
Matrix analysis:
178 papers retained
b
Original Web of
Science search
Ecological
Forecast
1326
527
142
200
111
Near-term
c
Citing and cited
papers
Ecological
Forecast
204
42
112
74
8
Near-term

916 Figure 2




917

Figure 3

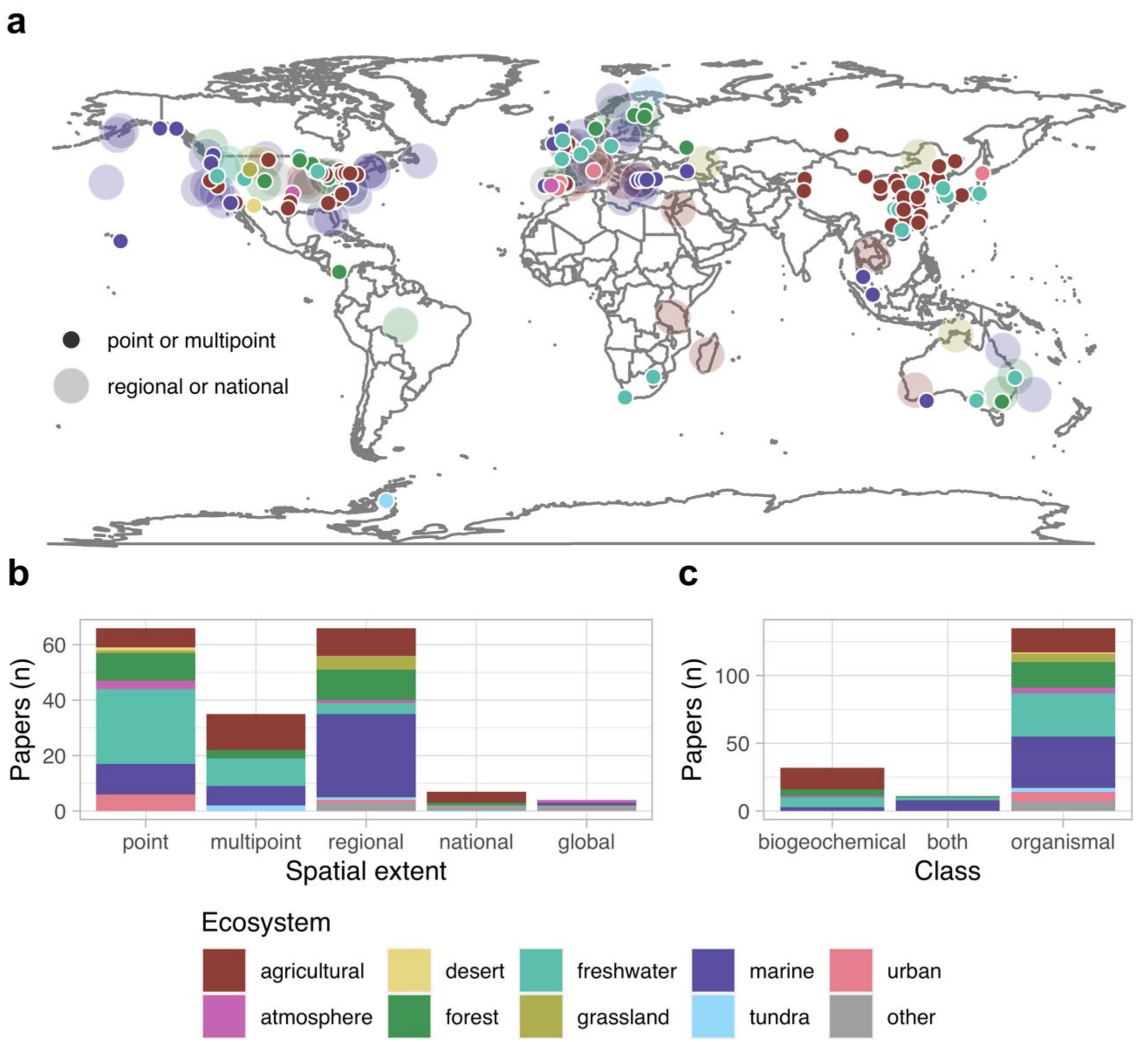

a
point or multipoint
regional or national
b
Papers (n)
60
40
20
0
point
multipoint
regional
national
global
Spatial extent
c
Papers (n)
100
50
0
biogeochemical
both
organismal
Class
Ecosystem
agricultural
desert
freshwater
marine
urban
atmosphere
forest
grassland
tundra
other

Figure 4

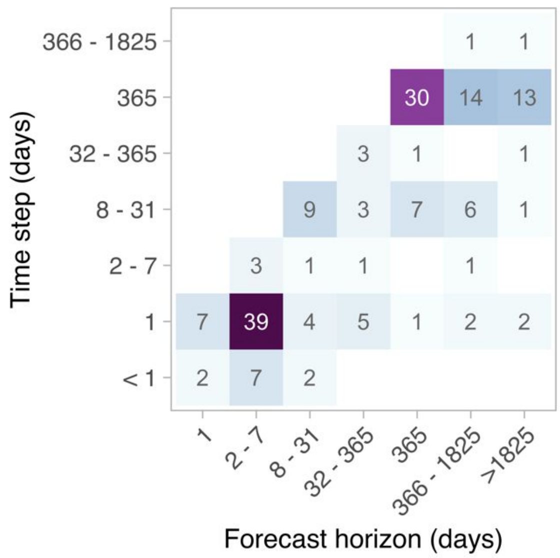
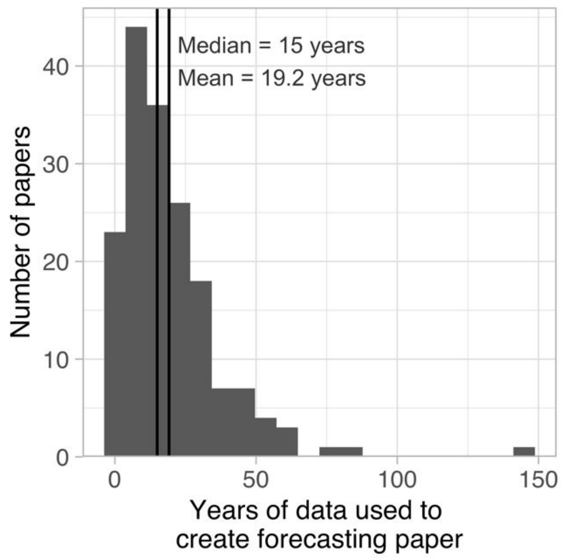
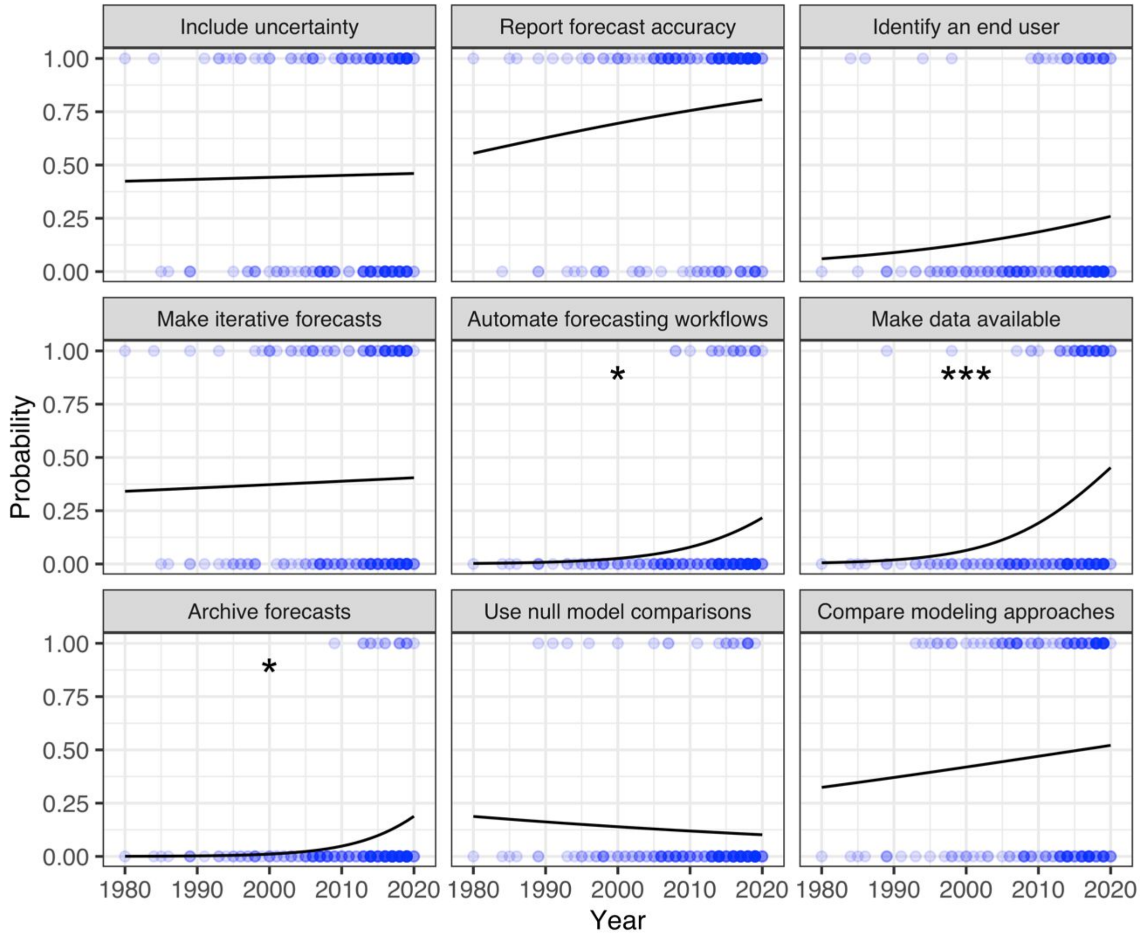

Time step (days)
366 - 1825
365
32 - 365
8 - 31
2 - 7
1
< 1
Forecast horizon (days)
1
2 - 7
8 - 31
32 - 365
365
366 - 1825
>1825
1 1
30 14 13
3 1 1
9 3 7 6 1
3 1 1 1
7 39 4 5 1 2 2
2 7 2

Figure 5

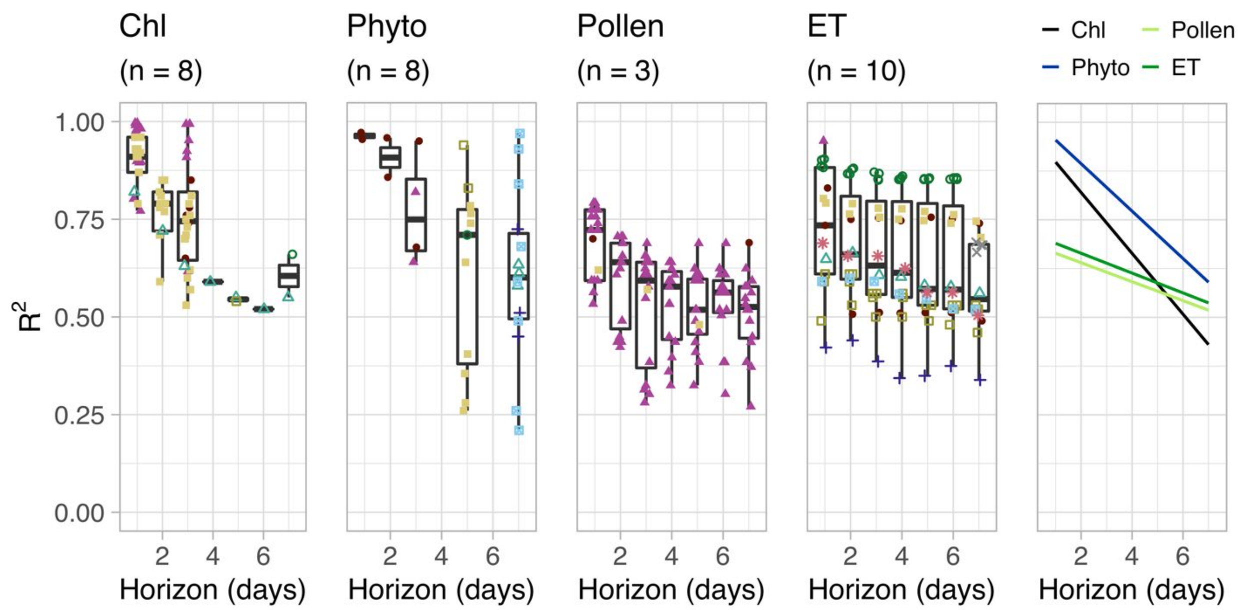

Median = 15 years
Mean = 19.2 years
Number of papers
0
10
20
30
40
0
50
100
150
Years of data used to
create forecasting paper

924 Figure 6




925

926 Figure 7




927

**Running head:** Best practices and forecastability

**Title:** Increased adoption of best practices in ecological forecasting enables comparisons of forecastability ~~across systems~~

**Authors:** Abigail S. L. Lewis[1a], Whitney M. Woelmer[1b], Heather L. Wander[1c], Dexter W. Howard[1d], John W. Smith[2e], Ryan P. McClure[1f], Mary E. Lofton[1g], Nicholas W. Hammond[3h], Rachel S. Corrigan[4i], R. Quinn Thomas[4j], Cayelan C. Carey[1k]

[1]Department of Biological Sciences, Virginia Tech, Blacksburg, Virginia, USA

[2]Department of Statistics, Virginia Tech, Blacksburg, Virginia, USA

[3]Department of Geosciences, Virginia Tech, Blacksburg, Virginia, USA

[4]Department of Forest Resources and Environmental Conservation, Virginia Tech, Blacksburg, Virginia, US

[a] Corresponding author. Address: Department of Biological Sciences, Derring Hall Room 2025, 926 West Campus Drive, Mail Code 0406, Blacksburg, VA 24061, USA. Phone: +1-540-231-0788. Fax: +1-540-231-9307. Email: aslewis@vt.edu, ORCID ID: 0000-0001-9933-4542

[b] Email: wwoelmer@vt.edu, ORCID ID: 0000-0001-5147-3877

[c] Email: hwander@vt.edu, ORCID ID: 0000-0002-3762-6045

[d] Email: dwh1998@vt.edu, ORCID ID: 0000-0002-6118-2149

[e] Email: wsjohn2@vt.edu, ORCID ID: 0000-0002-1564-3290

[f] Email: ryan333@vt.edu, ORCID ID: 0000-0001-6370-3852

[g] Email: melofton@vt.edu, ORCID ID: 0000-0003-3270-1330

[h] Email: hammondnw@vt.edu, ORCID ID: 0000-0003-2975-8280

[i] Email: rachelc1@vt.edu, ORCID ID: 0000-0001-6101-8085

[j] Email: rqthomas@vt.edu, ORCID ID: 0000-0003-1282-7825

[k] Email: cayelan@vt.edu, ORCID ID: 0000-0001-8835-4476

**Open data statement**

Data, ~~and~~ metadata, and analysis code are provided as a published data package ~~as private for peer review in a supplement and via the following link~~ in the Environmental Data Initiative (EDI) ~~staging repository (in the text below, we refer to this data publication as forthcoming)~~ ~~portal~~repository (Lewis et al. 2021).~~:~~ ~~https://portal-s.edirepository.org/nis/mapbrowse?scope=edi&identifier=196&revision=5~~

Submitted as a Research Article to *Ecological Applications*

Declarations of interest: none

ABSTRACT

Near-term iterative forecasting is a powerful tool for ecological decision support and has the potential to transform our understanding of ecological predictability. However, to this point, there has been no cross-ecosystem analysis of near-term ecological forecasts, making it difficult to synthesize diverse research efforts and prioritize future developments for this emerging field. In this study, we analyzed 178 near-term (≤10-year forecast horizon) ecological forecasting papers to understand the development and current state of near-term ecological forecasting literature and compare forecast ~~skill~~ accuracy across ~~ecosystems~~ scales and variables. Our results indicate that near-term ecological forecasting is widespread and growing: forecasts have been produced for sites on all seven continents and the rate of forecast publication is increasing over time. As forecast production has accelerated, a number of best practices have been proposed and application of these best practices is increasing. In particular, data publication, forecast archiving, and workflow automation have all increased significantly over time. However, adoption of proposed best practices remains low overall: for example, despite the fact that uncertainty is often cited as an essential component of an ecological forecast, only 45% of papers included uncertainty in their forecast outputs. As the use of these proposed best practices increases, near-term ecological forecasting has the potential to make significant contributions to our understanding of ~~predictability~~ forecastability across scales and variables. In this study, we found that forecastability (defined here as realized forecast accuracy)~~forecast skill~~ decreased in predictable patterns over 1–7 day forecast horizons. Variables that were closely related (i.e., chlorophyll and phytoplankton) displayed very similar trends in ~~predictability~~forecastability, while more distantly related variables (i.e., pollen and evapotranspiration) exhibited significantly different patterns. Increasing use of proposed best practices in ecological forecasting will allow

us to examine the forecastability of additional variables and timescales in the future, providing a robust analysis of the fundamental predictability of ecological variables.

