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Food for Thought

# Ethical considerations and unanticipated consequences associated with ecological forecasting for marine resources

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Forecasts of marine environmental and ecosystem conditions are now possible at a range of time scales, from nowcasts to forecasts over seasonal and longer time frames. Delivery of these products offers resource managers and users relevant insight into ecosystem patterns and future conditions to support decisions these stakeholders face associated with a range of objectives. The pace of progress in forecast development is so rapid that the scientific community may not be considering fully the impacts on stakeholders and their incentives. Delivery of information, particularly about future conditions and the uncertainties associated with it, involves a range of judgements, or "ethical" considerations, including treatment of forecast failure, inequity in stakeholder response options, and winners and losers in commercial markets. Here, we explore these often unanticipated considerations via a set of case studies spanning commercial fishing, recreational fishing, aquaculture, and conservation applications. We suggest that consideration of ethical issues by scientists and their research partners is needed to maintain scientific integrity and fairness to end users. Based on these case studies and our experience, we suggest a set of ten principles that might be considered by developers and users of ecological forecasts to avoid these ethical pitfalls. Overall, an interdisciplinary approach, and co-production with end users will provide insurance against many unanticipated consequences.

**Keywords:** conservation, decision-making, fisheries, seasonal forecast, social–ecological systems

## Introduction

Marine species distributions and abundances are highly dynamic in both space and time, thus management, conservation, and sustainable exploitation is difficult (Keyl and Wolff, 2008; Ritz *et al.*, 2011). Increasing human pressures on the ocean, in particular climate change, are resulting in changes in ecosystem characteristics and dynamics (Merrie *et al.*, 2014). This means historical experience for a range of marine managers and resource users is less reliable when planning future decisions (Hodgkinson *et al.*, 2014; Hobday *et al.*, 2016). At the same time, asynchronies in ecological dynamics, fishery science, and policy development are threatening the effectiveness of management and governance arrangements (Hennessey and Healey, 2000; Pinsky and Fogarty, 2012; Pershing *et al.*, 2015; Pinsky *et al.*, 2018). This ultimately affects the sustainability of fishing businesses and their delivery of seafood, and undermines the credibility of science and governance institutions.

If only humans could see the future or at least synoptically view the present, then these trends might be less problematic [While our focus here is on future predictions, nowcasts and short-term synoptic hindcasts of ocean conditions and species distribution are also important to managers and stakeholders. They reveal the spatial evolution of environmental conditions and species patterns which inevitably leads to short-term mental forecasts based on marine users experience and intuition (Eveson *et al.*, 2015). Hindcasts also reveal the importance of past environmental events such as heatwaves and provide insight into important mechanisms affecting occupancy dynamics of fish and fisheries in the present and near future that might be related to those events.]. Information about the future can support proactive, rather than reactive, decision-making (Hobday *et al.*, 2016) and forecasts have been delivered for agricultural sectors for many decades (see Asseng *et al.*, 2012; Marshall *et al.*, 2014). The rise of forecasting for marine resource management has been built on the accessibility of real-time ocean information, such as satellite-based temperature and ocean colour measurements as well as regional *in situ* mooring and autonomous observations (Hobday *et al.*, 2016; Siedlecki *et al.*, 2016; Payne *et al.*, 2017). Breakthroughs in recent years now offer the prospect of useful spatial and temporal views of the future ocean and its biology generally known as ecosystem forecasts [The ecological forecasts described here have a wide set of uses but at this time do not include age structure or vital rates, in contrast to stock assessments used by fishery managers to set quotas and allocate fishing effort. Most current stock assessments are made without environmental information, the few that are blur the current boundary between environmental forecasts and assessments (Punt *et al.*, 2014).]. For example, regional ocean models provide information on time and space scales that allow near-term forecasts of a range of environmental variables that influence the distribution, abundance, and phenology of marine species (Stock *et al.*, 2015; Tommasi *et al.*, 2017). Progress is also being made towards multi-year predictions (Salinger *et al.*, 2016; Payne *et al.*, 2017). These models predict spatio-temporal patterns in primary environmental variables (e.g. sea surface temperature, bottom oxygen) which can be delivered directly to end users (Spillman and Hobday, 2014; Siedlecki *et al.*, 2016) or incorporated into habitat models representing a proxy for distribution of a species of interest (Hobday *et al.*, 2011; Eveson *et al.*, 2015). New metrics of interest that closer approximate experienced species habitat are also being forecast, including eddies (Hobday and Hartog, 2014), hypoxic volume (Siedlecki *et al.*, 2016; Testa *et al.*, 2017), aragonite severity index (Siedlecki *et al.*, 2016), fine scale flow regimes (Scales *et al.*, 2018), degree heating days (Spillman, 2011; Liu *et al.*, 2018), habitat volume (Brodie *et al.*, 2018), and habitat duration (Champion *et al.*, 2019). Forecasts for other ecosystem impacts that build on primary environmental variables are also being developed, (e.g. harmful algal blooms, Brown *et al.*, 2013; Anderson *et al.*, 2016; noxious jellyfish, Gershwin *et al.*, 2014).

Providing information about the future, via forecasts, provides a range of benefits around informed decision-making but comes with a range of risks. Forecasting can lead to decisions that are different from those that would have been made without a forecast. Scientists tend to think such information is valuable, but it can also be disruptive to existing practice and decision-making. A formal ethical understanding of the risks (Lacey *et al.*, 2015) is beyond the scope of this paper, but we recognize a range of judgements are made in the forecast development and delivery process that could be classified as ethical considerations. We use the term "ethical" in a normative sense, as have other ocean researchers (Barbier *et al.*, 2018), to refer to principles of conduct or practice that would be considered good behaviours by other scientists and stakeholders. For example, forecast developers must recognize that not all people want to know about the future, with estimates of up to 90% of people preferring not to know about negative future events, and even 40–70% preferring to be ignorant regarding positive events (Gigerenzer and Garcia-Retamero, 2017). Just as people at risk of medical conditions may choose not to have probabilistic tests, forecast recipients may not always welcome information on future ocean conditions. Such views have been encountered amongst individuals that receive seasonal forecasts, with comments such as "*I don't want to know everything about the future*" commonly expressed to the authors. Some fishers, for example, like their business the way it is, and have confidence to manage in the face of environmental variability (Hodgkinson *et al.*, 2014). They may see such future information as removing their competitive advantage over less skilled operators. Information about the future can also be challenging to integrate, disruptive to existing mental models, and lead to "decision regret." An ethical response may be to respect that choice, or to address the cause of the motivation and seek to illustrate the advantage of information about a rapidly changing ocean in partnership with forecast users. While there are a range of additional motivations for not wanting to know about the future (Gigerenzer and Garcia-Retamero, 2017), we do not explore these here, but simply note that rational explanations exist.

