Canadian Science Publishing

ARTICLE

The jelly report: Forecasting jellyfish using email and social media

Nicholas R. Record, Benjamin Tupper, and Andrew J. Pershing

Abstract: Ecosystem forecasting has potential societal value, for industry, recreation, and human health applications to name a few. The complexities of ecological systems, the expenses associated with monitoring them, and the suddenness at which forecasts become needed often make forecasts impractical. We tested a novel rapid spin-up daily forecasting system for jellyfish — *Cyanea capillata* (lion's mane jellyfish), *Aurelia aurita* (moon jellyfish), and *Staurostoma mertensii* (whitecross jellyfish) — in the Gulf of Maine. The system blended satellite data with citizen reports collected via email and social media. The forecasting system took 1–3 weeks of tuning before performance plateaued, after which forecast performance was consistently high. Good model performance did not always correspond with good forecast performance, and predictor variables whose contribution improved model performance in some cases had the opposite effect on forecast performance. An adaptive learning mode provided a very modest improvement in performance. In a test of forecast range, forecast performance decreased significantly at a forecast range of around 1 week. Overall, the approach appeared to be a promising avenue toward rapid spin-up of forecasts for undermonitored systems.

Key words: jellyfish, forecast, social media, Twitter, ecosystem forecasting.

Introduction

> "If many jelly fish appear in the sea this is a sign of a stormy season." — Theophrastus ~300 BCE

Forecasting the natural world has been a scientific goal for many thousands of years (e.g., Theophrastus ~300 BCE, see Sider and Brunschön (2007)). While weather forecasts are an integral part of our daily lives — and regularly save lives — other types of forecasts, such as those for earthquakes or fish stocks, have proved more challenging and controversial. Ecosystem forecasting is maturing and has become a scientific priority (Clark et al. 2001; Kaplan et al. 2016), particularly as the variance around climate change trends drive unexpectedly rapid ecosystem changes (Pershing et al. 2015), emphasizing the value of adaptation tools.

Despite technical advances, ecosystem forecasting has been slow to gain a foothold in the mainstream. There are a few specialized ecosystem forecasting applications, such as for harmful algal blooms and pathogens (Stumpf et al. 2009; Ali 2011; Brown et al. 2013;

Received 2 October 2017. Accepted 15 March 2018.

N.R. Record and B. Tupper. Bigelow Laboratory for Ocean Sciences, East Boothbay ME 04544, USA.
A.J. Pershing. Gulf of Maine Research Institute, Portland ME 04101, USA.
Corresponding author: Nicholas R. Record (e-mail: nrecord@bigelow.org).

Payne et al. 2017), but there are still barriers to forecasting for many ecological phenomena. Challenges include: limited survey effort, rapid reproduction rates, lack of parameterization of physiological rates, and high uncertainty about the internal dynamics. As ecosystems begin to change more rapidly due to increasing human pressures, and as many systems enter no-analogue states, there is a potential demand to quickly implement ecosystem forecasts without a long history of monitoring and study. Given the challenges and uncertainties involved, is it feasible to rapidly spin up an ecosystem forecast that is reliable?

We addressed this question using jellyfish outbreaks in the coastal Gulf of Maine as a case study. The summer of 2014 in coastal Maine was marked by extensive jellyfish outbreaks. In the absence of any scientific survey, these outbreaks were reported in the press (e.g., Pols 2014). Anecdotal reports in the spring of 2015 warned of a possible repeat. There was interest in monitoring and predicting a potential 2015 outbreak, but the Gulf of Maine has over 10 000 km of coastline, and with no funding for a formal survey, monitoring posed a significant challenge. We leveraged the widespread interest among coastal residents and visitors in the jellyfish phenomenon as a means of monitoring, nowcasting, and forecasting the distribution of jellyfish. We addressed the question of how quickly a reliable forecasting system can be spun up. Because of the absence of previous survey effort and a general lack of knowledge of polyp distributions and life history parameters, a mechanistic forecasting approach was not feasible. This scenario will likely be common as environments begin to change more rapidly. Machine learning algorithms used in ecosystem forecasts (Record et al. 2010; Pendleton et al. 2012), when coupled with real-time observations, can overcome these challenges to some degree. The resulting program is a noteworthy case study of the potential to spin up a useful ecological forecasting system in a short period of time for an undermonitored phenomenon.

Materials and methods

Observation data

We collected jellyfish reports via an email address (jellyfish@bigelow.org) and a twitter hashtag (#MaineJellies). We advertised the reporting mechanisms through local press, social media, and institutional networks and maintained engagement through sustained correspondence with jellyfish reporters. Followup with jellyfish reporters enabled us to pinpoint the location and time and often the species, approximate size, and some measure of abundance. For the purposes of this analysis, we used presence reporting only, without the estimates of abundance and size, and included three species — *Cyanea capillata* (lion's mane jellyfish), *Aurelia aurita* (moon jellyfish), and *Staurostoma mertensii* (whitecross jellyfish) — as well as a nonspecific report classification that groups together all sightings, including the aforementioned species, other taxa, and unidentified taxa (Fig. 1).