KEY WORDS

Data assimilation, decision support, ecological predictability, forecast automation, forecast horizon, forecast ~~skill~~evaluation, forecast uncertainty, iterative forecasting, near-term forecast, null model, open science, uncertainty partitioning

INTRODUCTION

Nearly 90 years ago, Hodgson (1932) published what was arguably the first near-term ecological forecast, using demographic trends to predict herring age structure one year into the future. Hodgson concluded by stating "... we hope that before long these prognostications will be issued with the same confidence as those which are broadcast daily by the Meteorological Office, and, once they are received with confidence by the trade, they should be of considerable financial value" (p. 118). During the past 90 years, advances in data availability, computational power, and statistical methodologies have enabled a substantial increase in the development and application of near-term ecological forecasts (Luo et al. 2011, Petrovskii and Petrovskaya 2012, Hampton et al. 2013, LaDeau et al. 2017). Near-term ecological forecasting has become an increasingly powerful tool for ecological decision support (Dietze 2017a, Henden et al. 2020, Carey et al. 2021) and has the potential to provide new insights into fundamental questions about ecological functioning and predictability (Petchey et al. 2015, Dietze 2017b, Dietze et al. 2018). However, to this point, there has been no systematic analysis of the development or current state of near-term ecological forecasting literature, making it difficult to synthesize diverse research efforts and prioritize future developments for this emerging field.

Throughout the development of near-term ecological forecasting, there have been numerous calls for the adoption of standardized best practices (e.g., Clark et al. 2001, Pielke and Conant 2003, Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021). Developing and adhering to best practices advances the contributions of forecasting to both basic and applied research, as it allows for comparisons of forecast ~~skill~~ accuracy across forecast horizons (the amount of time into the future for which predictions are made) and increases the reliability of forecast products as decision support tools (Armstrong 2001). Recent interest in establishing best practices for ecological forecasting follows similar efforts in meteorology and economics, disciplines in which forecasting is well-established (Armstrong 2001, Hyndman and Athanasopoulos 2018).

While proposed best practices for near-term ecological forecasting differ among papers, a number of common themes related to forecast development, assessment, archiving, and decision support can be identified (Box 1; Appendix S1). As ecological forecasting has developed over the past several decades, we expect that adherence to these proposed best practices is increasing. However, without a comprehensive review of published ecological forecasts, it is difficult to assess which of the proposed best practices have been adopted and which should be prioritized for further advancement of the field (e.g., see Payne et al. 2017 for marine ecological forecasting). Ideally, best practices should evolve using a community-driven approach to enable buy-in and robustness to many applications (following Hanson et al. 2016); consequently, the list of proposed best practices in Box 1 is not exhaustive, and some of the practices may not be appropriate for every forecasting application. However, these practices provide a framework to begin analyzing the state of the field.

Adoption of these proposed best practices in near-term ecological forecasting may be particularly important to improving our understanding of ~~predictability~~ forecastability across ~~ecosystems and~~ scales and variables. As the number of published near-term ecological forecasts has increased over the past several decades (Luo et al. 2011, Dietze et al. 2018), we now have an unprecedented opportunity to compare across studies and analyze the relative forecastability (defined here as realized forecast accuracy) of environmental variables at varying forecast horizons. ~~Quantifying~~ Understanding ecological predictability is a fundamental goal in ecology (e.g., Gleason 1926, Clements 1936, Sutherland et al. 2013, Godfray and May 2014, Houlahan et al. 2017, and references therein) and provides valuable information regarding the nature of ecological processes (Petchey et al. 2015). Ecological forecasting can be a particularly powerful test of predictability, as forecasting requires predicting beyond the range of observed data (Dietze et al. 2018). Thus, comparisons of forecastability complement and extend~~Taking a data-driven approach to this problem complements and extends~~ existing theoretical and modeling-based work that has predicted how various factors (e.g., forecast horizon, computational irreducibility) influence the relative predictability of ecological variables (Beckage et al. 2011, Petchey et al. 2015).

In this study, we performed a systematic analysis of near-term ecological forecasting papers to examine the use of our proposed best practices over time (Box 1). To illustrate how proposed best practices can enable insights into fundamental ecological understanding, we then compared forecast ~~skill~~ accuracy across ~~ecosystems~~ scales and variables. We discuss the implications of our findings for further development and adoption of best practices within the near-term ecological forecasting research community.

## METHODS

We systematically reviewed literature on near-term ecological forecasting to determine how proposed best practices have been implemented over time and compare forecastability across ecosystems. First, we searched the Web of Science$^{TM}$ Core Collection [v.5.34] database (Clarivate Analytics, Philadelphia, USA) and reviewed abstracts to identify papers that reported near-term ecological forecasts (described in *Literature search* below). Two reviewers then independently read and analyzed each selected paper using a standardized matrix of criteria (*Matrix analysis*) and recorded forecast ~~skill~~ accuracy when reported. Once collated, we analyzed the full dataset to understand the development and current state of ecological forecasting (*Dataset description* and *Assessment of forecasting best practice adoption*). Finally, we analyzed forecast ~~skill~~ evaluation data to assess how forecast performance varied with forecast horizon for ecological variables with sufficient data (*Comparing forecast ~~skill~~ accuracy across ecosystem and models*).

**Literature search**

Creating an all-encompassing search query to identify near-term ecological forecasts presented three challenges: first, the term "near-term" was neither universally defined nor used in all papers that report near-term forecasts; second, there was no one search term that can match all papers describing ecological variables; and third, many papers used the word "forecast" when talking about implications of their research, despite not actually reporting forecasting results in the paper. To address these challenges, we began by querying the Web of Science Core Collection [v.5.34] for "forecast*" in the title, abstract, or keywords of papers published in 301 ecological journals, then manually screened abstracts of all resulting papers. We conducted the Web of Science search on 18 May 2020 and limited the search to articles and proceedings papers (hereafter, 'papers') published in English. This yielded 2711 results (Fig. 1).

We screened the abstracts of all 2711 papers and selected those that met three criteria:

1. Papers had to include at least one forecast, which we defined as a prediction of future conditions from the perspective of the model; forecasts could be developed retroactively (i.e., "hindcasts") but could only use driver data that were available before the forecast date (e.g., forecasted or time-lagged driver variables).

2. The forecast had to be near-term, which we defined as predicting ≤10 years into the future (following Dietze et al. 2018).
3. The forecast had to be ecological, which we defined as predicting a biogeochemical, population, or community response variable. This definition therefore excluded physical (e.g., streamflow or water temperature) and meteorological forecasts. Forecasts of human disease were only included if there was an animal vector.

If the abstract indicated that the paper met all three criteria, it was moved to the second round of screening. Here, a second reviewer read the full paper to ensure that at least one forecast in the paper met all three criteria.

By the end of this screening process, we identified 142 near-term ecological forecasting papers out of the 2711 Web of Science results (Fig. 1a, 1b). The initial Web of Science search did well at identifying studies with ecological focal variables, as 74% of the initial search results were marked as 'ecological' during our review process. However, only 36% of papers from this search actually included forecasts (predicting future conditions from the perspective of the forecast model). Furthermore, of the ecological forecasts identified in this search (n = 669), only 21% met our near-term criteria by including forecast horizons that were ≤10 years; the majority of forecasts predicted ecological changes over multidecadal timescales (Fig. 1b).

Because ecological forecasts may be published in journals that are not categorized as “ecological” by Web of Science, we then searched all papers that were cited by the 142 near-term ecological forecast papers we identified, as well as all papers that cited these studies. From the citing and cited papers, we selected those that were published in English and included “forecast*” in the title, abstract, or keywords, then screened the abstracts using our three criteria described above. Finally, a second reviewer read all papers that passed the abstract screening to confirm that at least one forecast in the paper met all three criteria. Searching the papers that cite and are cited by the near-term ecological forecasting papers from our initial search yielded proportionally more ecological forecasting papers than the initial Web of Science search. Of the 472 search results, 112 (24%) of these papers were identified as near-term ecological forecasts after two rounds of review (Fig. 1a, 1c). Furthermore, this search highlighted predominantly near-term forecasts; 73% of the ecological forecasts identified in this search included forecast horizons that were ≤10 years (Fig. 1c). After combining our initial search with the citing and cited papers, 254 papers were included in our dataset for matrix review (Fig. 1a).

**Matrix analysis**

We analyzed each of the 254 papers using a standardized matrix of questions (~~Lewis et al. Environmental Data Initiative repository forthcoming data publication~~Appendix S2). This matrix was co-developed over several months of iteration and discussion by all authors within an Ecological Forecasting graduate seminar at Virginia Tech (January–May 2020). The final matrix used for this study included 58~~7~~ fields of information about the forecast paper's model(s), evaluation, cyberinfrastructure, archiving, and decision support (Lewis et al. ~~Environmental Data Initiative repository forthcoming data publication~~2021).

During the graduate seminar, we read and analyzed 10 papers as a group, ensuring that all reviewers understood how to interpret and answer questions in a consistent manner. Prior to the start of this analysis, r~~R~~eviewers also screened several papers ~~individually~~ independently and checked their responses with another reviewer~~ prior to the start of this analysis~~, helping to ensure consistency between reviewers. For the matrix analysis described in this paper, all 254 papers were read and analyzed independently by two reviewers, and reviewers then compared any differing answers to reach consensus on a final set of responses for each paper.

During the matrix analysis, 76 papers were determined to not meet our criteria of being near-term ecological forecasts, despite having passed the initial rounds of screening. These papers typically used one or more data sources that became available after the forecast issue date, which was difficult to identify without reading the entire text, including all supplementary information, in detail. These papers were excluded from the analysis, leaving 178 papers in the final dataset (Fig. 1a).

**Dataset description**

To characterize the current state of near-term ecological forecasting, we began by analyzing the distribution of forecasts presented in the 178 papers across geographical locations, variables, and time scales, as described below.

We classified the spatial scale of each forecast into five categories: point (localized to one discrete site, such as pollen forecasts for a city or algal forecasts for a lake), multipoint (several distinct forecast locations, such as three different lakes), regional (localized to a broad geographic region, such as coral bleaching forecasts that span a sea), national (spanning all of one nation, such as nationwide production of an agricultural crop), or global (such as coral bleaching stress in world oceans), and we calculated the percentage of forecasting papers within each of these categories. We recorded latitude and longitude of the forecast site(s) for point or multipoint forecasts or of the approximate centroid of the site for regional and national forecasts.

Forecast variables were divided into two categories: organismal (population and community; e.g., white-tailed deer populations) and biogeochemical (e.g., evapotranspiration), and each paper was classified within one of 11 ecosystem types: forest, grassland, freshwater, marine, desert, tundra, atmosphere, agricultural, urban, global, other, where "other" included any ecosystem types that could not be classified within one of the other 10 categories (e.g., plant phenology across the entire United States). We recorded the number of years of data used to create each forecasting paper (summed across model development, training, evaluation, etc.) and calculated the percentage of papers that used long-term datasets in their analysis, using the definition of long-term as any dataset with more than 10~~ten~~ years of data (Lindenmayer et al. 2012).

**Assessment of forecasting best practice adoption**

We synthesized proposed best practices for ecological forecasting from four recent papers—Harris et al. (2018), Hobday et al. (2019), Carey et al. (2021), and White et al. (2019), then selected all practices that were mentioned in at least two of these papers (Appendix S1). To analyze how adherence to the nine ~~proposed~~ selected best practices has changed over time, we performed binary logistic regressions assessing how adoption of each best practice (binary yes/no) varied with publication year. Hodgson (1932) was excluded from this best practice analysis as a temporal outlier, leaving a dataset of papers published between 1980 and 2020. We used the following criteria in the matrix analysis to assess which proposed best practices (Box 1) were included in each forecasting paper:

*Forecast Requirements*

1. "Include uncertainty": uncertainty was included in forecast outputs

2. "~~Assess and r~~Report forecast ~~skill~~accuracy": any form of forecast evaluation was reported (this includes figures that compare forecasts and observations, as well as any ~~skill~~ evaluation metric~~score~~)

*Decision Support*

3. "Identify an end user": A specific end user was mentioned
4. "Make iterative forecasts": Forecasts were made repeatedly, incorporating new data over time. For this practice, we included all types of data assimilation, including those that only updated the initial conditions of the forecast. As a separate analysis, we also determined whether the use of data assimilation methods that updated the parameters of the model (not just initial conditions) have increased over time
5. "Automate forecasting workflows": at least one source of new driver and/or observation data was made available to the model in real time (<24 hours from collection) without any manual effort when the forecasting system was working as intended

*Research*

6. "Make data available": Data availability was specified
7. "Archive forecasts": Text specified that forecasts were archived and available
8. "Use null model comparisons": Forecasts were compared to a null model (e.g., a persistence or climatology null model)

~~8.~~9. “Compare modeling approaches”: At least two modeling approaches that have different model structures (not including null models) ~~are~~were compared

~~9. “Partition uncertainty”: At least two different sources of uncertainty were quantified and compared~~

All analyses were performed using R version 4.0.3 (R Core Team 2020).

**Comparison of forecast ~~skill~~ performance across ~~ecosystem~~ scales and variables~~and models~~**

To compare forecast performance across forecast variables, sites, and scales, it ~~is~~ was necessary to identify an evaluation ~~skill~~ metric that is not dependent on the units or range of the forecast variable. For reasons discussed below, we chose $R^2$ as our metric of forecast performance in this analysis. Petchey et al. (2015) recommend using the length of time until a forecast performs no better than a relevant threshold value as one way of comparing between papers. However, this type of analysis would require that a threshold value be determined equitably for each forecast variable, which would be challenging across the numerous variables in our dataset. Performance of null models offers one objective way of determining these threshold values, but null models were not commonly reported in this dataset. Another means of comparing forecast performance would be to directly compare forecast ~~skill~~ accuracy using a standardized statistical score. Commonly used forecast ~~skill~~ evaluation metrics include root mean squared error (RMSE), mean absolute error (MAE), the coefficient of determination ($R^2$), and bias (Petchey et al. 2015, Dietze 2017a). To fully assess probabilistic forecasts, the continuous ranked probability score (CRPS) and ignorance can also be used (Roulston and Smith 2002, Gneiting et al. 2005). Among these, only $R^2$ allows comparisons between forecasts that have different native units or forecasts for the same variable in very different ranges. Furthermore, more papers reported Pearson's r or $R^2$ (n = 56, 42%) than any other forecast performance metric in this dataset: for comparison, only 34% included RMSE and 20% included MAE. While the fact that $R^2$ is typically bias-corrected makes it an imperfect metric of forecast performance, it remains widely reported and uniquely suited to inter-study comparisons.

We recorded all $R^2$ and Pearson's r data reported in papers in the dataset. Pearson's r values were squared to yield $R^2$ (following Rousso et al. 2020). ~~Because a majority of papers that reported $R^2$ data had forecast horizons between one and seven days (n = 35; 56%), we restricted our analysis to papers within this range of time horizons.~~ We selected all forecast variables that had at least three papers and three forecast horizons represented, ~~over this interval and~~ and we plotted forecast performance (in $R^2$) as a function of forecast horizon for these variables. To allow comparability between variables, we limited the analysis to forecast horizons between one and seven days, which were reported for all variables selected. Because some papers reported $R^2$ individually for each plot, site, or year and others reported one overall evaluation per model, we averaged all $R^2$ across sites and years for forecasts that used the same model within each paper.

We used indicator variable analysis (Draper and Smith 1998) to compare the slope of $R^2$ values over 1–7 day horizons among forecast variables by performing a 50% quantile regression ~~predicting~~ that predicted $R^2$ based upon indicator ("dummy") predictors for all forecast variables, as well as terms for the interaction between all forecast variables and forecast horizon. Quantile regression was used rather than standard linear regression to account for heteroscedasticity and non-normal data distribution. The regression was performed using the package "quantreg" in R (Koenker et al. 2021). Indicator analysis compares the slope and intercept of the first indicator ("reference" indicator) to all subsequent indicators (Draper and Smith 1998). In this case, chlorophyll was used as the reference indicator to enable comparisons between phytoplankton and chlorophyll, two closely related forecast variables. We analyzed which terms were significant in the model to determine how patterns in forecast performance over time differed among forecast variables: significance was determined using the "wild" bootstrapping method to account for heteroskedasticity (Feng et al. 2011).

RESULTS

**Dataset description**

The number of ecological forecasts published each year has increased substantially over time: more papers were published in the last seven years of the dataset (2014–2020) than in the first 82 years (1932–2013; Fig. 2). Forecast sites for these papers were located on all seven continents (Fig 3a). The majority of forecast sites were located in the northern hemisphere (n = 211, 91%), especially the United States, China, and Western Europe (Fig. 3a). The geographic scale of the forecasts was most often either point (n = 66, 37%), or regional (n = 66, 37%; Fig. 3b).

More ecological forecasts predicted organismal (population and community) variables than biogeochemical variables. Very few papers included forecasts for both biogeochemical and organismal focal variables (organismal: n = 146, 82%; biogeochemical: n = 43, 24%; both: n = 11, 6%; Fig. 3c). The majority of papers predicted ecological processes in either marine (n = 49, 28%), freshwater (n = 41, 23%), or agricultural (n = 34, 19%) ecosystems (Fig. 3). In particular, many papers predicted fish taxa (n = 25), phytoplankton taxa (n = 20), chlorophyll (n = 14), evapotranspiration (n = 14), pollen (n = 10), and crop yield (n = 9).

Papers in this dataset included forecasts at a wide range of forecast horizons and were developed using diverse time steps, forecast horizons, and datasets. Among the forecasts surveyed in this analysis, 75% of papers predicted within one year into the future (n = 130; Fig. 4). In particular, many papers either predicted 2–7 days into the future on a daily time step (n = 39, 23% of all papers) or one year into the future on a yearly time step (n = 30, 17%; Fig. 4). The median temporal duration of data used to create a forecasting paper (summed over model development, training, evaluation, etc.) was 15 years (min. = 17 days, mean = 19.2 years, max. = 145 years; Fig. 5), and 60% of papers (n = 107) used more than 10 years of data in the forecast paper.

The 178 papers included in this analysis were published in 114 unique journals and conference proceedings (103 journals, 11 conferences). The journal with the greatest number of papers represented in the dataset was *Ecological Applications*, which published a total of 14 near-term ecological forecasting papers.