The ethical responsibilities of researchers with respect to their methodological choices in climate downscaling, and the potential consequences of these choices have been addressed by Hewitson *et al.* (2014), however, we see the need for additional consideration of the nature of risk and responsibility at the interface between seasonal forecasting research and operational decisions that these forecasts influence. Just as Hewitson *et al.* (2014) argue that downscaled climate information must address the criteria of being plausible, defensible, and actionable, forecast developers cannot absolve themselves of their ethical responsibility when informing end users and must, therefore, be diligent in ensuring any information provided does not lead to perverse outcomes (*sensu* Lacey *et al.*, 2018). For example, while most seasonal forecast teams now address plausibility (i.e. consistent with other mechanisms) and defensibility (e.g. skill assessment), substantial interaction between the forecaster and user is often required to understand actionable information (Hobday *et al.*, 2016; Payne *et al.*, 2017).

Scientists differ from medical and engineering professionals who have a charter of professional responsibility accompanied by oaths (e.g. do no harm) and recertifications, however, they must still be cognizant of judgements and ethical considerations (Lacey *et al.*, 2018). Forecast developers influence strategic and operational decisions, such as resource allocation and spatial and temporal fishing strategies, and outcomes of these decisions can hinge on the prediction, rather than actual experience. In the following section, we describe ethical issues encountered as early developers of marine ecological forecasts for stakeholders engaged in fisheries, aquaculture, and conservation. These case studies illustrate a range of ethical issues that are consistent with schemes presented by Lacey *et al.* (2015) and Hewitson *et al.* (2014). These issues are encountered in key forecast phases defined by Hobday *et al.* (2016): (i) scoping, (ii) development, (iii) delivery, and (iv) evaluation (Figure 1). We then describe a set of forecasting ethics based on ten principles in each of the four phases.

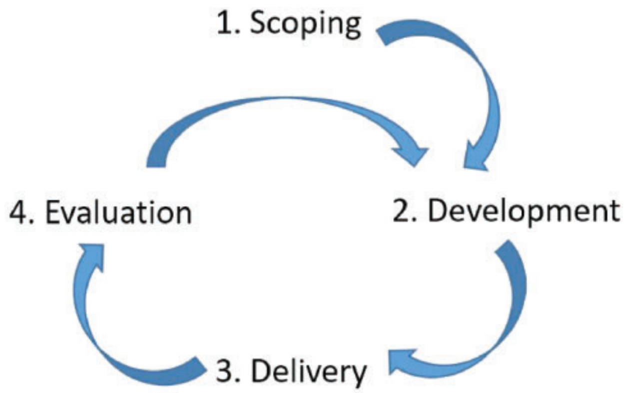


**Figure 1.** Phases of forecast development, modified from Hobday *et al.* (2016). Evaluation leads to improved development.

## Ethical issues—lessons from existing forecast systems

We reviewed seven examples of ecological forecast systems from both coasts of the United States and south-east Australia (Table 1). These forecasts served commercial and recreational fishing, aquaculture, and conservation stakeholders. Much of this work was motivated to help marine resource sectors cope with future uncertainty and promote dynamic and sustainable management. Based on review of these examples, we identified ethical issues in a range of categories in each phase of forecast development and delivery (Table 2). We developed these phase categories in a bottom-up iterative manner, based on discussion of our examples and reference to published literature, followed by review and refinement. Each of the examples revealed different issues across the phase categories, as discussed in the following sections.

### Phase 1—Scoping

The first phase of forecast development can be inwardly focused, motivated by a search for system understanding, or outwardly, in response to end user needs. Both motivations were revealed by the participants in these case studies. Issues associated with conflicts of interest and ecosystem health were recognized across the case studies.

#### *Conflicts of interest*

Enthusiasm for the technical challenge in developing a forecast should not ignore the perspectives of user groups that can emerge as conflicts of interest. This might result in stakeholders being coopted to a programme that is not in their best interests. However, in the northwest Atlantic (Example 5, Table 1), industry partners willingly engaged in the pilot programme and had the time to collaborate constructively with scientists. They were prepared to apply advanced technologies to both improve ecosystem-based fisheries science and enhance fishing efficiency. Many of these fishers operate innovative, sophisticated, successful businesses and are leaders in the industry. In this case, industry collaborators are full partners in the programme and helped shape the approaches adopted and products developed, an important feature of co-production (Cvitanovic *et al.*, 2015; Djenontin and Meadow, 2018). There may, however, be conflicts with other users—fishers involved in this programme are already "industry winners" and may be reaping additional competitive advantages associated with participation in the pilot programme, including privileged access to the environmental products. Thus, decisions regarding participants vs. non-participants represent an ethical dilemma when delivering future information (see Equity for users).

Conflicts of interest can also be suggested based on the perceived viewpoints of stakeholders. For example in the Delaware Bay Atlantic sturgeon conservation programme (Example 7, Table 1), conservation groups believe that gillnet fishers may use Atlantic sturgeon forecasts to illegally target, rather than avoid, Atlantic sturgeon. Illegally targeting sturgeon is a problem in the northwest United States, and conservation groups project these same motivations onto Delaware Bay fishers, thus assuming this is the reason fishers participate in the bycatch programme. Alternatively, fishers may be nervous about participating in this programme because it could be used by regulatory bodies to develop time-area closures that would affect their livelihood, even if they are not interacting with Atlantic sturgeon. In both cases, the delivery of these spatial forecasts is seen as a potential threat because of another group's perceived motivations.