Model

We used the maximum entropy model (Phillips et al. 2006, "MaxEnt") adapted for an operational mode. MaxEnt is able to make predictions based on presence-only observation data. MaxEnt has high prediction accuracy, confidence, and stability as compared to other distribution models (Elith et al. 2006; Duan et al. 2014), and has been used to make climate-based projections, but to our knowledge has not been used in an operational (e.g., day-to-day) forecasting mode. The spatiotemporal data layers informing the model were sea surface temperature (SST) and photosynthetically available radiation (PAR) from MODIS A 4 km daily, as well as zonal and meridional wind from North American regional reanalysis model (Mesinger et al. 2006). We chose the satellite data layers based on coverage and reliability in the dynamic and geographically complex coastal zone, and the the wind

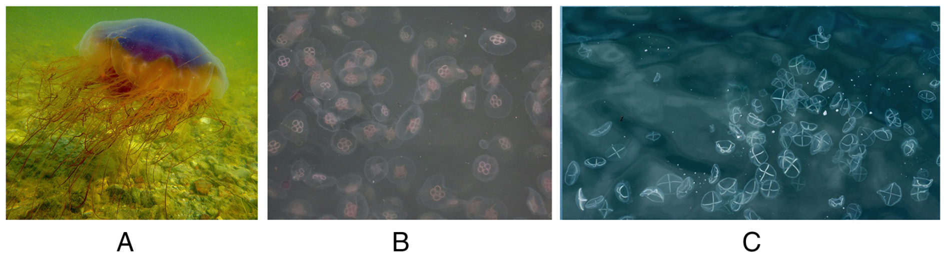


Fig. 1. Three jellyfish species most frequently reported in coastal Maine in 2015: (A) *C. capillata*, (B) *A. aurita*, (C) *S. mertensii*. Images provided with permission by Zoe Weil (A), Jacky McGowan (B), and Chris Sears (C).

fields based on their potential role in surface transport. We accounted for gaps in the PAR data using an 8 day mean.

We ran the model in an operational mode. That is, to forecast a particular day, the model was first tuned using data layers and observations from previous days. This tuning was computed as an ensemble, with each run using a subset of previous days, from the most recent day to the full collection of previous days. Only model configurations created with at least three separate reports were included in the ensemble. The various model configurations were computed and evaluated using two metrics: the area under the curve (AUC), based on the receiver operating characteristic curve as it is adapted for MaxEnt (Lobo et al. 2008, but see section entitled "Discussion"), and the forecast AUC, which computes the AUC on a forecasted data field once new sightings have been reported (FAUC). These two metrics distinguish model performance (AUC) from forecast performance (FAUC). That is, AUC indicates a fit to the data up to a certain date (the data used for tuning); FAUC indicates a fit to out-of-sample data that is a future state (i.e., a forecast). To determine when the FAUC was significantly better than a random forecast, we regressed the FAUC against sample number, and calculated the day on which the 95% confidence interval no longer included 0.5 (i.e., a random forecast).

We also ran the model in an adaptive learning mode. For each forecast day, the configuration from the ensemble was chosen that had the highest AUC from the previous day and was used to forecast the subsequent day. We ran a similar test using the highest FAUC from the previous day. We compared the learning mode performance to the ensemble performance. Finally, we tested the forecast range using an offset between data layers and observations. This simulated the true forecasting scenario, where we only have information up to a certain day, and we are aiming to forecast jellyfish encounters n days ahead, where n is the offset. To forecast at an offset of n days, data layers are associated with observations n days ahead during the model tuning, and the resulting forecast, given data layers for a particular day, will give a result for n days ahead (Fig. 2). We evaluated each offset using the FAUC.

Results

In total, there were 288 reports from June through August, 259 through email and 29 through twitter, distributed throughout the coast (Fig. 3). The most common report was *S. mertensii* at 41% (109 through email, 10 through twitter), followed by *C. capillata* at 24% (60 through email, 10 through twitter), and *A. aurita* at 18% (48 through email, 3 through twitter). The remainder were categorized as unknown, ctenophore, *Beroe spp.*, *mnemiopsis spp.*, and *Pleurobrachia spp.* For graphical purposes, we focus figures on the email reports of *C. capillata*, which constitute the intermediate sized dataset and therefore the best representative, and describe the other datasets with summary statistics.