**Adoption of proposed best practices is low but increasing over time**

Overall rates of ~~proposed~~ best practice use are low but may be increasing. On average, papers used ~~two~~ three of the proposed nine best practices (median and mode = 3~~2~~, mean = 2.83~~37~~), but there was considerable variation: seven ~~12~~ papers did not use any of the best practices, and one paper used eight~~seven~~ of the best practices. The ~~probability that a paper would use a best practice in the year 2020 (as calculated by logistic regression)~~percentage of papers that demonstrated a given best practice did not exceed 50% for any practice except "~~Assess and r~~Report forecast accuracy~~skill~~" (Fig. 6). All but one ("Use null model comparisons") of our proposed best practices have been increasingly adopted over time. However, the increase in adoption with time was only statistically significant ($p < 0.05$) for three practices: "Automate forecasting workflows," "Archive forecasts," and "Make data available" (Fig. 6; Table 1).

~~Both of the *Forecast Requirement* best practices ("Include uncertainty" and "Assess and report forecast skill") show a positive trend in adoption, though neither had a statistically significant relationship with publication year (Fig. 6; Table 1). Overall~~Of the *Forecast Requirement* best practices, "Include uncertainty" was demonstrated in 45% of papers and

“~~Assess and r~~Report forecast accuracy~~skill~~” was demonstrated in 75% of papers. Both of the *Forecast Requirement* best practices ~~(“Include uncertainty” and “Assess and report forecast skill”)~~ show a positive trend in adoption, though neither had a statistically significant relationship with publication year (Fig. 6; Table 1). When uncertainty was included in forecasts (n = 80), the most commonly included uncertainty sources were observation uncertainty (48%), process uncertainty (40%), and parameter uncertainty (35%). Driver uncertainty was included in 23% of papers that report uncertainty, and initial condition uncertainty was included in 18%. Of the 80 papers that reported uncertainty ~~(n = 80)~~, 55% did not specify a data-driven origin of this uncertainty (e.g., ensemble model parameters, forecasted meteorological driver data) in the text. Only three papers partitioned uncertainty sources (Caughlin et al. 2019, Geremia et al. 2014, Dietze 2017b), and all of these papers were published in or after 2014. All three papers quantified the influence of process, initial condition, and parameter uncertainty, and one partitioned driver uncertainty. Process uncertainty dominated total uncertainty for two papers (Geremia et al. 2014, Dietze 2017b), while initial condition uncertainty dominated in the third paper (Caughlin et al. 2019). Over 70% of forecasts that did not report forecast evaluation in the text (n = 44) predicted at forecast horizons of at least one year; in comparison, 47% predicted at forecast horizons of at least one year in the dataset as a whole. As noted in the Methods, the most commonly reported metric of forecast performance was $R^2$.

Overall, 20% of papers identified a specific~~n~~ end user, 39% of papers made iterative forecasts, and 11% of papers included automated forecasting workflows. ~~Within the *Decision Support* tier, a~~All three of these proposed best practices ("Identify an end user", "Make iterative forecasts", "Automate forecasting workflows") in the *Decision Support* tier showed positive relationships with publication year, but only "Automate forecasting workflows" significantly increased over time (Fig. 6, Table 1). ~~Overall, 20% of papers identified an end user, 39% of papers made iterative forecasts, and 11% of papers included automated forecasting workflows.~~ Of the papers that mentioned a specific end user (n = 35), 31% mentioned that the end user aided in forecast development and 46% mentioned that forecasts were in use by the end user. Data assimilation for iterative forecasts most often updated initial conditions but not parameters of the model (67% of the 69 iterative forecasts only updated initial conditions). However, data assimilation methods that updated the parameters of the model (not just initial conditions) have increased significantly over time (Table 1).

~~Two of the four *Research* tier practices have increased significantly over time ("Archive forecasts" and "Make data available"; Table 1). "Partition uncertainty" has not significantly increased over time, though the only three papers that partitioned uncertainty were published in or after 2014. "Use null model comparisons" was the only practice that has decreased in adoption over time (Fig. 6).~~ Overall, there was a wide range in the percentage of papers that used *Research* tier best practices. ~~"Archive forecasts" was demonstrated in 8% of papers,~~ "Make data available" was demonstrated in 25% of papers, ~~"Partition uncertainty" was demonstrated in 2% of papers, and~~ "Archive forecasts" was demonstrated in 8% of papers, "Use null model comparisons" was demonstrated in 12% of papers, and "Compare modeling approaches" was demonstrated in 47% of papers. Two of the ~~four~~five *Research* tier practices have increased significantly over time ("Make data available" and "Archive forecasts"; Table 1). "Use null model comparisons" was the only practice that has decreased in adoption over time (Fig. 6). For papers that described forecast archiving (n = 15), the most common repository for archived forecasts was Zenodo (used in 20% of papers that archive forecasts); other papers used websites or other archives specific to the forecasting project ~~to archive their forecasts~~. Only two of the seven papers that mentioned archiving forecasts on a website had links that were still functional as of 14 Jun 2021. Of the papers that used null models in this study (n = 21), 62% used persistence null models and 48% used climatology null models. Two papers used both persistence and climatology null models. Of the papers that compared multiple modeling approaches (n = 84), ~~papers compared~~ a median of 3 different approaches were included (not including null models; mean = 5.4, max. = 49).

~~All of the papers that partitioned uncertainty (n = 3) quantified the influence of process, initial condition, and parameter uncertainty, and only one partitioned driver uncertainty. Process uncertainty dominated total uncertainty for two papers, while initial condition uncertainty dominated in the third paper. Of the papers that used null models in this study (n = 21), 62% used persistence null models and 48% used climatology null models. Two papers used both persistence and climatology null models.~~

**Declines in forecast performance over increasing forecast horizons differ between variables**

Forecast ~~skill~~ accuracy data ($R^2$) from at least three papers on 1–7 day forecast horizons were available for four forecast variables: chlorophyll, phytoplankton taxa, pollen, and evapotranspiration (ET). Forecast performance decreased with increasing forecast horizon for all forecast variables (Fig. 7, Table 2). The slope and intercept of forecast ~~skill~~ accuracy over increasing forecast horizons differed between variables, as revealed in our indicator analysis: the intercepts for pollen and ET were significantly lower than for chlorophyll, the reference indicator. In comparison to chlorophyll, forecast ~~skill~~ accuracy for pollen and ET decreased significantly more slowly over time. Unsurprisingly, the intercept and slope of phytoplankton were not significantly different from the intercept and slope of chlorophyll, the reference indicator (Fig. 7, Table 2).

DISCUSSION

Our systematic analysis of 178 near-term ecological forecasting papers demonstrates that the field of near-term ecological forecasting is widespread and growing: forecasts have been produced on all seven continents, and the rate of forecast publication is increasing over time. Although the overall implementation of proposed best practices is low, best practice use is increasing. In particular, the use of automated forecasting workflows, making data available, and archiving forecasts are all increasing significantly over time. We ~~Using~~ used this dataset of published studies ~~we were able~~ to compare forecast ~~skill~~ accuracy across scales and variables, and we found that forecast ~~skill~~ accuracy decreased in consistent patterns over 1–7 day forecast horizons. Variables that were closely related (i.e., chlorophyll and phytoplankton) displayed very similar trends in predictability over increasing forecast horizons, while more distantly related variables (i.e., pollen, evapotranspiration) exhibited significantly different patterns.

**Near-term ecological forecasting: state of the field**

As publication of near-term ecological forecasts continues to accelerate, evaluating the state of the field now can provide critical insight to help prioritize areas of improvement moving forward. Below, we discuss aspects of near-term ecological forecasting that are well-developed, those that are improving over time, and areas that may need improvement based upon the results of this analysis.

*Well-developed practices in near-term ecological forecasting: high rates of forecast assessment and model comparison*

Only one out of the nine proposed best practices was demonstrated in more than half of the papers in this analysis: ~~rassess and r~~eport forecast ~~skill~~accuracy. In this study, high rates of forecast ~~skill~~ assessment and reporting allowed us to compare forecast performance across scales and variables. While $R^2$ was the most commonly reported forecast ~~skill~~ evaluation metric and served as an effective ~~skill~~ accuracy score for this preliminary analysis, it would be preferable to use a metric of forecast performance that is not bias-corrected. Other scale-independent metrics of forecast performance include percentage errors (e.g., mean absolute percentage error; MAPE) or scaled errors (e.g., mean absolute scaled error; MASE; Hyndman and Athanasopoulos 2018). Percentage errors are not universally applicable because they penalize a lack of precision more heavily in a range closer to zero (in the units of the forecast), which is not valid for a number of forecast variables (e.g., temperature in units of Fahrenheit or Celsius, net ecosystem exchange of carbon dioxide; Hyndman and Athanasopoulos 2018). Scaled errors may present the most effective means of comparing forecasts with different ranges and units, however, they require choosing a relevant null model (Hyndman and Athanasopoulos 2018), which is currently not common in near-term ecological forecasting literature (Fig. 6).

Of the papers that did not assess and report any metric of forecast ~~skill~~accuracy, many (77%) predicted at forecast horizons greater than or equal to one year, suggesting that part of the reason these papers did not assess forecast ~~skill~~ accuracy may be the long time lag before data would be available for forecast evaluation. In cases when the forecast horizon is too far into the future to evaluate results, researchers could consider making and evaluating additional forecasts at short ~~time~~ horizons to provide at least an intermediate evaluation of their forecasting system

(Harris et al. 2018). Assessing hindcasts ~~of historical data~~ may also provide a means of evaluating the forecasting system, given sufficient historical data.

Notably, many papers that included forecast assessment also compared multiple modeling approaches; 47% of papers in the dataset included model comparisons, despite the fact that this is a *Research* tier practice and may not be relevant to all applications. These high rates of model comparison may facilitate future analyses that determine relevant model structures for a variety of ecological applications (e.g., see Rousso et al. 2020).

*Developments in near-term ecological forecasting: ~~high rates of forecast assessment,~~ increasing automation and use of open science practices*

Over time, near-term ecological forecasting is becoming increasingly automated, creating forecast products that enable real-time decision support (Dietze et al. 2018). Forecast automation can be beneficial to decision support because it decreases the amount of manual effort required to create each forecast once the automated system is set up and thereby increases the sustainability of iterative forecasting workflows (White et al. 2019, Hobday et al. 2019, Carey et al. 2021). However, it is important to note that automated forecasting workflows may still require significant human effort to maintain cyberinfrastructure over time (Carey et al. 2021). While the increase in use of iterative forecasts over time was not statistically significant, the percentage of papers that use iterative workflows to update model parameters rather than just the initial conditions of the forecast has increased significantly (Table 1). Updating model parameters as new data are incorporated allows the forecasting system to learn over time and potentially make more accurate predictions in the future (Luo et al. 2011, Niu et al. 2014, Zwart et al. 2019).

Another area of promise is in the adoption of open scientific practices: both data publication and forecast archiving have increased significantly over the past 40 years. These advances likely reflect a broader movement for open scientific practices that has gained momentum over the past decade in response to intersecting needs for greater reproducible science, knowledge dissemination, and collaboration (e.g., Reichman et al. 2011, Fecher and Friesike 2013, Beardsley 2014, Wilkinson et al. 2016, Munafò et al. 2017, Powers and Hampton 2019). Further increases in the use of open scientific practices have the potential to increase the reproducibility of published forecasting literature while fostering collaboration and accelerating the development of the field.

*Priorities for the future development of near-term ecological forecasting: uncertainty, end user engagement, and null models*

One of the most notable gaps identified in this analysis is the lack of specified uncertainty in published forecasts. Meaningful representations of uncertainty are considered so critical to forecast interpretation and evaluation that many definitions of ecological forecasts include uncertainty as an essential component (e.g., Clark et al. 2001, Luo et al. 2011, Harris et al. 2018, Dietze et al. 2018, Carey et al. 2021). However, only 45% of papers included uncertainty in their forecasts. Lack of forecast uncertainty can be problematic in decision support because when uncertainty is not specified in a forecast output, forecast users create their own, often inaccurate, expectations of forecast uncertainty (Morss et al. 2008, Joslyn and Savelli 2010).

Moving beyond specifying uncertainty to~~In addition to aiding decision support,~~ partitioning uncertainty ~~partitioning has the potential to contribute to our forecast improvement and a broader understanding of the limits of ecological predictability. Partitioning uncertainty~~

into its ~~respective~~ component parts~~s~~ (e.g., initial condition, driver, parameter, and process uncertainty) provides information to help forecast developers prioritize improvements to their forecasting system and allows researchers to understand the constraints to predictability for a given ecological variable ~~and analyze how those constraints differ between forecast scales and horizons~~ (Dietze 2017b). ~~For example, i~~It is well established that forecasting meteorological conditions is a fundamentally chaotic problem, dominated by initial condition uncertainty (Kalnay 2003). Due to stabilizing feedbacks in ecological systems (e.g., carrying capacity, functional redundancy), other components of uncertainty are hypothesized to dominate ecological forecasts (Dietze 2017b). This hypothesis is partially supported by our dataset: initial condition uncertainty was the dominant source of forecast uncertainty in only one of three papers that partitioned uncertainty in this analysis. However, because uncertainty partitioning is a relatively new development in ecological forecasting, the small number of studies that partition uncertainty currently prevents us from making conclusions about the limiting factors for predictability across ~~ecosystems~~ variables and forecast horizons.

While not all of the near-term ecological forecasts described in our dataset were designed for decision support, approximately 20% of papers mentioned a specific end user for their forecasts. Of these, nearly half specify that the forecasting system was in use by the specified end user (e.g., drinking water management organization, coral reef conservation agency, etc.). Designing forecasts for end users involves a variety of ethical considerations, including equity for end users, communication of forecast ~~skill~~accuracy, and stakeholder education (Hobday et al. 2019). However, it was rare for a paper to include any explicit mention of ethical considerations made in designing the forecast (5% of papers overall; 25% of forecasts that are in use by an end user). Given the power of forecasts to inform decision support, education on how to ~~carefully~~

navigate ~~these decisions~~~~engaging~~engagement with end users, and particularly any ethical considerations that must be made, may be useful in improving the utility of forecasts for stakeholder use.

In this study, we found that the use of null model comparisons remains low and has not increased in adoption over time, despite the importance of this practice for contextualizing ~~model~~ forecast skill (Harris et al. 2018, Dietze et al. 2018, White et al. 2019). For meteorological forecasting, comparing forecasts to a climatological null model has proved useful as a means of analyzing the limit of predictive skill and the comparative performance of weather forecasts across spatial and temporal scales (Buizza and Leutbecher 2015). Parallel advances in ecological forecasting may be enabled through increased use of null model comparisons in the future (Petchey et al. 2015, Hyndman and Athanasopoulos 2018).

**Published forecasts provide insight into forecastability across ~~ecosystems~~ scales and ~~models~~variables**

Analyzing forecastability across variables, we found that aquatic chlorophyll and phytoplankton taxa were more predictable than pollen and evapotranspiration at the shortest ~~time~~ forecast horizons (chlorophyll: 1–5 days; phytoplankton: 1–7 days). However, the predictability of chlorophyll and phytoplankton decayed faster over increasing forecast horizons than that of evapotranspiration and pollen. Similar patterns in forecast performance for chlorophyll and phytoplankton likely result from the fact that these two ecological variables are closely related. Greater predictability of chlorophyll and phytoplankton than evapotranspiration and pollen at short ~~time~~ forecast horizons likely indicates a greater degree of autocorrelation in these processes (Reynolds 2006), but predictability quickly decays over time due to bloom dynamics (e.g., Rigosi et al. 2011, Recknagel et al. 2016). The consistency of these patterns across 3–10 different papers for each forecast variable suggests that the relationship between forecast performance and forecast horizon could be a robust indicator of the predictability of other ecological processes.

While this is a preliminary analysis limited to four ecological variables, it is among the first comparative tests that have analyzed forecastability across scales and variables, building on two previously published studies. Ward et al. (2014) analyzed the ability of multiple time-series models to predict 2379 vertebrate population datasets. They found that increased forecast performance (measured using MASE) was correlated with long lifespans and large body size for fish and high trophic level for birds over 1–5 year forecast horizons. Additionally, Rousso et al. (2020) performed a systematic review of cyanobacterial bloom forecasting literature and analyzed the relationship between forecast performance ($R^2$) and forecast horizon for three types of models: artificial neural networks, decision trees, and genetic programming. They found that forecast performance decreased over 1–30 day forecast horizons, and forecasts created using greater amounts of historical data had superior forecast performance. Altogether, these first analyses of the forecastability of ecological variables highlight the growing applicability of forecasting to inform our understanding of ecological predictability.

Accelerating forecast publication and increased adoption of proposed best practices will increase the statistical strength of future analyses to detect trends in forecast performance over increasing forecast horizons, including possible non-linear patterns. In particular, increased assessment and reporting of forecast ~~skill~~ accuracy ensures that published papers can be included in a meta-analysis of predictability; increased data publication allows reevaluation of forecasts; increased forecast archiving addresses publication biases in forecast results; increased use of null models allows researchers to analyze how the maximum length of time until a forecast performs no better than the null differs among variables; and increased ~~uncertainty partitioning~~quantification of uncertainty allows researchers to compare how uncertainty sources differ across scales and variables.