#### *Ecosystem health*

A second ethical issue in the scoping phase is consideration of ecosystem health, which was an issue for the dolphinfish and northwest Atlantic forecasting programmes (Examples 2 and 5, Table 2). Modelling technologies and information may confer efficiencies upon users, such as fishers, that eliminate the spatial and/or temporal refugia prey require for maintaining their populations. The east coast Australia recreational fishery for dolphinfish has no effort cap or required reporting, and the forecast development team was conscious of not contributing to overexploitation and actively considered options to limit impacts to ecosystem health. Initially, a latitude-only forecast was provided to limit its use as a fish finder, such that it represented general distribution only (Brodie *et al.*, 2017). At the same time, the project team sought to explore improvements in catch management that could accompany forecast delivery and reduce risks from over-harvesting (Example 2, Table 1).

Similar issues were confronted in the northwest Atlantic example (Example 5, Table 2), where it was recognized that efficiency as a result of model-guided fishing can result in declining ecosystem health. Ethical concerns about increased efficiency are being discussed with industry–science participants with two main aims. First, development of products to improve the accuracy of population assessments and support sustainable fishing is recognized as the primary goal of the industry–science partnerships. Second, efforts to increase catch efficiency that seek to reduce fishing costs must consider the externalities related to collateral damage to ecosystem services. Addressing these ethical considerations and engaging the fishing industry as full partners builds support for more accurate assessments and coherent regulations. It also provides industry partners with a deeper understanding of the science process, a greater acceptance of scientific results, as well as an increased sense of stewardship for the fish and ecosystems supporting their livelihoods.

While these two examples confronted this issue, commercial "fish forecasting" services designed to enhance fisher search efficiency have existed for decades (e.g. https://atlantniro.ru, http://www.catsat.com/, https://www.roffs.com/), and we hope these

**Table 1.** Summary of ecological forecasting examples describing the context for each system.

| | |
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| **Salmon aquaculture forecasts in Tasmania**<br><br>**Funding:** Industry<br>**Institution:** CSIRO/Bureau of Meteorology<br>**Stakeholders:** Salmon Farmers | Dynamical seasonal forecasts to predict water temperatures for south-east Tasmanian Atlantic salmon (*Salmo salar*) farm sites several months into the future are used to manage production risk (Spillman and Hobday, 2014). High summer temperatures pose a significant risk to production systems of these farms. Based on 20 years of historical validation, the model shows useful skill for all months of the year at lead-times of 0–1 months. Model skill is highest when forecasting for winter months, and lowest for December and January predictions. The poorer performance in summer is due to increased variability due to the convergence of several ocean currents offshore from the salmon farming region. Accuracy of probabilistic forecasts exceeds 80% for all months at lead-time 0 month for the upper tercile (warmest 33% of values) and exceeds 50% at a lead-time of 3 months. Industry engagement is high, and delivery of forecasts is ongoing, supplemented by industry–scientist discussions (Hobday *et al.*, 2016). |
| **Recreational dolphinfish forecasts in eastern Australia**<br><br>**Funding:** Researchers (University PhD)<br>**Institution:** CSIRO/Bureau of Meteorology/UNSW<br>**Stakeholders:** Recreational Fishers/Managers | A seasonal forecast of the habitat and density of dolphinfish (*Coryphaena hippurus*), based on sea surface temperatures, was developed for the east coast of New South Wales (NSW) Australia (Brodie *et al.*, 2017). Two prototype forecast products were created; geographic spatial forecasts of dolphinfish habitat and a latitudinal summary identifying the location of fish density peaks. The less detailed latitudinal summary was designed to limit the resolution of habitat information to prevent potential resource over-exploitation by fishers in the absence of total catch controls. The dolphinfish habitat forecast was accurate at the start of the annual dolphinfish migration in NSW (December) but other months (January–May) showed poor performance due to spatial and temporal variability in the catch data used in model validation. Habitat forecasts for December were useful up to 5 months ahead, with performance decreasing as forecasts were made further into the future. |
| **Commercial tuna forecasts in the Great Australia Bight**<br><br>**Funding:** Industry/FRDC<br>**Institution:** CSIRO/Bureau of Meteorology<br>**Stakeholders:** Fishing industry | A habitat forecast system based on a seasonal ocean model and electronic tagging data was developed in collaboration with the Southern Bluefin Tuna (SBT, *Thunnus maccoyii*) fishery in Australia to overcome challenges posed by novel environmental conditions (Eveson *et al.*, 2015). A dramatic change in the distribution of SBT compromised the ability of the fishery to efficiently locate and harvest the species. In partnership with industry representatives, a seasonal forecasting system was implemented to project the likely distribution of SBT several months into the future (Eveson *et al.*, 2015). Forecasts are delivered daily via an industry-specific website, which has assisted fishers to efficiently catch SBT under variable climatic conditions. There is a cap on catches so this system does not contribute to over-exploitation. |
| **Lobster forecasts in Maine**<br><br>**Funding:** Research agency<br>**Institution:** GMRI<br>**Stakeholders:** Fishing Industry/Managers | The American lobster (*Homarus americanus*) fishery is currently the highest-valued commercial fishery in the United States, worth nearly $670 million in landed value in 2016. Over 80% of the value is landed in the state of Maine. The 2012 Northwest Atlantic heat wave disrupted this fishery by prompting early warming of the ocean and an earlier-than-normal large influx of lobster landings. Since readiness for the product was not aligned throughout the supply chain, a glut of lobsters developed, resulting in a price collapse (Mills *et al.*, 2013). At that time, managers and key industry members in Maine questioned whether the early onset of the high-landings period could have been predicted, with the expectation that such information would give valuable early notice for the fishery and supply chain to prepare appropriately for the upcoming season. A regression-based seasonal forecast was developed to provide the expected timing of the summer uptick in landings (June–July) based on ocean temperatures in March–April (Mills *et al.*, 2017). This forecast was formally issued to the industry in 2015 and 2016 via a public website. While it proved technically reliable at predicting the summer uptick timing, it also created unexpected challenges and was not perceived as useful to the industry (Pershing *et al.*, 2018). |