Fig. 2. Diagram of the forecasting configuration, depicting one ensemble member. In this example, model tuning uses the 6 days prior to the forecast. The dashed lines indicate an adjustment for the offset experiments, here showing an offset of 2 days.

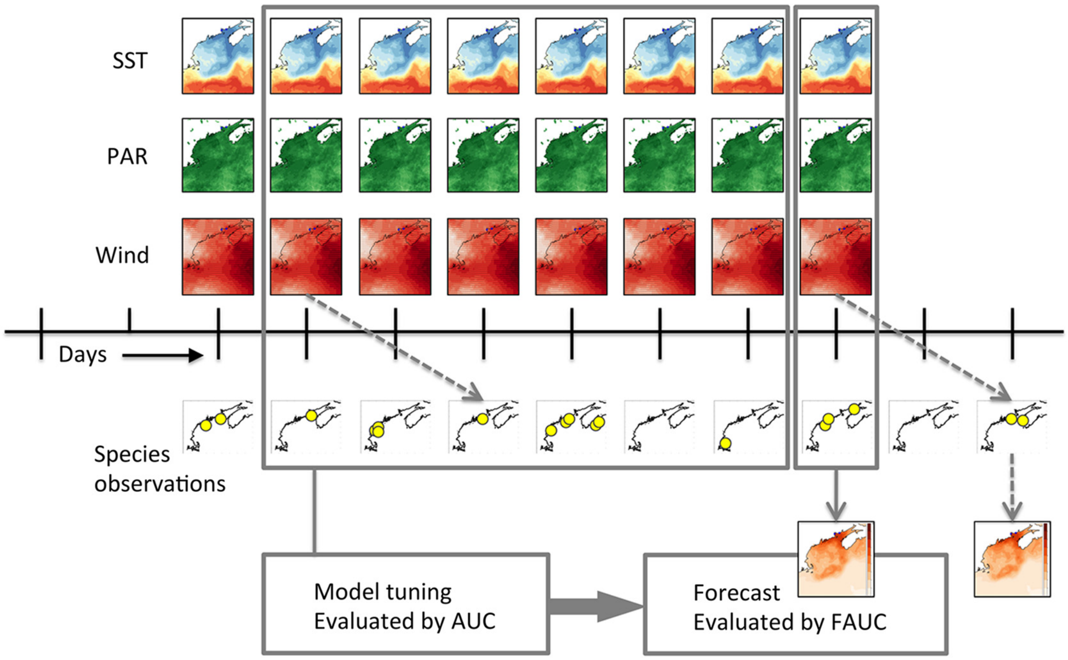
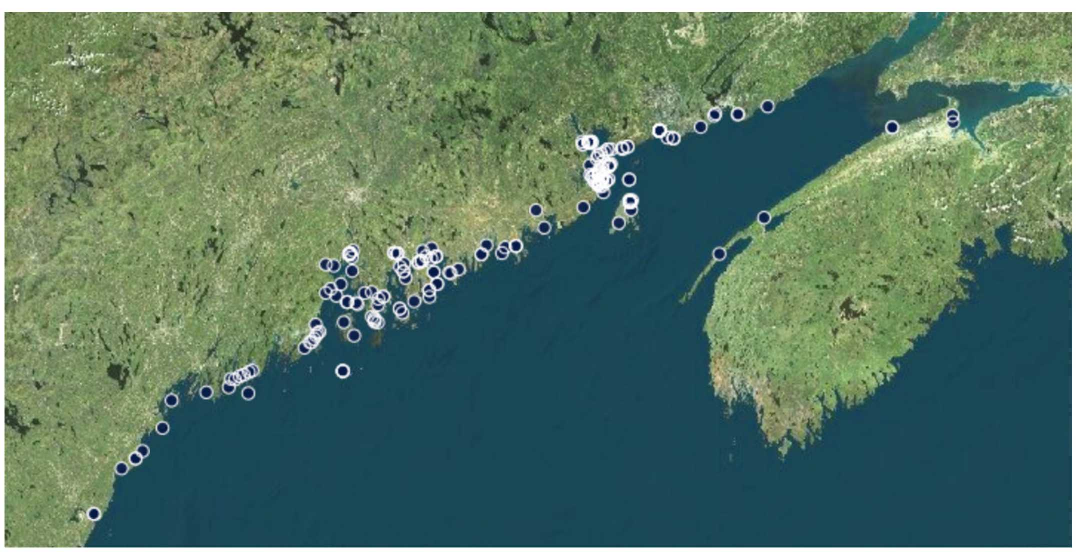


Fig. 3. Distribution of jellyfish reports along coastal Gulf of Maine in June–August 2015. Each circle represents one report at a location. There are 288 total reports. Map imagery attribution: CARTO, HERE satellite day map.