**Literature search process: observations and limitations**

While the rates of adoption of these proposed best practices (Box 1) are low overall, they are not necessarily unexpected. Different forecasting applications likely require different best practices; in this analysis, we have divided our selected best practices among three categories: *Forecast Requirements*, *Decision Support*, and *Research*. However, this is a coarse delineation, and the last two tiers are not mutually exclusive: *Decision Support* practices can also be important for ecological understanding and vice versa. Ecological forecasting is an emerging discipline and many of these methods are still in development; notably, our list of proposed best practices was derived from papers that were all published within the last ~~three~~ four years of the dataset (Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021; Appendix S1). Ideally, best practices should evolve using a community-driven approach to enable buy-in and robustness to many applications (following Hanson et al. 2016)~~; consequently, our list is not exhaustive and some of the proposed practices may not be appropriate for every forecasting application~~. Armstrong (2001) proposed as many as 139 principles for forecasting at large, all of which could be relevant to ecological forecasting applications. If one had to wait to publish a forecast until it satisfied all potential best practices, it is likely that no forecasting papers would ever be published. Increasing the number of published ecological forecasts benefits the field of ecological forecasting even if forecasts do not follow all proposed best practices because the research community gains increasingly more information about the ~~predictability~~ forecastability of ecological variables and the tools and techniques needed to make effective forecasts (Dietze et al. 2018). Still, as near-term ecological forecasting continues to grow, assessing the rate of best practice adoption now allows researchers to identify and prioritize areas for growth and education, simultaneously advancing the basic and applied value of ecological forecasting.

**Commented [1]:** Forecastability?

Results from our literature search process highlight the decentralized nature of near-term ecological forecasting and the challenges associated with systematically reviewing this literature. The 178 near-term ecological forecasting papers in this analysis came from 114 unique journals and conference proceedings, and no one journal published more than 15 near-term ecological forecasts papers in this analysis. Decentralized forecast publications may present a barrier to those interested in this literature, particularly because there is no one search term that comprehensively surveys the current near-term ecological forecasting literature. Many papers do not explicitly use the terms “near-term” or “ecological” when describing forecasts for a particular application, and only 5% of the results from our initial search for the term “forecast*” in ecology-related journal articles were identified as near-term ecological forecasts after two rounds of review (Fig. 1). By systematically reviewing and synthesizing near-term ecological forecasting literature published to date, we aim to begin addressing this gap.

Importantly, this comprehensive analysis of near-term ecological forecasting literature is limited to published forecast results. Operational forecasting systems that have not been described in peer-reviewed literature were not included (e.g., the U.S. National Oceanic and Atmospheric Administration, NOAA, has multiple operational forecasting systems for harmful algal blooms, fisheries, and coral reef bleaching that are available via websites). We anticipate that this exclusion may affect results in at least three ways: first, because unpublished operational forecasting systems are often used for decision support, the percentage of forecasting systems that connect to a specific end user is likely underrepresented in published literature. Second, both the need to refine forecasting models prior to paper submission and reviewer requests for forecast revisions may make it difficult to publish genuine forecasts. Because of this, most papers in this study are likely hindcasts or forecast reanalyses. Third, because of publication biases (Dickersin 1990, Mlinarić et al. 2017), we anticipate that average forecast performance is artificially inflated in published literature relative to unpublished operational forecasts. As coordination within the near-term ecological forecasting discipline increases, surveying and comparing operational forecasts may become increasingly possible over time.

**Future needs in near-term ecological forecasting**

Looking to the future, advancing the field of near-term ecological forecasting will involve a suite of technological, organizational, and educational advances. First, the low level of adoption of the proposed best practices suggests that increased coordination within the ecological forecasting research community for developing common forecasting standards (e.g., Dietze et al. 2021), best practices, and vocabulary will advance near-term ecological forecasting. Second, we find that incorporation ~~and partitioning~~ of uncertainty and use of null models are critical gaps in ecological forecasting literature where education may be needed. The creation of additional educational resources will enable more forecasts to be created and facilitate the adoption of best practices in ecological forecasting. Third, our analysis strongly suggests that long-term data are an important resource for near-term ecological forecast development and assessment. In our dataset, 60% of published near-term ecological forecasting studies used >10 years of ecological data when developing, calibrating, and assessing their forecasts (Fig. 5). Long-term support for data collection will likely be necessary to advance the field. Finally, our analysis indicates that near-term ecological forecasting may be disproportionately centered in the northern hemisphere, particularly the United States of America, Western Europe, and China. This result follows the disproportionate representation of these geographic regions across all sciences (UNESCO 2015). Lack of forecast locations in other countries, particularly in the southern hemisphere, is a detriment to the field as a whole, as the full diversity of ecological systems is not represented in ecological forecasting research to date.

While there are a variety of challenges and opportunities facing the development of near-term ecological forecasting, the literature indicates that the field has grown significantly over the past 90 years. Near-term ecological forecasting is now widespread and the rate of forecast publication continues to increase over time. Moving forward, near-term ecological forecasting is well-positioned to transform ecological management and provide critical insight into the predictability of ecological ~~systems~~variables.

ACKNOWLEDGMENTS

We thank members of the Ecological Forecasting Initiative (EFI), particularly the Theory working group and the EFI ~~RCN~~Research Coordination Network (RCN) ~~s~~Steering C~~c~~ommittee, for productive discussions throughout the process of writing this paper, and we thank two anonymous reviewers for their helpful revisions. ~~and Arpita Das for helping compile $R^2$ values.~~ We are also grateful for the assistance of ~~and~~ Arpita Das ~~for~~in helping compile $R^2$ values and~~.~~ the Virginia Tech libraries in planning this review and accessing the papers in the analysis. This project was supported by U.S. National Science Foundation (NSF) grants 1737424, 1926050, 1926388, 1933016, and 1933102, as well as NSF Graduate Research Fellowships ~~Program fellowships~~ to ASL and WMW (DGE-1651272).

Authorship contributions: This paper originated in an Ecological Forecasting graduate seminar at Virginia Tech led by CCC and RQT; all authors participated in the seminar and co-developed the matrix used for this analysis. Conceptualization of the project was led by ASL, CCC, JS, RPM, RQT, and WMW. ASL, CCC, MEL, and WMW led the development of methods for the project. All authors contributed to abstract screening and paper review. Data analysis was led by ASL, with input from CCC, HLW, and WMW. ASL, CCC, DWH, HLW, MEL, RPM, and WMW contributed to initial development of the manuscript, which was written by ASL. All authors edited and approved the final manuscript.

REFERENCES

Armstrong, J. S. 2001. Principles of forecasting: a handbook for researchers and practitioners. Springer Science & Business Media, New York.

Beardsley, T. M. 2014. Are you ready for open data? BioScience 64:855–855.

Beckage, B., L. J. Gross, and S. Kauffman. 2011. The limits to prediction in ecological systems. Ecosphere 2:art125.

Buizza, R., and M. Leutbecher. 2015. The forecast skill horizon. Quarterly Journal of the Royal Meteorological Society 141:3366–3382.

Carey, C. C., W. M. Woelmer, M. E. Lofton, R. J. Figueiredo, B. J. Bookout, R. S. Corrigan, V. Daneshmand, A. G. Hounshell, D. W. Howard, A. S. L. Lewis, R. P. McClure, H. L. Wander, N. K. Ward, and R. Q. Thomas. 2021. Advancing lake and reservoir water quality management with near-term, iterative ecological forecasting. Inland Waters. doi:

10.1080/20442041.2020.1816421

Caughlin T. T., E. I. Damschen, N. M. Haddad, D. J. Levey, C. Warneke, and L. A. Brudvig. 2019. Landscape heterogeneity is key to forecasting outcomes of plant reintroduction. Ecological Applications 29:e01850.

Clark, J. S., S. R. Carpenter, M. Barber, S. Collins, A. Dobson, J. A. Foley, D. M. Lodge, M. Pascual, R. Pielke, W. Pizer, C. Pringle, W. V. Reid, K. A. Rose, O. Sala, W. H. Schlesinger, D. H. Wall, and D. Wear. 2001. Ecological forecasts: an emerging imperative. Science 293:657–660.

Clements, F. E. 1936. Nature and structure of the climax. Journal of ecology, 24:252–284.

Dickersin, K. 1990. The existence of publication bias and risk factors for its occurrence. JAMA 263:1385–1389.

Dietze, M. C. 2017a. Ecological forecasting. Princeton University Press, Princeton.

Dietze, M. C. 2017b. Prediction in ecology: a first-principles framework. Ecological Applications 27:2048–2060.

Dietze, M. C., A. Fox, L. M. Beck-Johnson, J. L. Betancourt, M. B. Hooten, C. S. Jarnevich, T. H. Keitt, M. A. Kenney, C. M. Laney, L. G. Larsen, H. W. Loescher, C. K. Lunch, B. C. Pijanowski, J. T. Randerson, E. K. Read, A. T. Tredennick, R. Vargas, K. C. Weathers, and E. P. White. 2018. Iterative near-term ecological forecasting: Needs, opportunities, and challenges. Proceedings of the National Academy of Sciences 115:1424–1432.

Dietze, M. C., R. Q. Thomas, J. Peters, C. Boettiger, A. N. Shiklomanov, J. Ashander. 2021. A Community Convention for Ecological Forecasting: Output Files and Metadata. EcoEvoRxiv. doi: 10.32942/osf.io/9dgtq

Draper, N. R., and H. Smith. 1998. Applied regression analysis. John Wiley & Sons.

Fecher, B., and S. Friesike. 2013. Open science: one term, five schools of thought.

Feng, X., X. He, and J. Hu. 2011. Wild bootstrap for quantile regression. Biometrika 98:995–999.

Geremia, C., P. J. White, J. A. Hoeting, R. L. Wallen, F. G. R. Watson, D. Blanton, and N. T. Hobbs. 2014. Integrating population- and individual-level information in a movement model of Yellowstone bison. Ecological Applications 24:346–362.

Gleason, H. A. 1926. The individualistic concept of the plant association. Bulletin of the Torrey botanical club 7–26.

Gneiting, T., A. E. Raftery, A. H. Westveld, and T. Goldman. 2005. Calibrated probabilistic forecasting using ensemble model output statistics and minimum CRPS estimation. Monthly Weather Review 133:1098–1118.

Godfray, H. C. J., and R. M. May. 2014. Open questions: are the dynamics of ecological communities predictable? BMC Biology 12:22.

Hampton, S. E., C. A. Strasser, J. J. Tewksbury, W. K. Gram, A. E. Budden, A. L. Batcheller, C. S. Duke, and J. H. Porter. 2013. Big data and the future of ecology. Frontiers in Ecology and the Environment 11:156–162.

Hanson, P. C., K. C. Weathers, and T. K. Kratz. 2016. Networked lake science: how the Global Lake Ecological Observatory Network (GLEON) works to understand, predict, and communicate lake ecosystem response to global change. Inland Waters 6:543–554.

Harris, D. J., S. D. Taylor, and E. P. White. 2018. Forecasting biodiversity in breeding birds using best practices. PeerJ 6:e4278.

Henden, J.-A., R. A. Ims, N. G. Yoccoz, E. J. Asbjørnsen, A. Stien, J. P. Mellard, T. Tveraa, F. Marolla, and J. U. Jepsen. 2020. End-user involvement to improve predictions and management of populations with complex dynamics and multiple drivers. Ecological Applications 30:e02120.

Hobday, A. J., J. R. Hartog, J. P. Manderson, K. E. Mills, M. J. Oliver, A. J. Pershing, and S. Siedlecki. 2019. Ethical considerations and unanticipated consequences associated with ecological forecasting for marine resources. ICES Journal of Marine Science 76:1244–1256.

Hodgson, W. C. 1932. The forecasting of the East Anglian herring fishery. Journal of Animal Ecology 1:108–118.

Houlahan, J. E., S. T. McKinney, T. M. Anderson, and B. J. McGill. 2017. The priority of prediction in ecological understanding. Oikos 126:1–7.

Hyndman, R. J., and G. Athanasopoulos. 2018. Forecasting: principles and practice. OTexts.

Joslyn, S., and S. Savelli. 2010. Communicating forecast uncertainty: public perception of weather forecast uncertainty. Meteorological Applications 17:180–195.

Kalnay, E. 2003. Atmospheric modeling, data assimilation and predictability. Cambridge University Press, New York.

Koenker, R., S. Portnoy, P. T. Ng, B. Melly, A. Zeileis, P. Grosjean, C. Moler, Y. Saad, V. Chernozhukov, I. Fernandez-Val, and B. D. Ripley. 2021. quantreg: Quantile Regression.

LaDeau, S. L., B. A. Han, E. J. Rosi-Marshall, and K. C. Weathers. 2017. The next decade of big data in ecosystem science. Ecosystems 20:274–283.

Lewis, A. S. L., W. M. Woelmer, H. L. Wander, D. W. Howard, J. W. Smith, R. P. McClure, M. E. Lofton, N. W. Hammond, R. S. Corrigan, R. Q. Thomas, and C. C. Carey. 2021. Systematic review of near-term ecological forecasting literature published between 1932 and 2020. Environmental Data Initiative.

https://doi.org/10.6073/pasta/c4bea94f100f39a6b73c7b9a577df214

Lindenmayer, D. B., G. E. Likens, A. Andersen, D. Bowman, C. M. Bull, E. Burns, C. R. Dickman, A. A. Hoffmann, D. A. Keith, M. J. Liddell, A. J. Lowe, D. J. Metcalfe, S. R. Phinn, J. Russell-Smith, N. Thurgate, and G. M. Wardle. 2012. Value of long-term ecological studies. Austral Ecology 37:745–757.

Luo, Y., K. Ogle, C. Tucker, S. Fei, C. Gao, S. LaDeau, J. S. Clark, and D. S. Schimel. 2011. Ecological forecasting and data assimilation in a data-rich era. Ecological Applications 21:1429–1442.

Mlinarić, A., M. Horvat, and V. Šupak Smolčić. 2017. Dealing with the positive publication bias: why you should really publish your negative results. Biochemia Medica 27:447–452.

Morss, R. E., J. L. Demuth, and J. K. Lazo. 2008. Communicating uncertainty in weather forecasts: a survey of the U.S. public. Weather and Forecasting 23:974–991.

Munafò, M. R., B. A. Nosek, D. V. M. Bishop, K. S. Button, C. D. Chambers, N. Percie du Sert, U. Simonsohn, E.-J. Wagenmakers, J. J. Ware, and J. P. A. Ioannidis. 2017. A manifesto for reproducible science. Nature Human Behaviour 1:1–9.

Niu, S., Y. Luo, M. C. Dietze, T. F. Keenan, Z. Shi, J. Li, and F. S. C. Iii. 2014. The role of data assimilation in predictive ecology. Ecosphere 5:art65.

Payne, M. R., , A. J. Hobday, B. R. MacKenzie, D. Tommasi, D. P. Dempsey, S. M. M. Fässler, A. C. Haynie, R. Ji, G. Liu, P. D. Lynch, D. Matei, A. K. Miesner, K. E. Mills, K. O. Strand, and E. Villarino. 2017. Lessons from the first generation of marine ecological forecasts. Frontiers in Marine Science 4:289.

Pennekamp, F., A. C. Iles, J. Garland, G. Brennan, U. Brose, U. Gaedke, U. Jacob, P. Kratina, B. Matthews, S. Munch, M. Novak, G. M. Palamara, B. C. Rall, B. Rosenbaum, A. Tabi, C.

Ward, R. Williams, H. Ye, and O. L. Petchey. 2019. The intrinsic predictability of ecological time series and its potential to guide forecasting. Ecological Monographs 89:e01359.

Petchey, O. L., M. Pontarp, T. M. Massie, S. Kéfi, A. Ozgul, M. Weilenmann, G. M. Palamara, F. Altermatt, B. Matthews, J. M. Levine, D. Z. Childs, B. J. McGill, M. E. Schaepman, B. Schmid, P. Spaak, A. P. Beckerman, F. Pennekamp, and I. S. Pearse. 2015. The ecological forecast horizon, and examples of its uses and determinants. Ecology Letters 18:597–611.

Petrovskii, S., and N. Petrovskaya. 2012. Computational ecology as an emerging science. Interface Focus 2:241–254.

Pielke, R. A., and R. T. Conant. 2003. Best practices in prediction for decision-making: lessons from the atmospheric and earth sciences. Ecology 84:1351–1358.

Powers, S. M., and S. E. Hampton. 2019. Open science, reproducibility, and transparency in ecology. Ecological Applications 29:e01822.

R Core Team. 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Recknagel, F., R. Adrian, J. Köhler, and H. Cao. 2016. Threshold quantification and short-term forecasting of Anabaena, Aphanizomenon and Microcystis in the polymictic eutrophic Lake Müggelsee (Germany) by inferential modelling using the hybrid evolutionary algorithm HEA. Hydrobiologia 778:61–74.

Reichman, O. J., M. B. Jones, and M. P. Schildhauer. 2011. Challenges and opportunities of open data in ecology. Science 331:703–705.

Reynolds, C. S. 2006. The ecology of phytoplankton. Cambridge University Press.

Rigosi, A., R. Marcé, C. Escot, and F. J. Rueda. 2011. A calibration strategy for dynamic succession models including several phytoplankton groups. Environmental Modelling & Software 26:697–710.

Roulston, M. S., and L. A. Smith. 2002. Evaluating probabilistic forecasts using information theory. Monthly Weather Review 130:1653–1660.

Rousso, B. Z., E. Bertone, R. Stewart, and D. P. Hamilton. 2020. A systematic literature review of forecasting and predictive models for cyanobacteria blooms in freshwater lakes. Water Research 182:115959.

Sutherland, W. J., R. P. Freckleton, H. C. J. Godfray, S. R. Beissinger, T. Benton, D. D. Cameron, Y. Carmel, D. A. Coomes, T. Coulson, M. C. Emmerson, R. S. Hails, G. C. Hays, D. J. Hodgson, M. J. Hutchings, D. Johnson, J. P. G. Jones, M. J. Keeling, H. Kokko, W. E. Kunin, X. Lambin, O. T. Lewis, Y. Malhi, N. Mieszkowska, E. J. Milner-Gulland, K. Norris, A. B. Phillimore, D. W. Purves, J. M. Reid, D. C. Reuman, K. Thompson, J. M. J. Travis, L. A. Turnbull, D. A. Wardle, and T. Wiegand. 2013. Identification of 100 fundamental ecological questions. Journal of Ecology 101:58–67.