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|---|---|
| **Northwest Atlantic industry–science collaborative research programme**<br><br>**Funding:** Research agency<br>**Institution:** NOAA<br>**Stakeholders:** Fishing Industry | Inefficiencies in fisheries science and governance produce regulatory environments that can lag rapidly changing northwest Atlantic marine ecosystems and fisheries by 2–5 years (Hennessey and Healey, 2000; Pinsky and Fogarty, 2012). This pilot programme uses sustained embedding of collaborative research and ecosystem scale hindcasting and now-casting within operational fisheries, with the goal of developing products accounting for socioecological change in fishery assessments and management (NEFSC, 2014, 2018; Turner *et al.*, 2017). Fishery and ocean data and ocean model output are used in science–industry partnerships that co-develop, evaluate, and refine habitat nowcast models describing occupancy dynamics of species and fishing fleets. The primary goal is to develop models that can be applied in population assessments and tactical management to account for the effects of changing habitat dynamics on observed abundances, fishery landings, and productivity. The programme is also designed to increase fishing precision by reducing costs of harvesting quotas, including externalities such as bycatch and habitat impacts. Sustained engagement with industry experts provides important collateral benefits including the timely transfer of information about the socioecological dimensions currently impacting specific fisheries that are required for practical ecosystem-based fisheries assessment and management. |
| **Northeast Pacific Ocean ecological forecasts**<br><br>**Funding:** Research agency<br>**Institution:** NOAA<br>**Stakeholders:** Fishing Industry and Managers | In the northeast Pacific Ocean, marine resource managers at the state, federal, and tribal levels make decisions on a weekly to quarterly basis, and fishers operate on a similar timeframe. To determine the potential of a support tool for these efforts, a seasonal forecast system known as J-SCOPE (JISAO's Seasonal Coastal Ocean Prediction of the Ecosystem) has been developed (Kaplan *et al.*, 2016; Siedlecki *et al.*, 2016). This system features dynamical downscaling of regional ocean conditions in Washington and Oregon waters using a combination of a high-resolution regional model with biogeochemistry and forecasts from NOAA's Climate Forecast System). Model performance and predictability have been determined for sea surface temperature, bottom temperature, bottom oxygen, pH, and aragonite saturation state through model hindcasts, reforecast, and forecast comparisons with observations. Results indicate J-SCOPE forecasts have measurable skill on seasonal timescales (Siedlecki *et al.*, 2016). |
| **Delaware Bay Atlantic sturgeon by-catch forecasts**<br><br>**Funding:** University<br>**Institution:** NGO/Government/University<br>**Stakeholders:** Fishing Industry | Atlantic sturgeon (*Acipenser oxyrinchus*) is a long-lived anadromous species found on the east coast of North America (Vladykov and Greeley, 1963). Overfishing for caviar and flesh in the late 19th and early 20th century (Cobb, 1900; Borodin, 1925; Smith and Clugston, 1997), combined with habitat loss and degradation, severely diminished Atlantic sturgeon populations, and there has been little to no recovery despite a moratorium on directed fishing and improved water quality (Billard and Lecointre, 2000). The Delaware River and Bay historically supported the largest spawning population of Atlantic sturgeon in the world as well as the largest fishery. The Delaware River Atlantic sturgeon fishery was short lived; peak landings dropped more than 90% by the turn of the century (Cobb, 1900). Although directed harvest of Atlantic sturgeon ended in 1998, the results of historic overharvest, coupled with habitat change and ongoing issues of bycatch mortality, have resulted in a >99% decline from historic abundance of 360 000 spawning adults (Secor and Waldman, 1999) to <300 spawning adults annually (ASSRT, 2007). As a result, the National Marine Fisheries Service listed Atlantic sturgeon under the Endangered Species Act (ESA) on 6 April 2012 (United States Office of the Federal Registry, 2012) with incidental bycatch (Stein *et al.*, 2004) and vessel strikes (Simpson and Fox, 2009) identified as risk factors for the Delaware River. The ESA listing has the potential to have major impacts on commercial fisheries, shipping, and other industries that interact with Atlantic sturgeon during their coastal migration. These fishers are also motivated to avoid Atlantic sturgeon because interactions severely damage legal fishing gear, resulting in costly downtime. This action created the need for a short-term forecasting system to alert fishers in the Delaware Bay of their potential risk of interacting with an Atlantic sturgeon. The model was developed by fusing remote sensed data and historic acoustic telemetry observations (Breece *et al.*, 2017), and distributes a nowcast, 1, 2, and 3 days statistical forecasts. Recent satellite observations are not always available to constrain the model, so forecasts are flagged with a warning for users. Forecasts are distributed daily via web applications, and via SMS text messages to users. |

**Table 2.** Ethical issues encountered in the scoping, development, delivery, and evaluation phases of ecological forecasts for marine resources across seven case studies in three domains (X) as described in Table 1.

| Example (and domain) | Scoping | | Development | | Delivery | | | | | Evaluation |
|---|---|---|---|---|---|---|---|---|---|---|
| | Conflicts of interest | Ecosystem health | Skill assessment (inadequate) | Representation of uncertainty (inadequate) | Delivery of products | Engagement and education | Delivery failure | Equity for users | Unintended consequences | Review of performance of the whole system |
| 1. Tasmanian salmon (aquaculture) | | | | | X | X | X | X | CC? | |
| 2. Eastern Australia dolphinfish (fisheries) | | X | | X | | | | | | X |
| 3. Great Australia Bight tuna (fisheries) | | | | | | X | | | X | |
| 4. Maine lobster (fisheries) | | | | | | X | | X | X | X |
| 5. Northwest Atlantic fishers (fisheries) | X | X | X | X | | | | X | X | |
| 6. Northeast Pacific environments (fisheries) | | | | X | X | | X | | | |
| 7. Delaware Bay sturgeon (conservation) | X | | X | X | X | | X | | | |

Other issues may have been possible, but were not evident due to circumstance or practise.

providers also consider the impact on ocean environments. As ocean monitoring, modelling, and information sharing technologies rapidly advance and become available at lower costs, ethical concerns regarding ecosystem health outcomes and delivery of forecasting products should be examined more generally.

## Phase 2—Development

The ethical issues in the development phase were associated with technical judgements about the system. If these issues are not actively considered, then the end user may be misled, or not provided with sufficient context to evaluate the value of the forecast in their decision-making. These judgements are often based on experience, but can also be made on efficiency grounds, which we consider problematic.