The forecasting configurations generally produced reasonable forecasts that improved over time (Fig. 4). The AUC and FAUC were generally high — typically above 0.8 and often close to 1. The model typically required a learning period of 1–3 weeks before FAUC values were consistently high (Figs. 4 and 5). The time between the date of first reported

Fig. 4. Example forecasts for *C. capillata* on 23 June (A), 8 July (B), 15 August (C), and 18 August (D), illustrating the forecast's improvement over time. Each forecast in these examples used the previous 20 days for model tuning. Color scale indicates jellyfish relative encounter likelihood, indexed by MaxEnt prediction from 0 to 1. Circles indicate the locations of reported observations. Map imagery created by the authors.

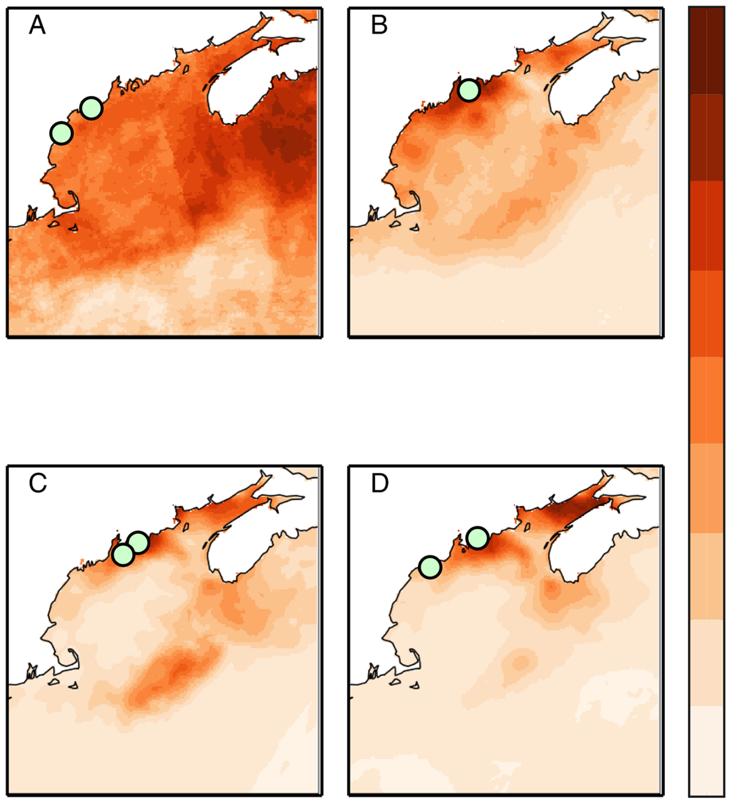


Fig. 5. Model performance over time for *C. capillata*, using email reports: (A) area under curve (AUC) by date, and (B) forecast area under curve (FAUC) by date. Standard box-and-whiskers plot showing median, first and third quartiles, and outliers (crosses). Black line indicates ensemble mean.

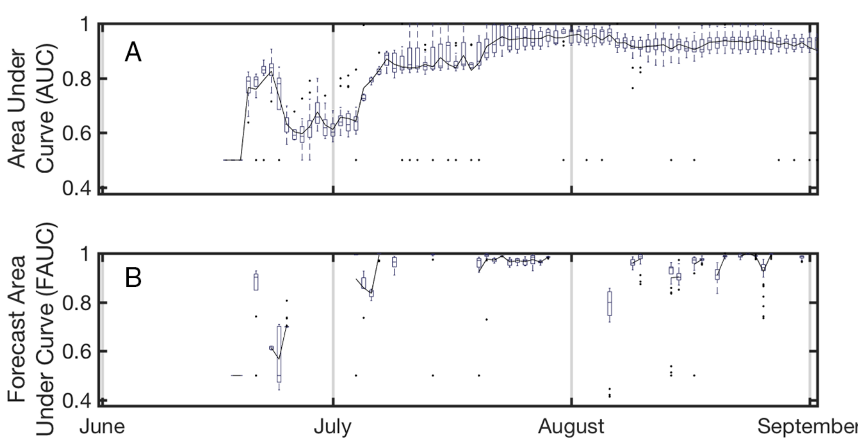
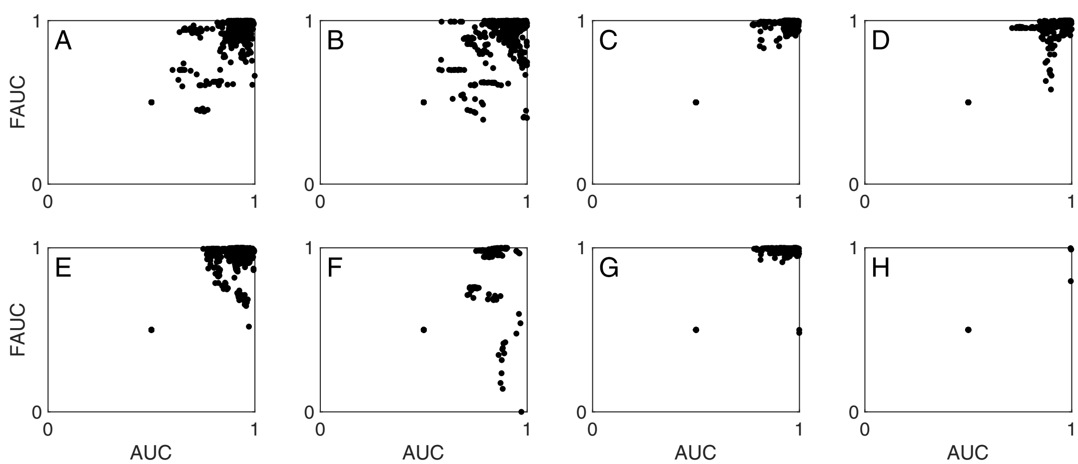