Ward, E. J., E. E. Holmes, J. T. Thorson, and B. Collen. 2014. Complexity is costly: a meta-analysis of parametric and non-parametric methods for short-term population forecasting. Oikos 123:652–661.

White, E. P., G. M. Yenni, S. D. Taylor, E. M. Christensen, E. K. Bledsoe, J. L. Simonis, and S. K. M. Ernest. 2019. Developing an automated iterative near-term forecasting system for an ecological study. Methods in Ecology and Evolution 10:332–344.

Wilkinson, M. D., M. Dumontier, I. J. Aalbersberg, G. Appleton, M. Axton, A. Baak, N. Blomberg, J.-W. Boiten, L. B. da Silva Santos, P. E. Bourne, J. Bouwman, A. J. Brookes,

T. Clark, M. Crosas, I. Dillo, O. Dumon, S. Edmunds, C. T. Evelo, R. Finkers, A. Gonzalez-Beltran, A. J. G. Gray, P. Groth, C. Goble, J. S. Grethe, J. Heringa, P. A. C. ’t Hoen, R. Hooft, T. Kuhn, R. Kok, J. Kok, S. J. Lusher, M. E. Martone, A. Mons, A. L. Packer, B. Persson, P. Rocca-Serra, M. Roos, R. van Schaik, S.-A. Sansone, E. Schultes, T. Sengstag, T. Slater, G. Strawn, M. A. Swertz, M. Thompson, J. van der Lei, E. van Mulligen, J. Velterop, A. Waagmeester, P. Wittenburg, K. Wolstencroft, J. Zhao, and B. Mons. 2016. The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data 3:160018.

Zwart, J. A., O. Hararuk, Y. T. Prairie, S. E. Jones, and C. T. Solomon. 2019. Improving estimates and forecasts of lake carbon dynamics using data assimilation. Limnology and Oceanography: Methods 17:97–111.

Box 1: Proposed best practices for ecological forecasting, drawn from peer-reviewed literature: ~~Dietze et al. (2018),~~ Harris et al. (2018), White et al. (2019), Hobday et al. (2019), and Carey et al. (2021). *Forecast Requirements* include traits of forecasting systems that are essential to the development of a forecast. *Decision Support* practices are those that are particularly helpful if the forecast will be applied as a decision support tool. *Research* practices include characteristics of a forecasting system that are particularly suited to enabling the advancement of fundamental ecological understanding across studies. Importantly, these last two tiers are not mutually exclusive: *D~~d~~ecision S~~s~~upport* practices can also be important for ecological understanding and vice versa.

*Forecast Requirements*

1. Include uncertainty
    a. Meaningful representations of uncertainty are important to forecast interpretation and evaluation, so much so that ~~in many definitions~~ uncertainty is identified as an essential component ~~of~~ of many ~~an~~ ecological forecast definitions (Clark et al. 2001, Luo et al. 2011, Harris et al. 2018, Dietze et al. 2018, Carey et al. 2021).
2. ~~Assess and r~~Report forecast accuracy~~skill~~
    a. Assessing and reporting forecast ~~skill~~ accuracy allows end users to understand the reliability of the forecasting system (Harris et al. 2018, Hobday et al. 2019) and provides the near-term ecological forecasting research community with increased insight into the tools and techniques needed to produce effective forecasts (Dietze et al. 2018). Furthermore, assessing and reporting forecast ~~skill~~ accuracy contributes to our understanding of ecological predictability by facilitating

comparisons of forecast ~~skill~~ accuracy across scales and variables (Beckage et al. 2011, Petchey et al. 2015).

*Decision Support*

3. Identify an end user
    a. One of the goals of ecological forecasting is to aid in decision-making. The first step in this process is to identify a specific~~n~~ end user and consider their needs throughout forecast development (Dietze et al. 2018, Hobday et al. 2019, Carey et al. 2021).
4. Make iterative forecasts
    a. Iterative forecasts incorporate new data as they become available, providing updated predictions that can aid in continuous decision-making and forecast improvement (Dietze et al. 2018, Hobday et al. 2019, Carey et al. 2021).
5. Automate forecasting workflows
    a. End-to-end automation of the forecasting workflow (from data processing to forecast communication) allows for more frequent forecast outputs and more sustainable forecasting infrastructure (Dietze et al. 2018, White et al. 2019, Hobday et al. 2019, Carey et al. 2021). This practice is particularly relevant for forecasts with horizons of days to months that are rerun often to provide updated information.

*Research*

6. Make data available
    a. To ensure full forecast reproducibility and allow future research to build off of existing forecasting workflows, all data and code used to create forecasts should

be findable, accessible, interoperable, and reusable (FAIR; Wilkinson et al. 2016, Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Carey et al. 2021).

7. Archive forecasts
    a. Archiving forecasts as they are created provides a means of demonstrating when forecasts were made and tracking forecast improvement over time (Harris et al. 2018, Dietze et al. 2018, White et al. 2019, Carey et al. 2021).
8. Use null model comparisons
    a. Comparing forecasts to simple, standard baselines (e.g., persistence or climatology null models) allows researchers to compare forecastability across systems (Petchey et al. 2015) and evaluate the amount of information contained in the forecasts (Harris et al. 2018, Dietze et al. 2018, White et al. 2019).
9. Compare modeling approaches
    ~~a.~~ Comparing multiple modeling approaches (e.g., process-based and empirical approaches, alternative model drivers,~~-~~ alternative mathematical representations of mechanistic processes) can provide insight into the nature of ecological processes and develop a better understanding of the circumstances under which different modeling approaches are most effective (Harris et al. 2018, White et al. 2019).

~~9. Partition uncertainty~~
    ~~a. Partitioning uncertainty into its respective components (e.g., initial conditions, drivers, parameters, process) is helpful when prioritizing improvements to the forecasting system (Dietze et al. 2018, Carey et al. 2021), and it allows for the comparison of limitations to predictability across time horizons and ecosystems.~~

Table 1: Logistic regression results for each proposed best practice based on n = 177 papers (one paper from 1932 was excluded from this analysis). Statistically significant p values are in bold. In addition to the nine proposed best practices, statistics are included for the use of iterative forecasting to update model parameters.

| | Estimate | Standard error | Z value | P value |
|---|---|---|---|---|
| Include uncertainty | | | | |
| Intercept | -7.615 | 35.157 | -0.217 | 0.83 |
| Year | 0.004 | 0.017 | 0.211 | 0.83 |
| ~~Assess and r~~Report forecast accuracy~~skill~~ | | | | |
| Intercept | -59.665 | 38.486 | -1.550 | 0.12 |
| Year | 0.030 | 0.019 | 1.579 | 0.11 |
| Identify an end user | | | | |
| Intercept | -86.809 | 52.611 | -1.650 | 0.10 |
| Year | 0.042 | 0.026 | 1.624 | 0.10 |
| Make iterative forecasts | | | | |
| Intercept | -14.147 | 36.152 | -0.391 | 0.70 |
| Year | 0.007 | 0.018 | 0.379 | 0.71 |
| Make iterative forecasts (updating model parameters) | | | | |
| Intercept | -182.741 | 85.680 | -2.133 | **0.03** |
| Year | 0.090 | 0.043 | 2.111 | **0.04** |
| Automate forecasting workflows | | | | |
| Intercept | -237.502 | 100.550 | -2.362 | **0.02** |
| Year | 0.117 | 0.050 | 2.344 | **0.02** |
| Make data available | | | | |
| Intercept | -252.217 | 69.775 | -3.615 | **<0.001** |
| Year | 0.125 | 0.035 | 3.602 | **<0.001** |
| Archive forecasts | | | | |
| Intercept | -308.891 | 136.546 | -2.262 | **0.02** |
| Year | 0.152 | 0.068 | 2.247 | **0.03** |
| Use null model comparisons | | | | |
| Intercept | 33.795 | 50.388 | 0.671 | 0.50 |
| Year | -0.018 | 0.025 | -0.710 | 0.48 |
| Compare modeling approaches | | | | |
| Intercept | -41.332 | 35.718 | -1.157 | 0.25~~47~~ |
| Year | 0.021 | 0.018 | 1.154 | 0.25~~48~~ |
| ~~Partition uncertainty~~ | | | | |

44

| | | | | |
|---|---|---|---|---|
| ~~Intercept~~ | ~~-384.450~~ | ~~355.406~~ | ~~-1.082~~ | ~~0.28~~ |
| ~~Year~~ | ~~0.189~~ | ~~0.176~~ | ~~1.071~~ | ~~0.28~~ |

Table 2: Indicator variable analysis results comparing the slope of $R^2$ values over 1–7 day horizons among forecast variables. Chlorophyll was treated as the reference variable for the analysis. Statistically significant p values are in bold.

| | Estimate | SE | t | P value |
|---|---|---|---|---|
| Chlorophyll (reference; n = 68 data points from 8 papers) | | | | |
| Intercept | 0.98 | 0.025 | 39.53 | **<0.001** |
| Horizon | -0.08 | 0.012 | -6.78 | **<0.001** |
| Phytoplankton (n = 33 data points from 8 papers) | | | | |
| Intercept | 0.04 | 0.055 | 0.71 | 0.48 |
| Horizon | 0.02 | 0.016 | 1.06 | 0.29 |
| Pollen (n = 110 data points from 3 papers) | | | | |
| Intercept | -0.29 | 0.043 | -6.62 | **<0.001** |
| Horizon | 0.05 | 0.014 | 3.94 | **<0.001** |
| Evapotranspiration (n = 113 data points from 10 papers) | | | | |
| Intercept | -0.26 | 0.059 | -4.40 | **<0.001** |
| Horizon | 0.05 | 0.015 | 3.46 | **<0.001** |

FIGURE LEGENDS

Figure 1: Systematic literature analysis methods. a: Flow chart of literature review process. b and c: Venn diagrams illustrating the number of studies that met each of our three criteria after two rounds of review (abstract and paper reviews) for our original Web of Science search (b) and a search of citing and cited papers (c).

Figure 2: Number of near-term ecological forecasts published per year. Five papers from the final year (2020) are not plotted because data for this year are incomplete: only papers indexed on Web of Science by the date of our search (18 May 2020) were included in this study.

Figure 3: Description of ecological forecasting papers identified in this study. a: Map of all forecasts: regional and national studies are shown in large transparent points near the center of the forecast region, while point and multipoint forecasts are shown in small opaque points. b: Bar chart illustrating the spatial extent of the forecast for each paper—point, multipoint (several distinct points), regional (a broad region that does not follow national bounds), national, or global (for details about how spatial extent was determined, see Lewis et al. ~~Environmental~~ 2021~~Data Initiative repository forthcoming data publication~~). c: Bar chart illustrating the class—organismal (population or community) or biogeochemical—of the forecast variable for each paper. Fill colors illustrate ecosystem type. Forecasts that could not be matched to one of our nine ecosystem types have been labeled “other.”

Figure 4: Relationship between time step and forecast~~time~~ horizon of forecasting papers. Colors and numbers within each square indicate the number of papers corresponding to that

combination of time step and forecast~~time~~ horizon (darker colors indicate more common combinations). White areas indicate combinations of time step and horizon that were not represented in the dataset. Papers that did not have a defined horizon (e.g., predicting end of summer harvest) or that did not specify time step/horizon were omitted (n = 10).

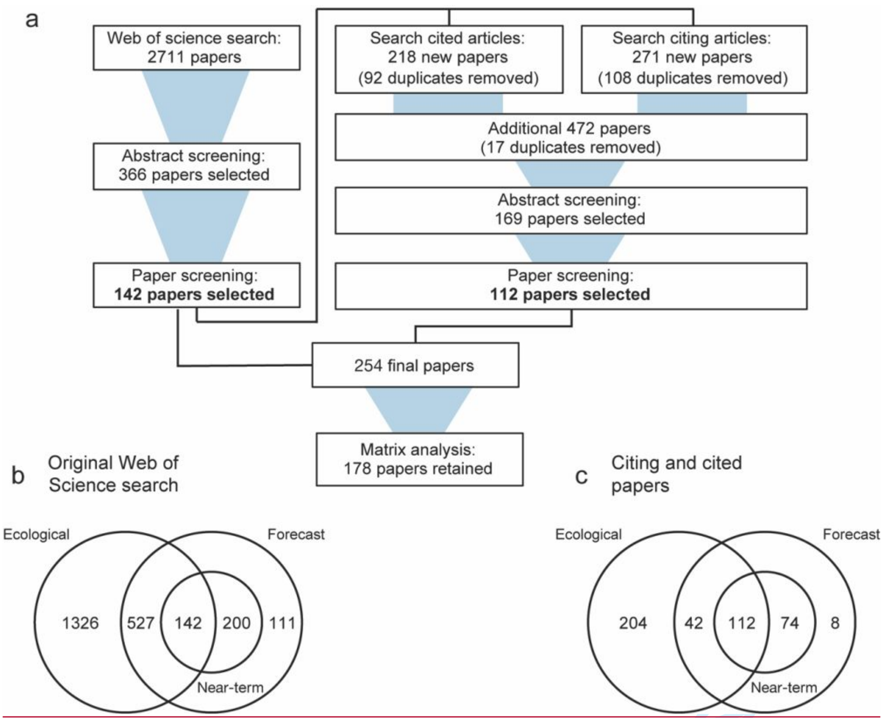
Figure 5: Histogram illustrating the total number of years of data used to develop each forecasting paper, summed across model development, training, evaluation, etc. Vertical lines represent the median (left) and mean (right) number of years used.

Figure 6: Best practice adoption over time. Points demarcate whether or not an individual paper demonstrated the best practice (1 = observed, 0 = not observed), and lines represent logistic regression results. Significance of the year term in the regression is indicated using asterisks: * indicates $p < 0.05$, *** indicates $p < 0.001$. One paper from 1932 was excluded from this analysis.

Figure 7: Relationship between forecast performance and forecast horizon (Horiz) for four forecast variables: chlorophyll (Chl), phytoplankton (Phyto), pollen, and evapotranspiration (ET). Different papers are indicated by points of different colors and shapes. Within a paper, forecasts using the same model were averaged (across sites, years, etc.). Rightmost panel: model predictions from the quantile regression indicator analysis.

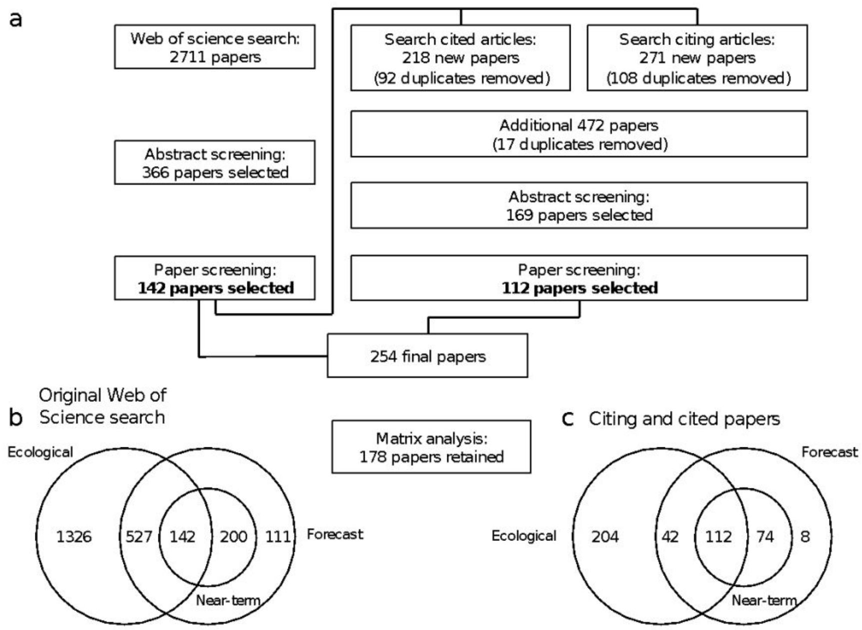
Figure 1

49

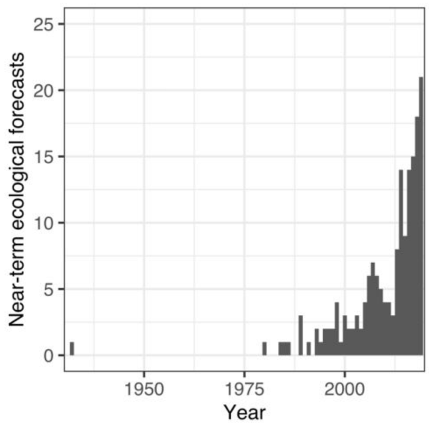

a
Web of science search: 2711 papers
Search cited articles: 218 new papers (92 duplicates removed)
Search citing articles: 271 new papers (108 duplicates removed)
Additional 472 papers (17 duplicates removed)
Abstract screening: 366 papers selected
Abstract screening: 169 papers selected
Paper screening: 142 papers selected
Paper screening: 112 papers selected
254 final papers
Matrix analysis: 178 papers retained
b Original Web of Science search
c Citing and cited papers
Ecological
Forecast
Near-term
1326
527
142
200
111
Ecological
Forecast
Near-term
204
42
112
74
8

966

50

967 
a
Web of science search: 2711 papers
Search cited articles: 218 new papers (92 duplicates removed)
Search citing articles: 271 new papers (108 duplicates removed)
Additional 472 papers (17 duplicates removed)
Abstract screening: 366 papers selected
Abstract screening: 169 papers selected
Paper screening: 142 papers selected
Paper screening: 112 papers selected
254 final papers
b Original Web of Science search
Matrix analysis: 178 papers retained
c Citing and cited papers
Ecological
Forecast
Near-term
1326
527
142
200
111
204
42
112
74
8