### *Skill assessment*

An important step in developing a forecast system is to understand the model performance. One measure of performance is model skill—defined as the ability of the model to outperform climatological or persistence forecasts (Hobday *et al.*, 2011; Hewitson *et al.*, 2014; Stock *et al.*, 2015). In evaluating skill, it is possible to unconsciously bias a forecast by restricting the set of models or explanatory variables, by varying the length of the sample that is fitted, by deciding to include or suppress influential observations, by focusing on short-term trends rather than long-term trends, and so on (Hewitson *et al.*, 2014). True skill assessment in a forecast system should use forward out-of-sample test data, such that the same test is being used as will be required when the system is forecasting the (unknown) future—or a *true* forecast (Kaplan *et al.*, 2016; Tommasi *et al.*, 2017). Hindcast data sets must be long enough (e.g. 10 years or more) that the performance of the forecast system can be evaluated under a range of conditions (e.g. *El Niño* and *La Niña* periods). Use of weak skill assessments (e.g. randomly dividing data sets, short time periods) or those based on absolute values rather than anomalies can lead to inflated skill estimates that are misleading to an end user. The skill assessment should not only give the forecasters confidence in the system but it should be used to inform the uncertainties of the system—no system can forecast everything. Knowing a system's strengths and weaknesses is vital to providing a good forecast. Strategies to improve performance include running a multi-model ensemble, applying a correction to potential bias in selected model, paying close attention to residual diagnostics, using out-of-sample validation, determining the relevant forecasting horizon, and taking into account the plausibility of the assumptions that underlie a given forecasting model.

If forecast skill cannot be evaluated based on past performance due to an absence of historical data, explicit discussion with stakeholders is critical to explain potential risks in using the forecast. The Delaware Bay Atlantic sturgeon system provides both 0 and 3 days forecasts and a climatological forecast based on 15 years of observations. Because Atlantic sturgeon distribution has a strong seasonal signal, the climatological forecast sometimes performs better than the forecast based on the latest satellite observations. However, forecast skill is difficult to assess in real time, therefore it is based on comparison of past forecasts with historical *in situ* Atlantic sturgeon observations. Past forecast analysis efforts or re-forecasts are an essential part of building a forecast system (Kaplan *et al.*, 2016; Siedlecki *et al.*, 2016), but cannot replace a true forecast. Overall, the ethical issue here is to ensure that the forecast team is applying best practice for the situation, rather than adequate practice.

### *Representation of uncertainty*

Forecasts are typically probabilistic—as a result presenting information on the associated uncertainty with any forecasts is complicated. As many stakeholders may be unfamiliar with representation of uncertainty, it is tempting to eliminate this confusion by discarding information on uncertainty. We consider this approach to be ethically flawed, even if it is defended on the basis of reducing complexity to enhance understanding.

Complexity in communicating uncertainty confronted the project team delivering dolphinfish forecasts (Example 2, Table 2). Skill declined and uncertainty generally increased over time, but the pattern varied over the annual cycle. In the presentation of different levels of predictability for different months, the project team could not provide a consistent lead time. Forecast periods occurred when skill did not decline and uncertainty was lower at longer lead times, which could not be explained. The project team considered removing the representation of uncertainty from the forecasts being provided, but ultimately included it with considerable warning to the end user about the perceived problem.

Uncertainty can be due to the use of research products, which are works in progress, as in the case of the northwest Atlantic system (Example 5, Table 1). Industry collaborators are involved in model development and evaluation and thus the programme is fully transparent about limits of resolution, accuracy, and utility of the models. Components underlying the habitat predictions (e.g. species niche models, ocean models, and observations) are evaluated individually. Predictions are also assessed qualitatively by industry collaborators and quantitatively using out of sample statistical evaluation techniques and fishery dependent and independent data. Uncertainties of models applied in stock assessments are computed and presented as required by the assessment science process. Finally, forecasts are labelled “for research only” which indicates less confidence in model results compared to operational systems.

Limitations in the forecast model that result in uncertainty, are important to stress when delivering information to stakeholders. In the J-SCOPE system used in the northeast Pacific (Example 6, Table 1), the transition from the summer upwelling season to autumn conditions (that typically happens sometime in September) is not well forecasted from the April-initialized forecast. This is mainly because the fall transition is driven primarily by storm events, which has low predictive skill on seasonal time scales (Siedlecki *et al.*, 2016). In this case, the project team explicitly communicates this in text attached to forecasts—and provides additional information on the project website where evaluation of past performance suggests this portion of the forecast should be disregarded.

Storms and cloud cover also contribute to uncertainty in the Delaware Bay Atlantic sturgeon system. Storm events create large time gaps in the satellite record, therefore statistical reconstructions of satellite observations that are used to predict the occurrence of Atlantic sturgeon are poor. In this case, a forecast is still issued with a degradation warning, and users are directed to a climatological prediction as the best estimate.

## Phase 3—Delivery

After a forecast system has been developed and tested, forecasts of upcoming conditions at a range of time scales are delivered to the user community, via a range of methods. This can create an expectation for ongoing delivery of products, requires education and engagement, raises issues around delivery failures, and can also have unintended consequences (Table 2).

### *Delivery of products*

The development of a forecast system is typically a research endeavour, with a finite funding period to accomplish the work. Stakeholders involved in such projects may have expectations about the ongoing delivery of information, unless this is clearly ruled out by the project team. In development of applications in Australia, project teams have sought to build systems that can be maintained with little intervention after a project ends (Hobday *et al.*, 2016). The ultimate solution is to pass the forecast system to an operational system, such as a national weather service (e.g. coral reef bleaching—Spillman, 2011).

In the northeast Pacific (Example 6, Table 1), experimental forecasts were delivered to improve representation of uncertainty and build confidence with a user group as discussed earlier. While the experimental forecasts were visible to the public (via J-SCOPE website) or announced to a user community (e.g. bulletin or email), delivery of experimental forecasts enabled a dialogue that shaped the form of the forecast product into a useable decision support tool. These forecasts were clearly labelled as experimental. The first true forecast was issued on the website in 2013, however, scientific papers describing these forecasts were not published until 2016 (Kaplan *et al.*, 2016; Siedlecki *et al.*, 2016). This early delivery of forecasts—prior to peer review—was criticized by some in the scientific community, although industry welcomed the information.