Table 1. Summary information of forecast configurations.

Taxon	Report	Forecast reliability time (days)	Mean FAUC post reliable	r^2	Adaptive mode improvement (AUC)
All reports	Email	8	0.95 ± 0.08	0.48	0.03
C. capillata	Email	7	0.94 ± 0.07	0.27	—
S. mertensii	Email	6	0.98 ± 0.02	0.35	0.03
A. aurita	Email	7	0.96 ± 0.05	0.43	—
All reports	Twitter	10	0.93 ± 0.08	0.28	0.05
C. capillata	Twitter	43	0.95 ± 0	0.40	0.02
S. mertensii	Twitter	17	0.97 ± 0.02	0.63	—
A. aurita	Twitter	—	—	0.15	—

Note: The forecast reliability time is the number of days before a forecast becomes consistently reliable (i.e., when an FAUC of 0.5 falls below the 95% confidence interval). The mean FAUC reported is the mean after the forecast is reliable. Dashes indicate that forecasts were never significantly different from random. Correlation coefficients comparing AUC against FAUC for different forecasting configurations. All r^2 values are significant at $p < 10^{-8}$. Adaptive mode improvement indicates how much better the model performed (by AUC; FAUC did not have any significant differences) in the adaptive learning mode than in the ensemble; comparison uses a *t*-test, and significant values are shown ($p < 0.05$).

Fig. 6. Comparison of the area under curve (AUC) metric to the FAUC for each forecast configuration: Email reports for all observations (A), *C. capillata* (B), *S. mertensii* (C), and *A. aurita* (D), and Twitter reports for all observations (E), *C. capillata* (F), *S. mertensii* (G), and *A. aurita* (H).



observation and the date by which the series of FAUC values were significantly different from 0.5 (i.e., a random forecast) ranged from 6 to 43 days (Table 1), depending on the rate at which reports came in, with all but one plateauing within 3 weeks. High AUC correlated significantly with high FAUC. However, there was significant spread around these relationships, and a well performing model often did not produce as good a forecast as a less well performing model (Fig. 6). Over all runs, FAUC was greater than AUC by an average of 0.02 ($p < 10^{-7}$, *t*-test).

When run in the adaptive learning mode, each forecast used the model from the previous day with the best performance, either by AUC or FAUC. When choosing models by AUC, there was a modest statistically significant improvement in model performance from 0.02 to 0.05 (AUC, Table 1), but not in forecast performance (FAUC). When choosing models by FAUC, there was no statistically significant improvement in forecast performance. However, it is notable that when choosing models by FAUC, there was a bimodal

Fig. 7. Histogram of models selected in the adaptive learning mode from forecasts using email reports. The time period is scaled from 0 to 1 (i.e., all reports (the full reporting period) to the most recent reports) so that all models align within the same axes.

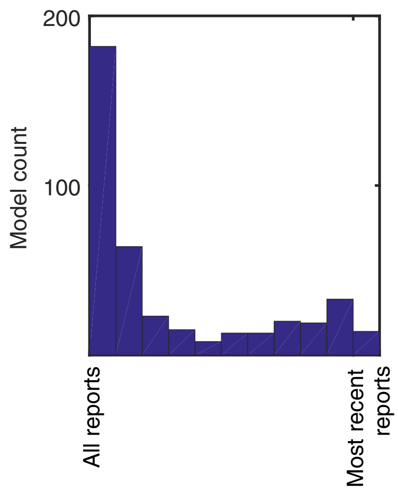


Table 2. Correlation (r) between the percent contribution of each predictor variable (SST, PAR, zonal wind, meridional wind) and the model performance (AUC or FAUC) for the different forecasting configurations (i.e., taxa and reporting methods).