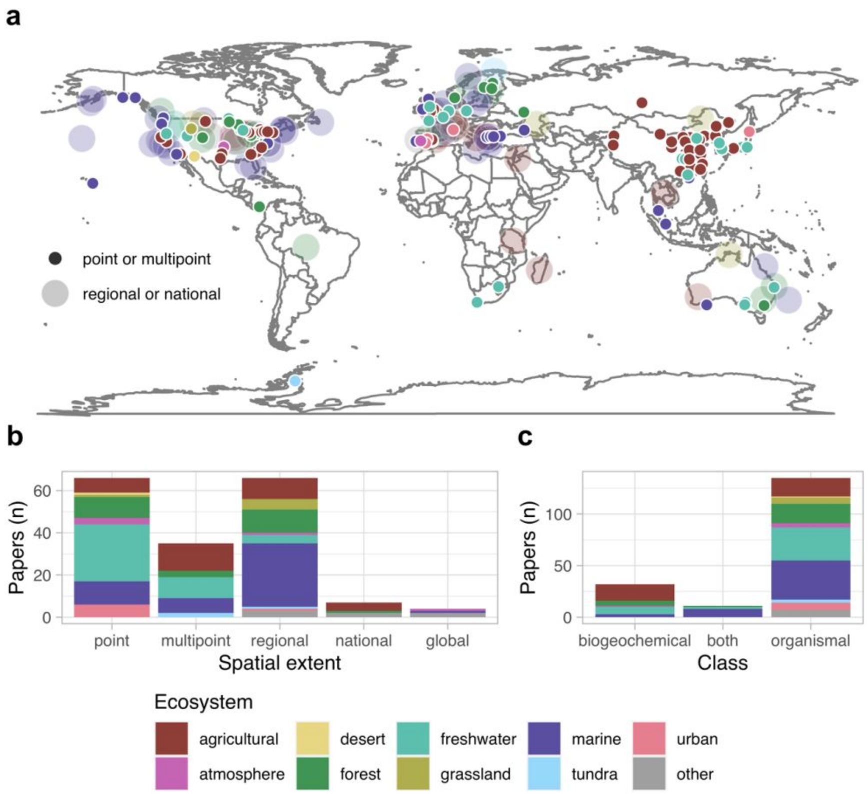
968 Figure 2




969

52

970 Figure 3




971

Figure 4

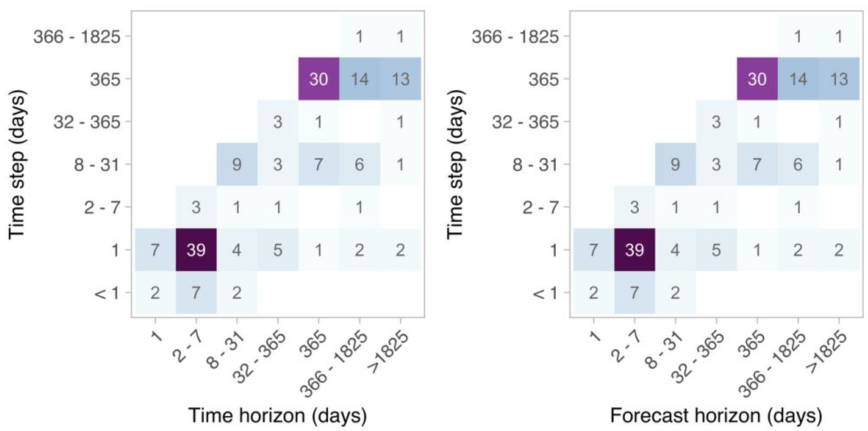

Time step (days)
366 - 1825
365
32 - 365
8 - 31
2 - 7
1
< 1
1
2 - 7
8 - 31
32 - 365
365
366 - 1825
>1825
Time horizon (days)
Forecast horizon (days)

Figure 5

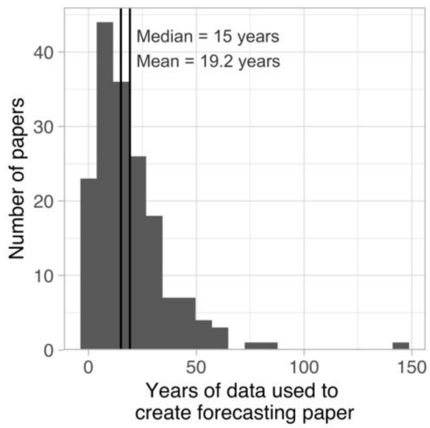
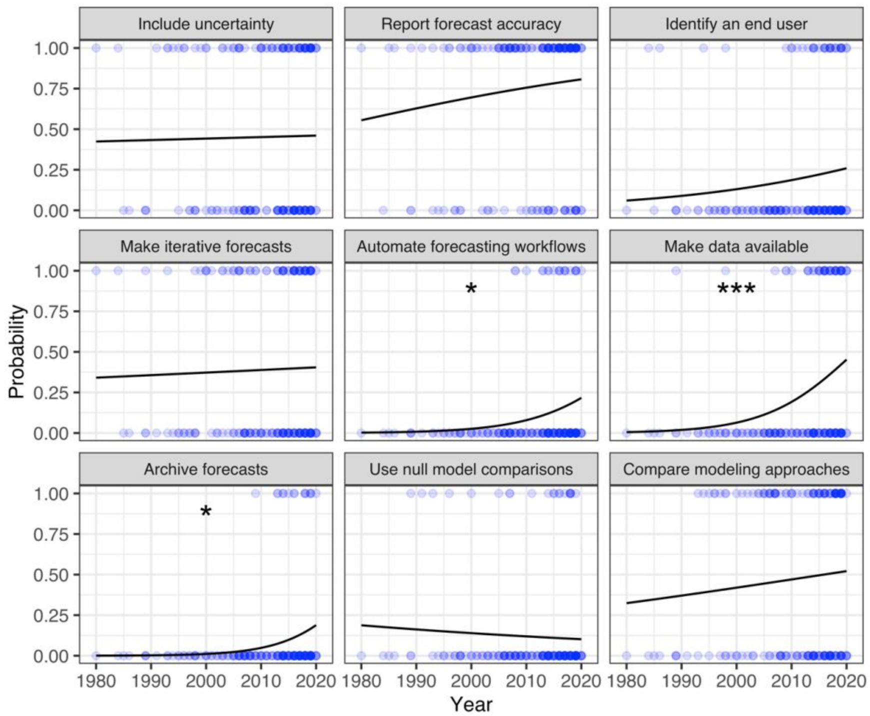

Median = 15 years
Mean = 19.2 years
Number of papers
0
10
20
30
40
0
50
100
150
Years of data used to
create forecasting paper

Figure 6

56


Include uncertainty
Report forecast accuracy
Identify an end user
Make iterative forecasts
Automate forecasting workflows
Make data available
Archive forecasts
Use null model comparisons
Compare modeling approaches
*
***
*
1.00
0.75
0.50
0.25
0.00
Probability
1980
1990
2000
2010
2020
Year

977

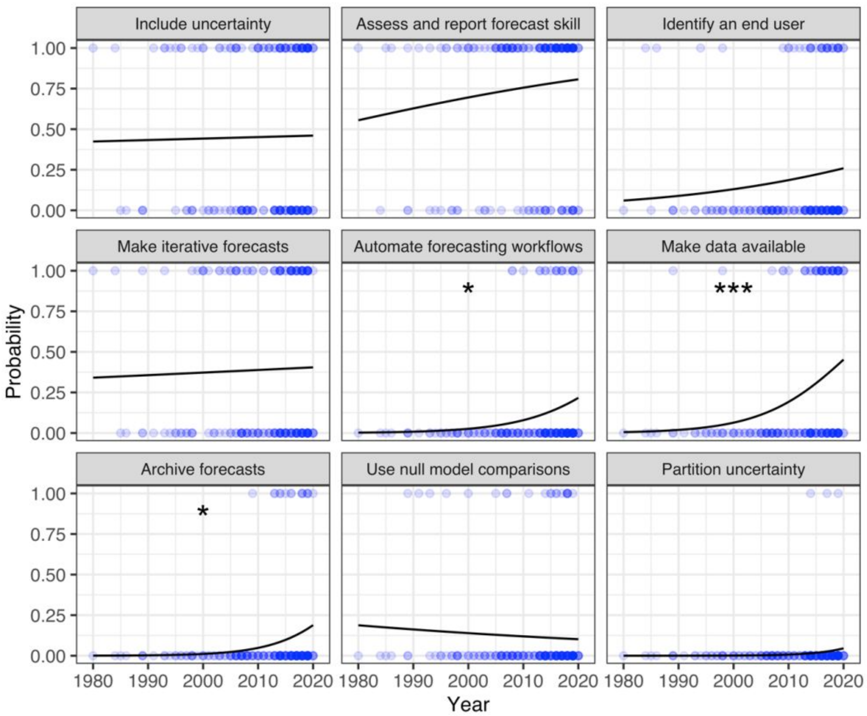
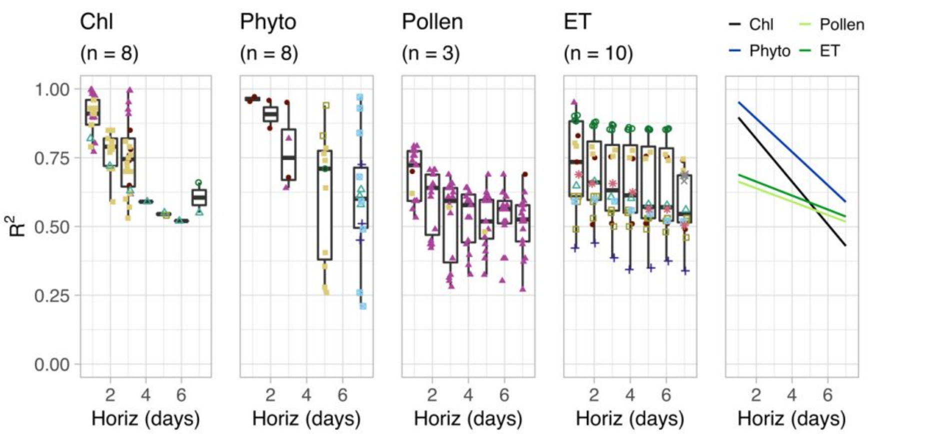
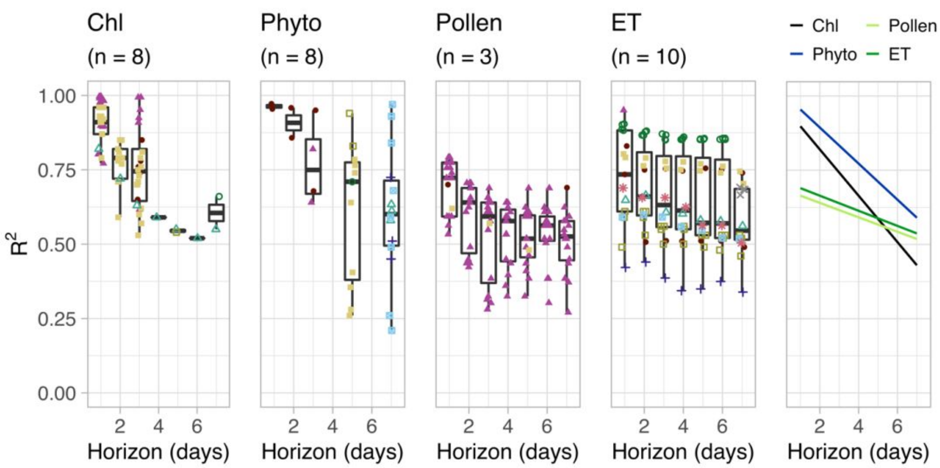

Include uncertainty
Assess and report forecast skill
Identify an end user
Make iterative forecasts
Automate forecasting workflows
Make data available
Archive forecasts
Use null model comparisons
Partition uncertainty
*
***
*
Probability
0.00
0.25
0.50
0.75
1.00
1980 1990 2000 2010 2020
Year

Figure 7


Chl
(n = 8)
Phyto
(n = 8)
Pollen
(n = 3)
ET
(n = 10)
Chl
Pollen
Phyto
ET
$R^2$
1.00
0.75
0.50
0.25
0.00
2 4 6
Horiz (days)


Chl
(n = 8)
Phyto
(n = 8)
Pollen
(n = 3)
ET
(n = 10)
Chl
Pollen
Phyto
ET
$R^2$
1.00
0.75
0.50
0.25
0.00
2 4 6
Horizon (days)

Lewis, A. S. L., W. M. Woelmer, H. L. Wander, D. W. Howard, J. W. Smith, R. P. McClure, M. E. Lofton, N. W. Hammond, R. S. Corrigan, R. Q. Thomas, and C. C. Carey. 2021. Increased adoption of best practices in ecological forecasting enables comparisons of forecastability. *Ecological Applications.*

## Appendix S1: Table of best practices referenced in previous publications

Table 1: Proposed best practices for ecological forecasting. Each column lists the practices that are specifically outlined in a given paper, and practices are aligned into rows with the same or similar proposed practices. We note that White et al. (2019) synthesized many of the best practices mentioned by Dietze et al. (2018). The Dietze et al. (2018) paper is not included here because it did not provide a defined list of practices (as provided by the four other papers in this table).



| Reference | This manuscript | Harris et al. (2018) | White et al. (2019) | Hobday et al. (2019) | Carey et al. (2021) |
|---|---|---|---|---|---|
| Title | Increased adoption of best practices in ecological forecasting enables comparisons of forecastability | Forecasting biodiversity in breeding birds using best practices. | Developing an automated iterative near-term forecasting system for an ecological study | Ethical considerations and unanticipated consequences associated with ecological forecasting for marine resources | Advancing lake and reservoir water quality management with near-term, iterative ecological forecasting |
| Description | Proposed best practices | Best practices for making and evaluating ecological forecasts | Key practices for automated iterative near-term ecological forecasting | Principles for ethical forecasting | Lessons learned from iterative near-term forecasting for management |
| | Include uncertainty | Pay attention to uncertainty | Focus on uncertainty | Representation of uncertainty | |
| | Assess and report forecast skill | Validate using hindcasting | | Skill assessment | |

| | | | | |
|---|---|---|---|---|
| Identify an end user | | | Engagement and education | Human-centered design improves the utility of forecasts for managers |
| Make iterative forecasts | | | Delivery failures | Sustainability plans are needed for short- and long-term forecasting system maintenance |
| Automate forecasting workflows | | Automated end-to-end reproducibility | Ongoing delivery | Cyberinfrastructure is not trivial |
| Make data available | | Rapid data release under open licenses | | Forecasts should be reproducible and archived |
| Archive forecasts | Publicly archive forecasts | Publicly archive forecasts | | Forecasts should be reproducible and archived |
| Use null model comparisons | Compare multiple modeling approaches (specifically mentions null models) | Compare forecasts to simple baselines | | |
| Compare modeling approaches | Compare multiple modeling approaches | Compare and combine multiple modelling approaches | | |
| | Use time-series data when possible | | | |

| | | | | |
|---|---|---|---|---|
| | Use predictors related to the question | | | |
| | Address unknown or unmeasured predictors | | | |
| | Include an observation model | | | |
| | Assess how forecast accuracy changes with time-lag | | | |
| | | Frequent data collection | | |
| | | Best practices in data structure | | |
| | | Best practices in software development | | |
| | | Support easy inclusion of new models | | |
| | | | Conflicts of interest | |
| | | | Ecosystem health | |
| | | | Equity for end users | |

| | | | | |
|---|---|---|---|---|
| | | | Unintended consequences | |
| | | | Review of performance | |
| | | | | Uncertainty partitioning informs forecast interpretation and forecast improvement |
| | | | | Building and maintaining a forecasting system takes an interdisciplinary, highly coordinated team |
| | | | | Let your forecasting goals guide your modeling approach |

**References**

Carey, C. C., W. M. Woelmer, M. E. Lofton, R. J. Figueiredo, B. J. Bookout, R. S. Corrigan, V. Daneshmand, A. G. Hounshell, D. W. Howard, A. S. L. Lewis, R. P. McClure, H. L. Wander, N. K. Ward, and R. Q. Thomas. 2021. Advancing lake and reservoir water quality management with near-term, iterative ecological forecasting. Inland Waters. doi: 10.1080/20442041.2020.1816421

Dietze, M. C., A. Fox, L. M. Beck-Johnson, J. L. Betancourt, M. B. Hooten, C. S. Jarnevich, T. H. Keitt, M. A. Kenney, C. M. Laney, L. G. Larsen, H. W. Loescher, C. K. Lunch, B. C. Pijanowski, J. T. Randerson, E. K. Read, A. T. Tredennick, R. Vargas, K. C. Weathers, and E. P. White. 2018. Iterative near-term ecological forecasting: Needs, opportunities, and challenges. Proceedings of the National Academy of Sciences 115:1424–1432.

Harris, D. J., S. D. Taylor, and E. P. White. 2018. Forecasting biodiversity in breeding birds using best practices. PeerJ 6:e4278.

Hobday, A. J., J. R. Hartog, J. P. Manderson, K. E. Mills, M. J. Oliver, A. J. Pershing, and S. Siedlecki. 2019. Ethical considerations and unanticipated consequences associated with ecological forecasting for marine resources. ICES Journal of Marine Science 76:1244–1256.

White, E. P., G. M. Yenni, S. D. Taylor, E. M. Christensen, E. K. Bledsoe, J. L. Simonis, and S. K. M. Ernest. 2019. Developing an automated iterative near-term forecasting system for an ecological study. Methods in Ecology and Evolution 10:332–344.