Unfortunately, the risk of providing a *bad* forecast—defined here as one that ends up proving false can be costly to the experimental system in terms of end user trust and impacts, even if skill has been explained. For the northeast Pacific system, one example occurred in early June of 2018. A seemingly widespread low oxygen event caused Dungeness crab fishers to catch dead crabs in their traps. The Ocean Observatories Initiative Coastal Endurance array real-time observations of bottom oxygen near Cape Elizabeth, WA suggested that the event began in early June and lasted for over a week. The forecasts initialized in January indicated the potential for such an event, but the subsequent April-initialized forecast did not. All prior forecast performance statistics indicated the April-initialized forecast should perform better than the January-initialized forecasts for the onset of hypoxia at this location. The project team could explain this after the event, and learned more about the forecast system, including aspects of the delivery of uncertainty through this event. While delivery of a less mature forecast system to the public domain is a reputational risk, the timescale for full scientific rigour may not be fast enough to match end user needs. The lessons learned in the process of providing true research forecasts also provide valuable feedback to the forecast team, speeding the rate of learning. Because of the lag between utility and understanding, it is essential that forecasters communicate the likelihood of improvements in understanding as well as the technical limitations in the existing forecasts through clear estimates of uncertainty during a research forecasting period.

Stakeholder expectations regarding the ongoing delivery of a forecast and the performance quality of the product may also need to be explicitly managed. In the case of the Tasmanian salmon and Great Australia Bight tuna forecasts (Examples 1 and 3), a new underlying seasonal physical forecast model will replace the tested system in 2019. Should forecast delivery be discontinued for several years until new skill assessments and uncertainty treatments are resolved (scientifically correct), or should stakeholder expectations (ongoing forecast delivery) be given primacy?

Forecast delivery systems must also recognize that users do not all access information in the same ways, which can raise ethical issues related to fair and equitable delivery of information. In the Delaware Bay Atlantic sturgeon system, forecast delivery was designed for both managerial and on-the-water users. The forecast is primarily a web-based mapping application featuring low-, medium-, and high-risk regions for Atlantic sturgeon interaction. However, these maps are not well transmitted to users that are out actively fishing, or those without Internet access. Therefore, SMS text messages were used to communicate to make sure that the forecast delivery system allowed access across different user types.

### *Education and engagement*

Traditional education and engagement involves working with end users of forecasts to build their capacity to interpret information. An insufficient commitment to work with end users can be considered as ethically irresponsible, even if this is not the primary function of a forecast development team. Use of industry representatives or knowledge brokers can be considered to build stakeholder capacity and maintain long-term relationships (Eveson *et al.*, 2015; Cvitanovic *et al.*, 2016).

Different levels of interest in the forecast often require a range of products, without dumbing down the messages and complexity. In the case of the tuna forecasts (Example 3, Table 1), the project team was tempted to interpolate the relatively coarse model grid to make the maps easier for stakeholders to compare to satellite-based products, before ultimately deciding this was not scientifically responsible, as it hid the true model resolution and may have led to higher confidence in the products than was warranted. Issues of scale were also confronted in the Gulf of Maine seasonal lobster forecasts (Example 4, Table 1). Users found the state-wide scale of the forecast information disconnected from their local experiences. Users found it hard to relate "normal" for their location to the state-wide "normal" start of the high-landings period and, moreover, to apply the forecasted offset from "normal" to their local experience. Based on discussions, the project team now plans to make these forecasts more spatially explicit so that there is a greater ability to act on locally relevant information.

An ecological forecast is not the only source of information about future conditions, and end users should be made aware of these alternative sources of information. Climate modes and extreme events also influence the overall ocean patterns, but may not be represented well in current forecast systems. Thus, there is a need to communicate how output from a single forecast system fits the landscape of available information, and to present any contradictions that may exist. For example, the forecast package provided to Tasmanian salmon farmers (Example 1, Table 1) includes seasonal El Nino-Southern Oscillation (ENSO) forecasts based on the core model (Predictive Ocean Atmosphere Model for Australia). The predictions can be inconsistent with other models from around the world. The forecast team alerts users to this inconsistency and the potential implications, and a higher level of risk management may be used by the stakeholders until greater consistency emerges. Extreme events or processes that are not reflected in the model system can also reduce the accuracy of a single forecast. In such cases, rather than delivering a forecast as if nothing were of concern, expert interpretation can be provided to end users. Stakeholders can then look to other sources of information, such as *in situ* monitoring to inform their decision-making.

### *Delivery failure*

A forecast team may have achieved success and industry support as a result of forecast delivery, which can be a barrier to action when there are delivery failures. In the Tasmanian salmon system (Example 1, Table 1), despite mature data delivery practices that underpinned forecast delivery, unanticipated errors in model products were uncovered in late 2016. Forecasts were not consistent with project team expectations and pointed to data assimilation problems in underlying models. These errors could not be resolved quickly, and the team grappled with the potential loss of confidence as a result of halting forecast delivery. It would have been unethical to continue forecast delivery, and despite reputational risk, delivery was halted until the errors could be resolved.

A team might also proactively quantify the sensitivity of the forecast products to missing data, because dissemination streams for observed (i.e. remotely sensed or directly sampled) data can experience delays or gaps (Welch *et al.*, 2018). This will inform the forecast team as to the data situation for which forecasts can still be delivered, or halted.

### *Equity for users*

Delivery of forecasts to one group may advantage or disadvantage them relative to another, and consideration of equity arose in several case studies. The Gulf of Maine lobster experience revealed different outcomes for users across the supply chain (Example 4, Table 1). Experiences in 2016 indicated that the forecast may have influenced winners and losers in the system (Pershing *et al.*, 2018). In 2012, early, high catches of lobsters and an unprepared supply chain meant that harvesters felt the impact of a rapid drop in price, as the value of the product brought to the docks barely covered fishing expenses. Some dealers also incurred increased costs associated with transporting and storing lobsters. This motivated the development of the forecast system. In 2016, the March forecast for expected early high catches impacted directly on the dealers as they tried to sell existing inventory and establish contracts for the remainder of the year (Pershing *et al.*, 2018). However, if dealers cleared existing inventory (even at lower prices), it may have made space in the supply chain for product as it came in over the course of the summer, a move that may have supported the higher prices later in the season which had benefits across the industry, particularly for harvesters. This revealed trade-offs in benefits and costs associated with forecast information for these two distinct industry groups.