		AUC vs % contribution of:				FAUC vs % contribution of:			
Taxon	Report	SST	PAR	Zonal wind	Merid. wind	SST	PAR	Zonal wind	Merid. wind
All reports	Email	−0.05	−0.11	0.05	0.14	0.07	−0.28	—	0.13
C. capillata	Email	—	—	−0.12	0.04	—	−0.24	0.11	0.13
S. mertensii	Email	0.15	−0.13	−0.11	−0.08	—	—	—	—
A. aurita	Email	0.29	−0.24	−0.22	−0.07	0.19	−0.19	−0.22	0.09
All reports	Twitter	0.31	−0.39	−0.06	0.12	0.40	−0.50	0.10	—
C. capillata	Twitter	—	—	0.21	−0.05	—	—	0.33	—
S. mertensii	Twitter	0.39	−0.28	−0.32	−0.34	0.36	−0.44	−0.24	—
A. aurita	Twitter	0.32	−0.38	—	−0.17	—	—	—	—

Note: Only correlations with $p < 0.05$ shown.

distribution in the models with the best performance with modes at models that used all reports (i.e., the full dataset) or models that used only the most recent reports (Fig. 7).

MaxEnt provides a measure of the percent contribution of each predictor variable, which can give insights into what drives the underlying relationships. The ensemble approach used here allows for comparison of the contribution of each predictor variable to model performance (Table 2, Fig. 8). SST is generally the strongest predictor, and a higher contribution by SST generally correlated with a higher AUC and FAUC across all but one forecast configuration. In contrast, a higher contribution by PAR generally correlated with a lower AUC and FAUC across all forecast configurations. For both of these predictor variables, the effect of contribution was the same on AUC as on FAUC. For zonal and meridional winds, however, there was an opposite effect on AUC than on FAUC: when the wind contribution was higher, the AUC was lower, but the FAUC was higher across most forecast configurations.

Running the model with an offset provided a way to test the forecast range. The FAUC dropped slightly as the offset increased, with a sharp drop after about a week (Fig. 9).

Fig. 8. Model performance (AUC and FAUC) as a function of the contribution of each predictor (SST, PAR, zonal wind, and meridional wind) for *C. capillata*, using email reports.

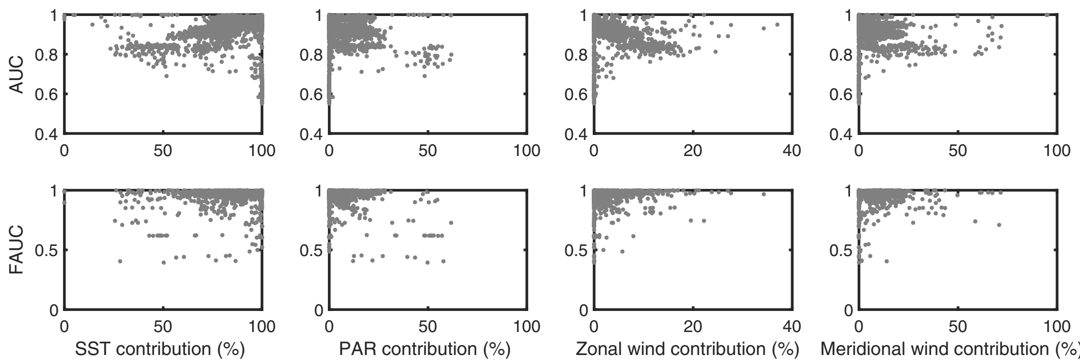
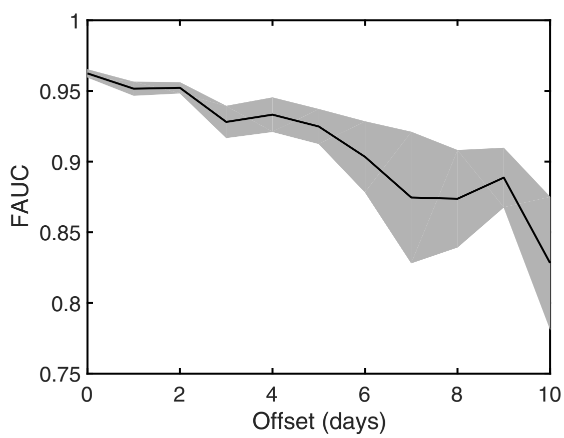


Fig. 9. Test of forecast range: FAUC as a function of offset, averaged for all taxa and all forecast days. Shaded area shows variance around mean.



Increasing offsets restricts the number of observations available for model tuning. When we included only model configurations with at least 20 observations, the forecast was effectively random (i.e., FAUC = 0.50 ± 0.02) at an offset of 9 days.