Lewis, A. S. L., W. M. Woelmer, H. L. Wander, D. W. Howard, J. W. Smith, R. P. McClure, M. E. Lofton, N. W. Hammond, R. S. Corrigan, R. Q. Thomas, and C. C. Carey. 2021. Increased adoption of best practices in ecological forecasting enables comparisons of forecastability. *Ecological Applications.*

## Appendix S2: List of standardized criteria used to assess each paper

1. Paper title
2. Digital object identifier (doi)
3. Author list
4. Year of publication
5. Journal or conference in which the paper was published
6. Forecast spatial scale, classified into five categories
7. Geographic coordinates of the forecast site using decimal degrees. Locations for regional and national forecasts are approximately the center of the forecast area
8. Forecast ecosystem: forest, grassland, freshwater, marine, desert, tundra, atmosphere, agricultural, urban, global, other
9. Forecast class: biogeochemical or organismal (population or community)
10. Identity of forecast variables
11. Model dimension: 0D, 1D, 2D, 3D
12. Model type: empirical (dependent on correlative or statistical relationships) or process-based (explicitly simulating ecological processes). For forecasting workflows that involve a pipeline of multiple models, this refers to the "final" model that forecasts the forecast variable of interest
13. If specified: more detailed description of model: for example, Bayesian hierarchical, machine learning, named model (e.g., PROTECH), etc.
14. Are meteorological covariates used in this forecast? 1 = yes, 0 = no
15. Are physical covariates (e.g., streamflow) used in this forecast? 1 = yes, 0 = no
16. Are biological covariates used in this forecast? 1 = yes, 0 = no
17. Are chemical covariates used in this forecast? 1 = yes, 0 = no
18. Does the paper include an ensemble forecast (ensemble within model)? 1 = yes, 0 = no
19. Number of ensemble members
20. Does the paper use an ensemble of models to produce one output? 1 = yes, 0 = no
21. How many models in the ensemble model
22. Are multiple models with different model structures compared (NOT including null models)? 1 = yes, 0 = no
23. How many models with different structures are compared?
24. Was a forecast null model (persistence or climatology) included? 1 = yes, 0 = no
25. How many null models?
26. What type of null model (climatology or persistence)?
27. Maximum time into the future that the forecast predicts in this paper, described in days
28. Time step of forecast output. For example, a forecast that gives predictions for the next 16 days but was only run once a week would have a time step of one day (not one week)
29. Are the forecasts described in the papers iterative (i.e., data updating forecasts iteratively)? Any form of iteration counts here: updating initial conditions with new data,

refitting the model to incorporate new dta, updating parameter values, etc. State updating via the autoregressive term counts as data assimilation for autoregressive models

30. What technique of data assimilation was used? For example, KF, enKF, refit, update IC, etc.
31. Extent to which uncertainty is included in the forecast, classified within 5 categories:
    a. no (this model does not contain uncertainty)
    b. contains (the model contains uncertainty, but uncertainty is not derived from data; e.g. uncertainty comes from spin-up initial conditions or hand-tuned parameters)
    c. data_driven (the model contains data-driven uncertainty; e.g. uncertainty in meteorological drivers)
    d. propagates (the model propagates some source of uncertainty)
    e. assimilates (the model iteratively updates uncertainty through data assimilation)
    f. NOTE: this is assumed to be a hierarchy (e.g. if the forecast contains data driven uncertainty and propagates that uncertainty, it would be marked "propagates")
32. What sources of uncertainty were incorporated?
33. Was observation uncertainty included? 1 = yes, 0 = no
34. Are at least two different sources of uncertainty quantified and compared? 1 = yes, 0 = no. NOTE: the two sources may be in the same category of uncertainty—e.g. two forms of driver data)
35. Initial condition uncertainty partitioned? 1 = yes, 0 = no
36. Driver uncertainty partitioned? 1 = yes, 0 = no
37. Parameter uncertainty partitioned? 1 = yes, 0 = no
38. Process uncertainty partitioned? 1 = yes, 0 = no
39. Other partitioned sources of uncertainty? 1 = yes, 0 = no
40. If at least two categories of uncertainty were partitioned, what was the dominant source of uncertainty?
41. If the dominant source varies by forecast horizon, season, etc. please describe here
42. Paper states that forecast was evaluated? 1 = yes, 0 = no
43. Forecast evaluation results reported in paper? 1 = yes, 0 = no
44. List all skill metrics used (e.g. R2, RMSE, bias, MAE). SD and Bayesian credible intervals are not skill metrics
45. Is forecast performance assessed at multiple forecast horizons (results must be reported in paper/supplemental info)? 1 = yes, 0 = no
46. Maximum forecast horizon such that the forecast was better than the null model (out of any models used)
47. Temporal coverage of data used to create this forecasting paper
48. Was new data (driver and/or observations) available to the model in real time (<24 hours from collection) without any manual effort when the system was working as intended? 1 = yes, 0 = no
49. Forecast archiving described in text? 1 = yes, 0 = no
50. Repository in which forecasts are archived
51. Archiving website is still accessible via the link in the paper as of 14 Jun 2021? 1 = yes, 0 = no
52. Text specifies that driver data are publicly available to reproduce the forecasts? 1 = yes, 0 = no
53. Specific end user identified (proper noun)? 1 = yes, 0 = no

54. Partnership with the end user in forecast development mentioned in paper? 1 = yes, 0 = no
55. Forecast being used by the end user according to paper? 1 = yes, 0 = no
56. Forecast delivery method identified? 1 = yes, 0 = no
57. Forecast delivery method?
58. Any ethical considerations mentioned? 1 = yes, 0 = no

Dear Dr. Corley,

Please find attached our revised manuscript, "Increased adoption of best practices in ecological forecasting enables comparisons of forecastability." In response to the Reviewers' comments, we have made many changes to the manuscript, which we think have substantially improved the text. Importantly, we have published the data associated with the study to the Ecological Data Initiative (EDI) repository and submitted a new supplemental file with the matrix screening questions used in this study, resolving Reviewer 2's concern about data accessibility.

In response to Reviewer 1's question about how our best practices were selected, we created a new supplemental table that outlines all practices identified in the four papers we are aware of that provide best practices for near-term ecological forecasting. We added one new best practice ("Compare modeling approaches") to our manuscript and removed one practice ("Partition uncertainty"), so that we now analyze all practices that are mentioned in at least two of the four papers. "Compare modeling approaches" is demonstrated in 47% of papers and exhibits a non-significant upward trend over time. Adding this practice did not change any conclusions of the paper, but makes our selection of proposed best practices more robust. Likewise, removing "partition uncertainty" did not alter our conclusions. Below, we respond to each Reviewer's point in bold. We hope that the revised manuscript is now suitable for publication in *Ecological Applications* and look forward to hearing from you.

Sincerely,

Abby Lewis, on behalf of the co-authors



Reviewer(s)' Comments to Author:
Reviewer: 1

Comments to the Author
This paper describes a literature search, both structured and secondary based on the first search, to detect how often a set of best practices are used for near-term ecological forecasting. It is clearly written, well described, and the choice of analytical metrics as well defended. I suggest only minor revision, including some expansion of justification of the selection criteria of the nine best practices selected.

**We appreciate the Reviewer's positive feedback! We have made multiple changes throughout the manuscript to expand our justification of the best practices included in this analysis (described below, with line numbers provided).**

The title is the slight overreach. This is because the comparisons are forecasting across systems is relatively limited in the paper. This is more an aspirational claim than a delivered one. I'm not sure that forecastability is a word we need either!

**We appreciate the Reviewer's comment, and have removed "across systems" from the title. We consider the analysis of forecastability across scales and variables to be an important contribution of this paper, and have therefore retained the word "forecastability" in the title. To address the Reviewer's concern, we have clarified how we are defining forecastability in the Abstract and Introduction of the manuscript, saying that it is "defined here as realized forecast accuracy" (lines 39, 94–95). We have also added additional text to the Introduction to clarify the relationship between forecastability and predictability. The modified text now reads: "Ecological forecasting can be a particularly powerful test of predictability, as forecasting requires predicting beyond the range of observed data. Thus, comparisons of forecastability complement and extend existing theoretical and modeling-based work that has predicted how various factors (e.g., forecast horizon, computational irreducibility) influence the relative predictability of ecological variables (Beckage et al. 2011, Petchey et al. 2015)" (lines 99–103).**

**With respect to whether forecastability is a useful word more generally, we have chosen to use this word for two reasons: first, ecological variables may be highly predictable based on existing data without being highly forecastable (e.g., if they are sensitive to an environmental driver that cannot be forecasted with sufficient accuracy), and second, use of the word "forecastable" is already common in previous published literature (e.g., see Clark et al. 2001, Petchey et al. 2015).**

The abstract is clearly written. The near-term definition could be introduced here too. Later in the paper, near term is defined as less than 10 years, which in my view conflates two timescales seasonal and decadal. Much of the analysis is then also completed on forecasts with a timescale of less than seven days, which is weather time scale forecasting.

**We thank the Reviewer for their positive feedback. To address the Reviewer's comments, we now specify in the Abstract that we are defining near-term as forecasts with a horizon ≤10 years (line 26). This is in agreement with previous literature, particularly Dietze et al. (2018), who define near-term as "daily to decadal." While we agree that this may include weather-scale, seasonal, and decadal patterns, the timescale that constitutes a near-term forecast likely depends upon the scale of the process being measured. For example, a near-term forecast of lake chlorophyll-a would typically be seasonal or subseasonal, while a near-term forecast of tree diameter might be annual or longer. Consequently, using an expansive criterion (10 years) allowed us to encompass most near-term forecasts on a relevant timescale for each forecast variable. Furthermore, the majority of papers (75%) in our final dataset predicted within one year into the future, suggesting that a larger body of decadal and multi-decadal forecasting literature was effectively screened out in our literature search.**

I think the paper would be improved if it had a table, or box of interesting forecasting examples that you came across in your search. You could profile three or four case studies.

**While we thank the Reviewer for this suggestion, we feel uncomfortable choosing just 3 of 178 near-term ecological forecasting papers to highlight, as we want to focus our manuscript on the data-driven analysis, rather than a qualitative review of near-term ecological forecasting literature. That being said, we have now published the entire dataset of papers to the Environmental Data Initiative repository for readers to explore (see Lewis et al. 2021). Additionally, we added citations for three papers to the Results section to highlight how they quantified uncertainty (lines 340–344), which we hope helps direct readers to papers that might be of interest for demonstrating specific best practices.**

**Lewis, A. S. L., W. M. Woelmer, H. L. Wander, D. W. Howard, J. W. Smith, R. P. McClure, M. E. Lofton, N. W. Hammond, R. S. Corrigan, R. Q. Thomas, and C. C. Carey. 2021. Systematic review of near-term ecological forecasting literature published between 1932 and 2020. Environmental Data Initiative. https://doi.org/10.6073/pasta/c4bea94f100f39a6b73c7b9a577df214**



The selection of the best practices is not clear. While the box 1 indicates which papers identify particular features, you have not chosen the set that is used in all these papers. How did you arrive at the set that you propose as best practice? I think you need to have more explanation on how you arrived at the set.

**We thank the Reviewer for this very helpful comment, which inspired us to create a table summarizing and synthesizing the best practices presented in Harris et al. (2018), White et al. (2019), Hobday et al. (2019) and Carey et al. (2021). This table is now included in a new supplement, Appendix S1. We reference this new table in the manuscript main text on lines 80, 217, and 554.**

**In creating this table, we found that we had included all best practices that were referenced in at least two papers except "compare multiple modeling approaches." We had already assessed whether multiple approaches were compared in each paper using our matrix analysis. Therefore, we were able to add this as a best practice in the manuscript. In the revised manuscript, "Compare modeling approaches" has been added as a best practice in Box 1 (lines 856–861), and how we assessed whether papers demonstrated this practice has been added to the Methods (lines 243–244). We report the percentage of papers that demonstrate this practice on line 363 and the number of approaches they compare on lines 372–374. Summary statistics for logistic regression results have been added to Table 1 (line 866), and a brief discussion of these results is added on lines 432–436.**

**One of our previous best practices was only included in one of the four best practice sources: "partition uncertainty." Following our new criteria of including all practices that were referenced in at least two papers, we have since removed this best practice. In the updated manuscript, we retain previous text relating to uncertainty partitioning in the**

**Results and Discussion. However, we now refer to uncertainty partitioning as an additional step that expands on "include uncertainty" rather than as its own best practice (lines 339–344, 473).**

Just a comment on both forecast requirement number one, uncertainty, and number two, assess and report forecast skill. From the perspective of end users scale is sometimes all they are interested in. The measures of skill will incorporate the uncertainty in the overall forecast. The uncertainty, and I agree with your suggestion of breaking down uncertainty, will be most useful to forecast developers when they try and improve the forecast. I think you could expand on this point in the discussion.

**We appreciate the Reviewer's comments about how uncertainty can be useful for forecast improvement, and have added text on this point to the Discussion. The section now reads: "Moving beyond specifying uncertainty to partitioning uncertainty into its component parts (e.g., initial condition, driver, parameter, and process uncertainty) provides information to help forecast developers prioritize improvements to their forecasting system and allows researchers to understand the constraints to predictability for a given ecological variable (Dietze 2017b)" (lines 473–477).**

You might also identify best practices that are good for end users, and best practices which serve the research community. Do you have a mix of these in your set. You would be able to add some material in the discussion noting that the different groups would require different best practices.

**We agree wholeheartedly with the Reviewer that some best practices are more useful for end users and some are more useful for research purposes. For this reason, we had previously divided the best practices into three categories (Forecast Requirements, Decision Support, and Research; Box 1). To address the Reviewer's comment, we have also added additional text on this point to the Discussion to make this delineation more clear. The modified text now reads: "While the rates of adoption of these proposed best practices (Box 1) are low overall, they are not necessarily unexpected. Different forecasting applications likely require different best practices; in this analysis, we have divided our selected best practices among three categories: forecast requirements, decision support, and research. However, this is a coarse delineation, and the last two tiers are not mutually exclusive: decision support practices can also be important for ecological understanding and vice versa" (lines 545–550).**

You have also minimised the ethical aspects of best practice forecasting in this paper.

**We strongly agree that ethical aspects of forecasting best practices are critically important, and our analysis reveals that they are underrepresented in current literature. In particular, we highlight that only 5% of papers overall and 25% of forecasts that are in use by an end user mention any ethical considerations (line 494). To respond to the Reviewer's comment, we added text to be more explicit about how training is needed to**

**advance the consideration of ethics in forecasting. This section of the Discussion now reads: "Given the power of forecasts to inform decision support, education on how to navigate engagement with end users, and particularly any ethical considerations that must be made, may be useful in improving the utility of forecasts for stakeholder use" (lines 495–497).**

The supplementary data are all provided, which allows good use into the future and reproducibility of these results.

**We thank the Reviewer for their positive feedback!**

Specific comments
Line 66. I consider Payne et al a good review of the state of marine ecological forecasting - maybe 4 years is a long time....

**We agree with the Reviewer that Payne et al. (2017) is an excellent review of marine ecological forecasting literature. We have chosen not to cite Payne et al. (2017) for this particular sentence because that analysis is neither systematic (the authors reviewed papers they were familiar with and conducted a brief literature survey), nor a comprehensive review of all ecological forecasting (it focuses on marine systems only). Instead, we have added this citation later in the Introduction (lines 84–85) to demonstrate how previous forecasting efforts can provide insight into the development of the field.**

Line 95. Can you suggest some classical ecology papers from the 1950s that defined this aspect of predictability for the field of ecology?

**There are many possible examples of classic ecological concepts that are centered in ecological predictability, including Lotka Volterra predator prey dynamics, island biogeography, and more. Here, we chose to add Clements (1936) and Gleason (1926), highlighting how the question of whether plant communities are primarily characterized by climax communities (Clements 1936) or individualistic responses (Gleason 1926) is fundamentally a question of ecological stability and predictability. The modified sentence reads as follows: "Understanding ecological predictability is a fundamental goal in ecology (Gleason 1926, Clements 1936, Sutherland et al. 2013, Godfray and May 2014, Houlahan et al. 2017, and references therein) and provides valuable information regarding the nature of ecological processes (Petchey et al. 2015)" (lines 95–98).**

Line 138. The definition of near term is less than 10 years. This is quite long and covers weather scale forecasting, seasonal forecasting, multi year, and decade. Each of these timescales have been a focus in their own right, as they require different focus on initial conditions, relative to boundary conditions.

**We hope the Reviewer supports our justification for the decadal threshold, which is detailed in a comment above. In brief, we are using this near-term threshold so our work**

**aligns with previous ecological forecasting literature and is inclusive of the relevant timescale of each forecasted variable (e.g., phytoplankton chlorophyll to tree diameter). To respond to this point, we have also cited Dietze et al. (2018) here (line 140).**

Line 152. Just be clear that this was 21% of 142 papers rather than 21% of 2711 papers.

**We appreciate the Reviewer's comment and have added "(n = 669)" on line 154 to clarify this point.**

Line 598. This is the claim made in the title that this attention to best practice will provide critical insight into the predictability. This aspect is underdone in the paper, and can either be removed or expanded. For example the variables you tracked over seven days Fig 7 were both marine and terrestrial. Does the difference in slopes indicate that the terrestrial environment is more predictable than the marine? Or are you analysing to few variables to make any suggestion (I think too few variables).

**We agree with the Reviewer that we are analyzing too few variables to make any comparison between aquatic and terrestrial ecosystems, which was not the intent of the manuscript. Consequently, we have modified the title and section headers so they no longer include mention of comparing forecastability "across systems." Further, we have modified this concluding sentence to say that near-term ecological forecasting can provide insight into the predictability of ecological "variables" rather than ecological "systems" (line 619). While this is a preliminary analysis, we feel justified in saying that "near-term ecological forecasting is well-positioned to transform ecological management and provide critical insight into the predictability of ecological variables" because (a) the rate of forecast publication is increasing, (b) adoption of best practices that facilitate comparisons across studies are increasing, and (c) forecast accuracy can be compared across scales and variables, as demonstrated in this analysis.**



Most figures are clearly drawn and high-quality.