Fishing is a competitive occupation, and maintaining confidentiality about fishing and business practices is essential for maintaining the trust between industry and scientists that is so difficult to develop and easy to lose. In the northwest Atlantic programme (Example 5, Table 1), nowcast models based on underlying information co-developed with individual industry collaborators are considered proprietary and not shared with other industry partners except in aggregate "crowd-sourced" form. Knowledge of business practices and fishery monitoring information are never shared. This can create inequity among businesses, however, new participants are welcomed. With regard to Tasmanian salmon (Example 1, Table 1), access to forecasts is now restricted to companies that pay for the service. While this is a private arrangement, other companies are aware that forecasts are possible, and they could seek involvement if they desired.

Equity can be sought via education and training in the use of forecasts, and this was the approach amongst these case studies when the target group is small. However, if forecasts are made widely available, contact with all end users is impossible. The ethical solution is to be transparent and "equitable" with regard to forecast interpretation, but as with any knowledge system, some users will make more of the information than others, and there may be winners and losers at a range of time scales such that system change is needed (Bell *et al.*, 2013).

### *Unintended consequences*

Evaluation of the case studies revealed some unanticipated consequences of forecast development and delivery that do not fit within the above categories. These surprises can pose a range of challenges, for which forecast developers may be unprepared or ill-equipped to handle.

Unanticipated consequences with wide reaching implications were encountered by the Gulf of Maine lobster forecast team (Example 4, Table 1) as result of anomalous years. A heatwave in 2012 created a difficult year for the industry (Mills *et al.*, 2013) and motivated development of the forecast (Mills *et al.*, 2017). When the forecast was initially issued, it was discussed in the media and in public venues relative to 2012, with sensational headlines such as "2015-On track for 2012 molt replay?" (Crowe, 2015), even though 2015 was expected to be a "normal" year. As the forecasts were issued weekly over a 2-month period each year (which enables users to track uncertainty in the forecast over the forecasting period), there were frequent opportunities for new media stories, that tended to highlight risks to the industry. This public discussion added stress to the industry. Industry users encouraged the forecast team to consider issuing a forecast only if an extremely early lobster molt year was expected in hopes that such a change would reduce ongoing discussion of whether a major disruption may arise in a "normal" year.

In addition, in both 2015 and 2016, the lobster forecast was released in early March at the Maine Fishermen's Forum, an important event attended by many in the lobster fishery. In 2016, this event occurred a few days before a large regional seafood exposition where many seafood purchases for the upcoming season are negotiated. Buyers were not familiar with the forecast, only with the news coverage, which suggested the industry would face a 2012-like price collapse again in 2016. This created a real price effect for dealers who needed to sell product and commit to future deliveries at the seafood exposition. The price for lobster declined in March 2016, a month in which it typically increases, after which it recovered and remained higher than expected (given the high landings) over the course of the year (Pershing *et al.*, 2018). Clearly, disseminating the forecast through a public website led to an unanticipated price effect in this year, and stakeholders asked that forecast information be communicated only to certain segments of the industry. However, distributing the forecast in industry publications or even via a subscription service would not ensure that access to the information would remain restricted (see Equity for users). Further, non-traditional stakeholders who would not be considered part of the industry, such as culinary tour operators, also used the forecasts. Ultimately, the project team decided that information created with public grant funding should not be provided only to select users; instead, if it is issued, it should remain available to all potential users, particularly since unexpected user groups emerged once the forecasts became available.

In the case of the tuna forecasting system (Example 3, Table 1), while there was a low risk to ecosystem health due to a quota system (Eveson *et al.*, 2015), an unintended consequence was an decrease in time at sea fishing, and hence an increase in economic efficiency due to higher certainty about fish location. The project team was surprised to hear of impacts on social benefits—fish are caught faster, and as wages are higher at sea, total crew wages declined and they could be considered as losers from the forecasts. This issue may be overstated, as crew are generally employed in other activities by the fishing companies, such as working on the grow-out facilities.

With regard to salmon forecasts (Example 1, Table 1), community concerns around expansion of salmon farming (see van Putten *et al.*, 2018) has seen interest groups seeking to obtain forecasts to show that the industry is threatened by warming waters. Thus, forecasts of warm conditions, instead of helping an industry adapt (Hobday *et al.*, 2016), could be used by others to argue against continuation of that industry.

A positive unintended consequence in the northwest Atlantic system (Example 5, Table 1), was that development of nowcast models offered the opportunity for fishers and scientists to discuss empirical patterns occurring at scales finer than was known from traditional reporting systems. This had the effect of improving ecosystem understanding for both parties, and might ultimately help fishers to reduce bycatch and minimize trawl impacts. Sometimes, an improvement in information can lead to an unanticipated and rapid change in system understanding. In the same region, work with the Atlantic mackerel fleet to account for distribution shifts of adults and juvenile in fishery independent survey indices contributed to a revision of stock status from unknown to overfished. Not all stakeholders saw this as a positive outcome.

## Phase 4—Evaluation

Review of performance is an important step in adaptive management, but has not been widely attempted for forecasts systems. We distinguish performance here from the assessment of model skill, and refer to holistic evaluation to see if the system achieved the overall goal—improved decision-making and sustainable use or conservation of marine resources.

### *Review of performance*

Despite demonstrating technical skill and delivery of forecasts, two of the seven examples presented here halted delivery after a trial period, due to a range of issues. The forecast system for dolphinfish in eastern Australia was successfully trialled for 1 year with stakeholders (Brodie *et al.*, 2017), however, the project team decided not to proceed with ongoing delivery, as they did not want to offer a "fish-finding" service without management controls to limit overfishing. This ethical decision was consistent with their agency goal of supporting sustainable fisheries.

The Gulf of Maine lobster team also confronted an ethical decision regarding continuation of forecast delivery (Example 4, Table 2). As scientists working from public funds, they felt an obligation to share what was learned, which argued for continuing the forecast. As stakeholders working in a complex community of harvesters, dealers, managers, and scientists, they also recognized obligations to be constructive and to listen to feedback. This would argue for stopping the forecast. At the time of writing (2018), the team has decided to stop issuing forecasts. This decision was reached after the experience during 2016 when the forecast led to undesirable industry impacts and outcomes. Three factors drove the decision: (i) harvesters found the statewide scale of the forecast difficult to apply to their local experiences, (ii) dealers absorbed a direct price impact upon release of the 2016 forecast, and (iii) other changes in the supply chain (e.g. enhanced processing capacity, Pershing *et al.*, 2018) made the information in the forecast less valuable. The disconnect between the scale of the forecast and the harvesters' scale of operation was particularly problematic. It led to the mistaken perception that the forecast was inaccurate, which risked undermining other forecasting efforts. The team continues to work towards an improved forecast product that addresses the local needs of harvesters, and are also adapting the forecast methods and analyses to biological questions relevant to management decisions. It is hoped that an ongoing dialogue with the industry will shape future forecast products and plans for their communication.