Discussion

Theophrastus's *De signis*, penned more than two millennia ago, used methods that modern forecasters might scoff at: "A seal making its loud sound in the harbor while holding an octopus is a sign of storm" (Sider and Brunschön 2007). Modern weather forecasting, by contrast, combines mechanism with calculus in a deterministic manner. This approach is useful in ecosystem forecasting as well, particularly as we improve forecasts of the underlying variables (Tommasi et al. 2017). However, chaos poses limits on the deterministic method (Lorenz 1963), and similar limitations apply to deterministic ecological forecasts (Record et al. 2013; Petchey et al. 2015). Machine learning approaches that have arisen in the Big Data Era are an interesting echo of Theophrastus's approach — essentially looking for signs in data without necessarily understanding the mechanism. New computational tools for searching vast datascapes give new relevance to the approach used in *De signis*.

Like weather, ecology is part of people's everyday lives. Daily ecological forecasts would be useful for recreation, health, safety, and industry. New methods are a departure from the methodology of weather forecasting, but they also offer new potential. One example is the potential to launch low-cost forecasting systems quickly, without expensive monitoring and computational infrastructure. The approach could work for a wide variety of problems as long as a sufficient number of observers can be engaged quickly.

For jellyfish in the Gulf of Maine in 2015, the system required a few weeks of observations before a substantial increase in performance. Within 1–3 weeks, forecast performance maintained a high level. High performance was primarily associated with a strong contribution by SST, which is consistent with reported associations between jellyfish and temperature (Han and Uye 2010; Zhang et al. 2012). SST also has a strong spatio-temporal autocorrelation, capturing the tendency of jellyfish outbreaks to move coherently with a water mass. Autocorrelation is also evident in the test of forecast range, where forecasts performed well even at an offset of a few days but then dropped. Ocean conditions generally change more slowly than atmospheric conditions, so signals can persist over a few days. Some of the other predictor variables showed unexpected results. Higher contributions of winds reduced model fit performance but increased forecast performance. This may have to do with the sporadic effect of wind on jellyfish transport (i.e., a wind event in the right direction can concentrate a population of jellyfish near the shore). These effects can be less important in evaluating model performance over an extended fitting period, but very important in evaluating forecast performance for a particular day. Modifications of data layers, such as taking integrals or derivatives, could be one way to capture these effects.

There are some caveats to the approach presented here. First, the approach is heavily empirical, and so good model performance does not necessarily imply good forecast performance. This can be hedged to some degree by perpetual tuning, as in the adaptive learning mode. The bimodal distribution in model selection (Fig. 7) suggests nonstationarity in the underlying empirical relationships (i.e., the best forecast often used only the most recent reports). We expect this effect to be more pronounced in longer time series, possibly warranting an ensemble weighting in an adaptive mode. There is also the possibility of building mechanistic data layers into this type of model, which can improve model performance (e.g., Record et al. 2010; Pendleton et al. 2012). For such data layers to work in a fast-spin-up forecasting context, one must be able to compute them on an operational time scale. A second caveat is that when interpreting model performance, one must keep in mind that AUC and FAUC are very difficult to compare across studies (Lobo et al. 2008). Forecast performance should be assessed in a relative sense, as we have done in this study. Finally, because ecological systems vary so much in their dynamics, mechanisms, and time scales, there will be some systems for which this forecasting approach does not work. The generality of the approach will become more clear as more forecasts come online.

As the environment begins to change more rapidly, and more regions enter no-analogue states (e.g., Pershing et al. 2015), we will need adaptation tools for dealing rapidly with ecological hazards. Changes in conditions and introduced species can lead to increased pathogens, harmful algal blooms, and other costly and dangerous outbreaks. By tapping into public engagement in ecological phenomena, we have new potential to forecast ecosystems. This could be an important asset if Earth Science loses significant governmental funding support. Moreover, there are added benefits to involving people in the process of environmental observation: (*i*) it can give people direct access to environmental information relevant to them; (*ii*) it exposes a wider audience to the scientific process; and (*iii*) by engaging people, there is the potential to build a more science-friendly public (Record 2017). In this way, we might increase the presence of ecology and of science in people's everyday lives.

Acknowledgements

Funding for this work came from the National Aeronautics and Space Administration (grant No. NNX14AN14A), with additional support from the National Science Foundation Research Experience for Undergraduates in the Gulf of Maine and the World Ocean (No. 1460861) and Bigelow Laboratory institutional funds. This manuscript benefitted from conversations at the congress of the People's Institute for Science of the Future. Thanks for contributions from Emma Posega Rappleye. Many thanks to the hundreds of people who contributed jellyfish reports and continue to do so.