**We appreciate the Reviewer's positive feedback.**

Figure 1, a B and C could be separated a bit more in space on the page . My figure 1a also lacked connecting arrows between some of the boxes.

**We thank the Reviewer for their attention to detail, and have modified the figure to fix these issues.**

Suggested refs

Payne, M. R., A. J. Hobday, B. R. Mackenzie and D. Tommasi (2019). Editorial: Seasonal-to-decadal prediction of marine ecosystems: opportunities, approaches and applications. Frontiers in Marine Science: doi: 10.3389/fmars.2019.00100

Payne, M. R., A. J. Hobday, B. R. MacKenzie, D. Tommasi, D. P. Dempsey, S. M. M. Fässler, A. C. Haynie, R. Ji, G. Liu, P. D. Lynch, D. Matei, A. K. Miesner, K. E. Mills, K. O. Strand and E. Villarino (2017). Lessons from the first generation of marine ecological forecasts. Frontiers in Marine Science: doi: 10.3389/fmars.2017.00289

Reviewer: 2

Comments to the Author
This paper provides a quantitative review of the ecological forecasting literature, reflecting specifically on the degree to which “best practices” have been adopted and changes in those practices over time. In addition, the paper provides numerous insightful nuggets about the state of ecological forecasting, such as where we’re seeing the most forecasts (in space and by topic), the grain and extent of forecasts, the amount of data folks are using to calibrate data, and the trends in model skill with lead time for common forecast areas. Overall the paper is well written and accessible, the analyses are performed well, and the interpretation is sounds. I just have a few tiny suggestions, mostly focused on places where the authors could increase clarity.

**We thank the Reviewer for their positive feedback!**

Line 94: “forecastability” was used here, in the title, abstract, and few places later in the paper, but isn’t specifically defined anywhere. This seems like the best place to do so, and to provide a clear distinction between prediction, predictability, and forecastability (even without introducing “forecastability”, I see too many folk convolve the first two terms).

**We appreciate the Reviewer’s comments, and have provided an operational definition of forecastability as “realized forecast accuracy” in the Abstract (line 39) and Introduction (line 94–95). We also modified the text in this section to better illustrate the distinction between forecastability and predictability. This section now reads “Ecological forecasting can be a particularly powerful test of predictability, as forecasting requires predicting beyond the range of observed data (Dietze et al. 2018). Thus, comparisons of forecastability complement and extend existing theoretical and modeling-based work that has predicted how various factors (e.g., forecast horizon, computational irreducibility) influence the relative predictability of ecological variables (Beckage et al. 2011, Petchey et al. 2015)” (lines 99–103).**

Line 171-177: I think my biggest true critique of the paper is that the standardized matrix of questions that the authors used analyze these papers is never provided. Instead of putting this information in a supplement/appendix, as one normally would do, they instead put their scoring rubric inside a “forthcoming data publication” that is not accessible to reviewers. I came very close to sending the paper back at this point as non-replicable and noncompliant with ESA’s data policy. I also found it very odd that the matrix/rubric itself would be considered a data publication, while the dataset itself *IS* provided as a supplement. That said, it’s worth noting that that the datasets are likewise provided without any metadata (e.g. defining column names and units). All of these things should have been provided the reviewers and definitely need to be provided to the reviewers in the next revision.

**The "forthcoming data publication" in our initial submission was provided to Reviewers via an accessible link in the Open Data Statement as a provisional data product. This data publication contained all of the analysis data and metadata with column descriptions and units, as well as the R code used to analyze the data.**

**As we did not receive any requested edits on this data publication from Reviewers, we have now published the dataset to the EDI repository so it has been assigned a permanent DOI (Lewis et al. 2021, reference provided above). We have changed all mentions of the "forthcoming data publication" to citations of this data publication. Additionally, to address the Reviewer's concerns about the matrix/rubric itself, we have submitted an additional file for publication as supplemental information (Appendix S2). This file includes a list of the questions used to screen papers in the analysis to ease access to this information for readers.**

L180: Unclear what was actually done here. If reviewers screened papers individually, what were they checking with reviewers that didn't screen that paper?

**Two reviewers first analyzed each paper independently (without consulting the other reviewer), and then second compared responses with each other. To clarify this point, we changed the word "individually" to "independently" on line 180.**

L216: Totally optional, but this section also made me curious how some of the best practices vary with forecast grain and limit (e.g. it wouldn't surprise me if less frequent forecasts adhered to fewer of the best practices).

**We agree that this could be interesting! We did a preliminary analysis analyzing how best practice use changes with forecast horizon (Figure 1 below) and model time step (Figure 2). Intuitively, forecasts with longer horizons are less likely to be iterative and less likely to assess and report forecast accuracy, likely due to long latency before data become available to assess the forecast (Figure 1). Likewise, forecasts with long model time steps are less likely to be iterative or automated, for the same reason. Interestingly, the use of uncertainty increases with increasing forecast horizons and model time steps. While these figures are interesting and we appreciate the Reviewer's suggestion, we have decided this analysis is beyond the scope of this manuscript. As more and more new forecasts become published, we are excited to further explore this topic in future work.**

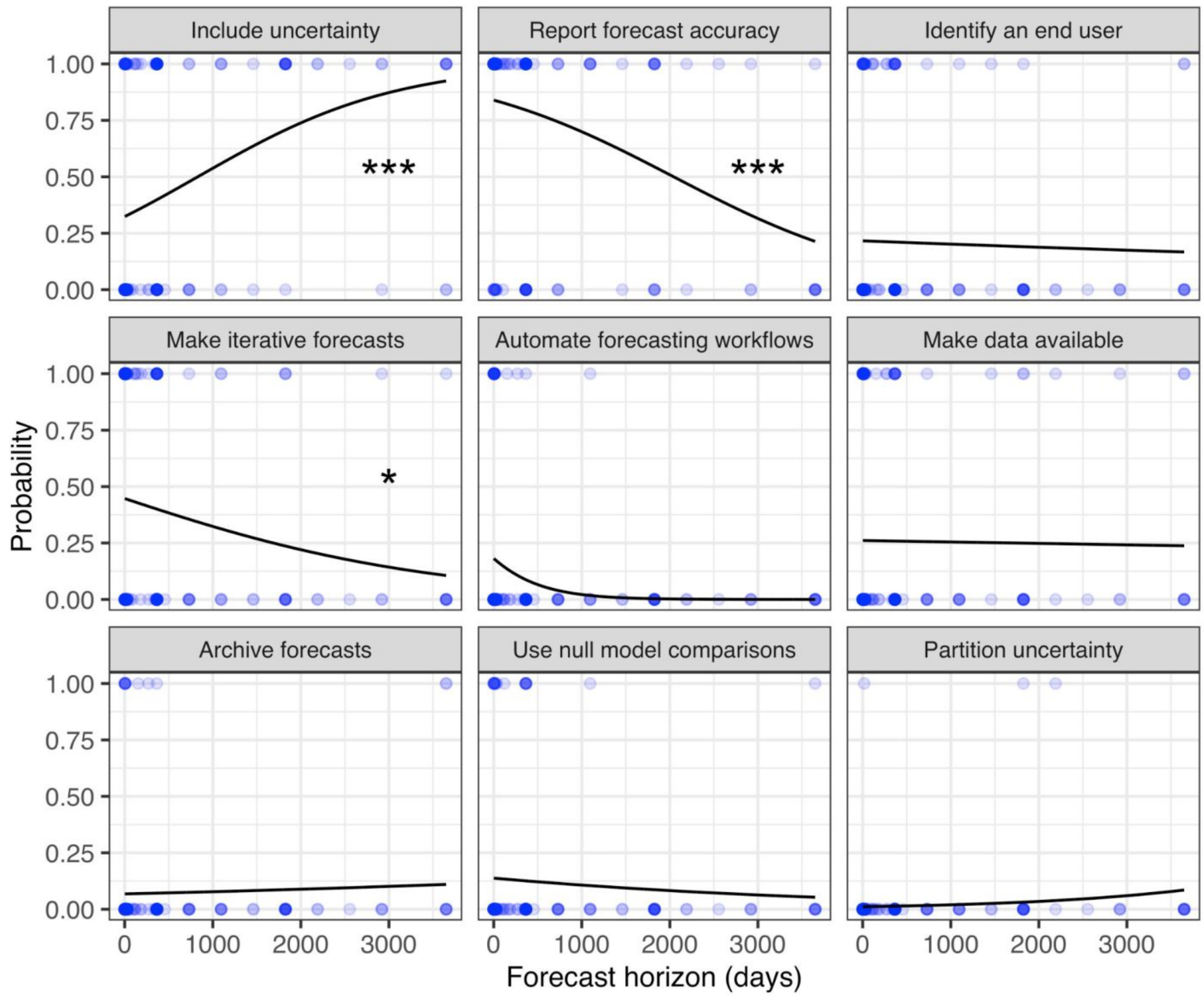



**Figure 1: Best practice adoption relative to forecast horizon. Points demarcate whether or not an individual paper demonstrated the best practice (1 = observed, 0 = not observed), and lines represent logistic regression results. Significance of the year term in the regression is indicated using asterisks: * indicates $p < 0.05$, *** indicates $p < 0.001$.**

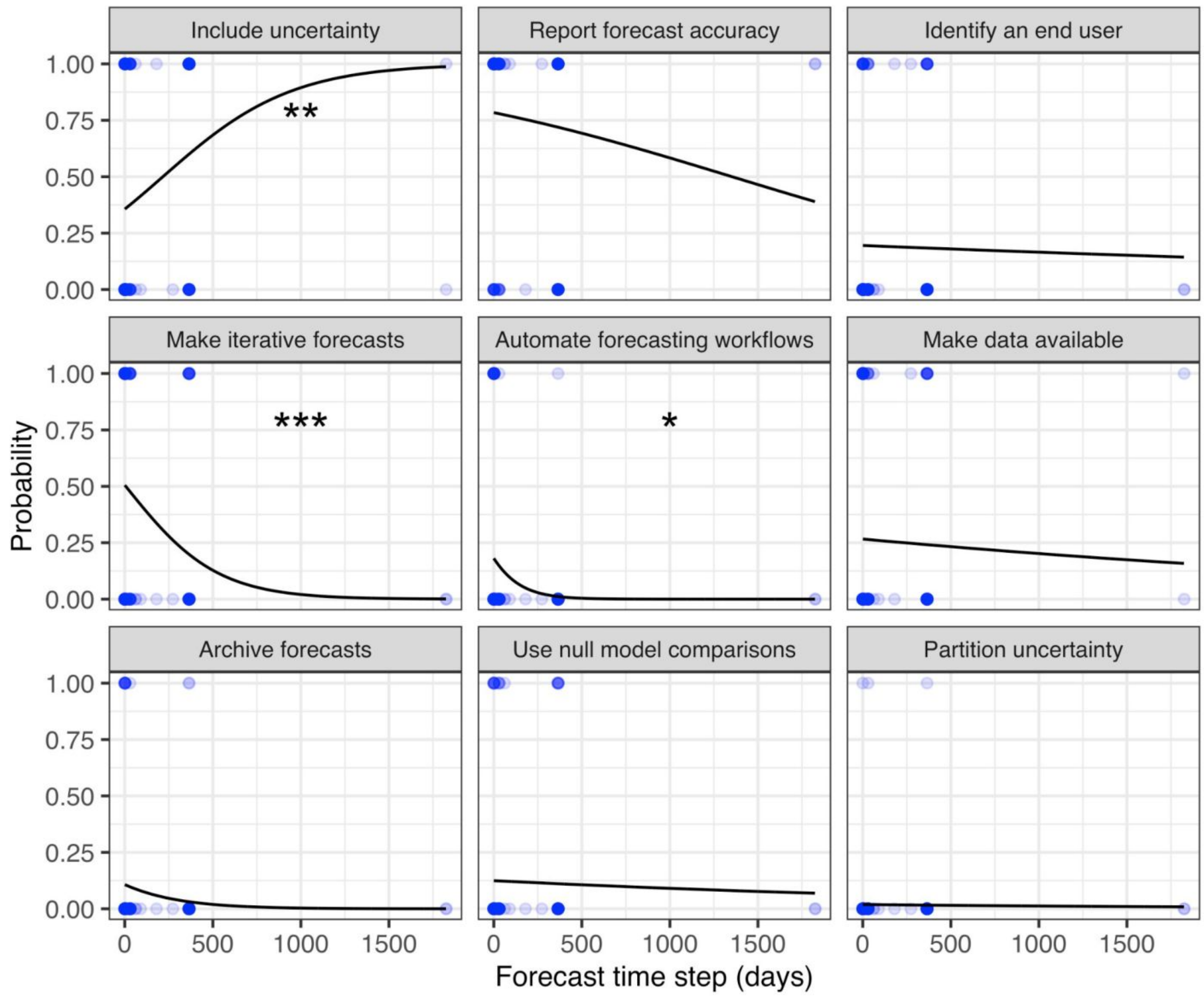



**Figure 2: Best practice adoption relative to model time step. Points demarcate whether or not an individual paper demonstrated the best practice (1 = observed, 0 = not observed), and lines represent logistic regression results. Significance of the year term in the regression is indicated using asterisks: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.**

L263: The authors here state that "R2 is bias-corrected" but that's not universally true. Some people calculate R2 as the square of r, some calculate it around a regression line between predictions and observations, and some calculate it as the variance explained by the forecast (i.e. around the predicted-observed 1:1 line instead of the bias-correction line). Thus it's not universally true that all R2 are bias corrected (indeed, I've called out previous papers I've reviewed for presenting bias-corrected statistics when they should have been presenting the actual model skill). Was it true that 100% of the R2 values you came across were bias corrected? Did your matrix/rubric provide space for distinguishing these cases?

**We anticipate that all of the $R^2$ values used in this dataset were bias-corrected. However, the method by which $R^2$ was calculated was not always reported in papers, and was not**

**recorded in our matrix analysis. To address the Reviewer's comment, we clarified that $R^2$ is typically (but not always) bias-corrected in the revised version: "While the fact that $R^2$ is typically bias-corrected makes it an imperfect metric of forecast performance, it remains widely reported and uniquely suited to inter-study comparisons" (lines 265–267).**

L267: The rational for further restricting this analysis to a small majority of papers (56%) isn't obvious. Please explain more about why this choice was made.

**We agree with the Reviewer that this was unclear in the original submission, and we have updated the text to clarify our motivation. The text now reads: "We selected all forecast variables that had at least three papers and three forecast horizons represented, and we plotted forecast performance (in $R^2$) as a function of forecast horizon for these variables. To allow comparability between variables, we limited the analysis to forecast horizons between one and seven days, which were reported for all variables selected" (lines 269–273).**

L274: A rational for why this analysis was done using quantile regression, as opposed to standard linear regression, is not provided. Please explain the argument for this choice.

**We thank the Reviewer for their observation, and have added text to address this omission. The new text reads as follows: "Quantile regression was used rather than standard linear regression to account for heteroscedasticity and non-normal data distribution" (lines 279–281).**

L321: Here you say "all but one" but then you don't tell us which one. You do eventually tell us this later, but that itself points to possible organizational issues and repetition with the Results.

**To address this comment, we added a parenthetical specification of the practice that has not increased in adoption over time. The sentence now reads: "All but one ("Use null model comparisons") of our proposed best practices have been increasingly adopted over time" (lines 325–327).**

L345: While this stat is interesting, the crucial bit of missing information here is how many of the papers you reviewed were using DA in the first place. Does 67% represent 2 of 3 paper or 46 of 69 papers?

**We appreciate the Reviewer's attention to detail, and have added the number of papers that used DA to this sentence: "67% of the 69 iterative forecasts only updated initial conditions" (line 357).**

Line 352-359: I find it odd that you present info about the trends in best practices (lines 349-352) BEFORE the more basic info presented here about their overall prevalence.

**We appreciate this organizational comment, and have restructured the three paragraphs that describe best practice adoption results to begin with statistics about overall prevalence before describing trends in adoption over time (lines 330–374).**

Line 358: of the papers that claim to be archiving forecasts on their own specific webpages, how many of those webpages actually still exist? How many contain accessible forecast archives (as opposed to just the current forecast)?

**This is an important point. We went back and checked and found that most were not available. We have added the following sentence to the results: "Only two of the seven papers that mentioned archiving forecasts on a website had links that were still functional as of 14 Jun 2021" (lines 369–370). We also added this this field of information to our data publication to ensure reproducibility.**



L359: If you're down to n=3 papers, I think it would be useful to go ahead and cite them. Also, the separation between this text and line 351 about trends and line 355 about prevalence is an example of where the Results are bit disjointed/repetitive.

**We have added citations for the three papers that partition uncertainty (line 340), and we hope that our modification of the structure of this sentence following the Reviewer comment above has addressed this comment.**

L455-456: Great point!

**We appreciate the Reviewer's enthusiasm and agree that research into the use and interpretation of forecast uncertainty has been important and productive!**

L602: EFI is a pretty big group, was this a specific working group or workshop?

**Multiple coauthors are involved with the Ecological Forecasting Initiative (EFI), and this paper has benefited from years of interactions and collaboration with EFI members at large, making it difficult to choose any one working group or workshop to reference. However, we do appreciate the Reviewer's comment that EFI is a relatively large community, and we have modified the text to particularly highlight the contributions of the Theory working group and the RCN steering committee: "We thank members of the Ecological Forecasting Initiative (EFI), particularly the Theory working group and the Research Coordination Network (RCN) steering committee, for productive discussions throughout the process of writing this paper, and we thank two anonymous reviewers for their helpful revisions." (lines 622–625).**