A final ethical issue, while not explicitly a concern in any of the examples covered here, is if the forecast programme is successful and becomes operational, it risks a degree of *scientific/regulatory capture* by the subset of fisherman who participated in and helped shape the programme in a manner consistent with their own business interests, to the exclusion of others (see Equity for users). They may also fail to sufficiently challenge the forecast system if trust is overdeveloped (Lacey *et al.*, 2018) and may miss other opportunities for enhancing performance or sustainability. Scientists should continue to work with stakeholders to ensure the support systems remain fit for purpose.

## Principles for ethical forecasting

As a result of reviewing these case studies and our experiences, we suggest a set of principles that should be considered when scoping, developing, delivering, and evaluating ecological forecasts for marine resource users.

### Phase 1. Scoping the forecast system

1. Conflicts of interest:

- **Principle 1:** Be open and transparent. Work with diverse stakeholders to understand their needs and concerns. Address these concerns if possible, striving for "win–wins." Tread carefully around zero-sum situations, where a forecast advantage for one group may be a disadvantage for another.

2. Ecosystem health:

- **Principle 2:** Do not deliver forecasts that would lead to unregulated impacts on the ocean (e.g. for fisheries without clear catch limits and/or enforcement).

### Phase 2. Developing the forecast system

3. Skill assessment:

- **Principle 3:** Undertake best practice skill assessment that tests the true skill of a model with out-of-sample testing. In forecasting science, this involves comparing a forecasted and a hindcasted fields once the climatology has been removed, using rigourous statistics.

4. Representation of uncertainty:

- **Principle 4:** Do not ignore uncertainty. Traditionally, uncertainty is computed through an ensemble or with permutations on the initial state and provided as a percent agreement between the trajectories of the simulations. While this mostly addresses the uncertainty in the forcing into the future, the uncertainty due to model construction is not easy to incorporate objectively, and needs additional work. Provide a discussion and metrics of uncertainty that include a perspective based on model performance, and the interpretation of probabilistic forecasts.

### Phase 3. Forecast delivery

5. Ongoing delivery:

- **Principle 5:** Plan for and manage stakeholder expectations regarding continued delivery. Planning for and enabling a mechanism for ongoing delivery after a project ends (if possible) and engaging stakeholder representatives early can be important for ensuring a smooth transition. Ultimately, a transition to operational forecasts as delivered by national weather services should be considered.

6. Engagement and education:

- **Principle 6:** Work to improve the literacy of all stakeholders around forecast use and interpretation, particularly on skill and uncertainty.

7. Delivery failures:

- **Principle 7:** Proactively explore the impact of loss of a predictor variable in a forecast system, and be able to explain what the loss of performance is when one variable is removed. Prepare stakeholders for potential breaks in delivery, and never compromise with delivery of substandard forecast products.

8. Equity for end users:

- **Principle 8:** Be vigilant for inequity in use of forecasts between users, and the creation of winners and losers arising from provision of information. Decide when open access is warranted, and when it is not. Include stakeholders in the formulation stage to understand these risks. If risks remain, work at a scale where benefits are clear.

9. Unintended consequences:

- **Principle 9:** Scope the system context widely, seek deep domain and system knowledge, and consider scenario testing, as happens for fishery management regulations now (e.g. management strategy evaluation). Seek feedback and learn from mistakes.

### Phase 4. Evaluation

10. Review of performance:

- **Principle 10:** Consider the holistic outcome of forecast system—if it is not achieving the overall goals, suspend delivery and work on improving the interaction of the forecast and the context in which it operates.

In time, or based on other experiences, this list may change, expand or contract, however, it serves to stimulate thinking in each of the four phases of forecast development and delivery. We suggest project teams use this as a guide when working on forecast systems—particularly as research progress allows development on multi-year timescales (Salinger *et al.*, 2016; Tommasi *et al.*, 2017). These discussions should take place with forecast users too—in line with principles of co-production to maximize benefits (Cvitanovic *et al.*, 2015).

## The future of marine ecological forecasts

Development and delivery of forecast systems for marine resource managers and users has increased over the past decade (Payne *et al.*, 2017), and this review has summarized some non-technical challenges for development teams around the world. A range of judgements and associated ethical issues occur in each phase of forecast development and delivery, including in the final evaluation stage. These issues arise in part because forecasts are developed to assist decision-making, and decision-making carries elements of risk. Most forecast systems we reviewed here were developed as scientist-led endeavours, in regions with strong marine management systems. Forecast teams could also benefit from including local and traditional knowledge about the biological system in question (Leite and Gasalla, 2013), particularly in areas where information on species–environmental relationships may be limited. Such engagement would also offer extra opportunity to identify unwanted consequences from forecast use.

Overall, we contend that the benefits from developing forecasting systems outweigh the risks. For example, engagement with users can reveal novel information about the social and economic aspects of the industry (e.g. fishery, aquaculture business) and expose stakeholders to the nature of scientific processes. Regular forecasting offers the potential for continued learning in real time. Forecasting can be a beneficial and important contributor to ecosystem-based management systems. For example, spatial forecasts can improve economic efficiency (Eveson *et al.*, 2015), which might reduce pressures on marine ecosystems, provided catch limits are in place. Precision fishing, an analogue to precision agriculture, is expected to increase in the future and should reduce collateral damage to ecosystem components, processes and services.

The principles we propose can help other developers of forecast systems avoid pitfalls encountered to date. Many of these pitfalls arise from issues that extend beyond the technical aspects that are the primary focus of forecast scientists (Hobday *et al.*, 2016). By considering the wider context, seeking input from a range of disciplines and stakeholders when constructing forecasts, supporting forecast users, and appreciating the different perspectives on the value of a forecast, unanticipated outcomes may be reduced and the primary goal of marine ecological forecasts—to enhance ocean sustainability—will come closer to reality.

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