References

Ali, G. 2011. Arch, garch, and armax models for forecasting pathogen indicators and advisories at marine recreational sites. Mar. Resour. Econ. **26**(3): 211–224. doi: 10.5950/0738-1360-26.3.211.

Brown, C., Hood, R.R., Long, W., Jacobs, J., Ramers, D., Wazniak, C., et al. 2013. Ecological forecasting in chesapeake bay: Using a mechanistic–empirical modeling approach. J. Mar. Syst. **125**: 113–125. doi: 10.1016/j.jmarsys.2012.12.007.

Clark, J.S., Carpenter, S.R., Barber, M., Collins, S., Dobson, A., Foley, J.A., et al. 2001. Ecological forecasts: An emerging imperative. Science, **293**(5530): 657–660. doi: 10.1126/science.293.5530.657. PMID: 11474103.

Duan, R.-Y., Kong, X.-Q., Huang, M.-Y., Fan, W.-Y., and Wang, Z.-G. 2014. The predictive performance and stability of six species distribution models. PLoS ONE, **9**(11): e112764. doi: 10.1371/journal.pone.0112764. PMID: 25383906.

Elith, J., Graham, C.H., Anderson, R.P., Dudík, M., Ferrier, S., and Guisan, A. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography, **29**(2): 129–151. doi: 10.1111/j.2006.0906-7590.04596.x.

Han, C.-H., and Uye, S.-i. 2010. Combined effects of food supply and temperature on asexual reproduction and somatic growth of polyps of the common jellyfish aurelia aurita sl. Plankton Benthos Res. **5**(3): 98–105. doi: 10.3800/pbr.5.98.

Kaplan, I.C., Williams, G.D., Bond, N.A., Hermann, A.J., and Siedlecki, S.A. 2016. Cloudy with a chance of sardines: Forecasting sardine distributions using regional climate models. Fish. Oceanogr. **25**(1): 15–27. doi: 10.1111/fog.12131.

Lobo, J.M., JiménezValverde, A., and Real, R. 2008. Auc: A misleading measure of the performance of predictive distribution models. Global Ecol. Biogeogr. **17**(2): 145–151. doi: 10.1111/j.1466-8238.2007.00358.x.

Lorenz, E.N. 1963. Deterministic nonperiodic flow. J. Atmos. Sci. **20**(2): 130–141. doi: 10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2.

Mesinger, F., DiMego, G., Kalnay, E., and Mitchell, K. 2006. North American regional reanalysis. Bull. Am. Meteorol. Soc. **87**(3): 343–360. doi: 10.1175/BAMS-87-3-343.

Payne, M.R., Hobday, A.J., MacKenzie, B.R., Tommasi, D., Dempsey, D.P., Fässler, S.M., et al. 2017. Lessons from the first generation of marine ecological forecast products. Front. Mar. Sci. **4**: 289. doi: 10.3389/fmars.2017.00289.

Pendleton, D.E., Sullivan, P.J., Brown, M.W., Cole, T.V., Good, C.P., Mayo, C.A., et al. 2012. Weekly predictions of north Atlantic right whale eubalaena glacialis habitat reveal influence of prey abundance and seasonality of habitat preferences. Endangered Species Res. **18**(2): 147–161. doi: 10.3354/esr00433.

Pershing, A.J., Alexander, M.A., Hernandez, C.M., Kerr, L.A., Le Bris, A., Mills, K.E., et al. 2015. Slow adaptation in the face of rapid warming leads to collapse of the gulf of Maine cod fishery. Science, **350**(6262): 809–812. doi: 10.1126/science.aac9819. PMID: 26516197.

Petchey, O.L., Pontarp, M., Massie, T.M., Kéfi, S., Ozgul, A., Weilenmann, M., et al. 2015. The ecological forecast horizon, and examples of its uses and determinants. Ecol. Lett. **18**(7): 597–611. doi: 10.1111/ele.12443. PMID: 25960188.

Pols, M. As jellyfish come in waves off Maine coast, questions follow. Portland Press Herald. 16 July 2018. Available from https://www.pressherald.com/2014/07/16/jellyfish-come-waves-maine-coast-questions-follow/.

Phillips, S.J., Anderson, R.P., and Schapire, R.E. 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. **190**(3): 231–259. doi: 10.1016/j.ecolmodel.2005.03.026.

Record, N.R. 2017. A people's science. Limnol. Oceanogr. Bull. **26**: 36–37. doi: 10.1002/lob.10171.

Record, N.R., Pershing, A., Runge, J., Mayo, C., Monger, B., and Chen, C. 2010. Improving ecological forecasts of copepod community dynamics using genetic algorithms. J. Mar. Syst. **82**(3): 96–110. doi: 10.1016/j.jmarsys.2010.04.001.

Record, N.R., Pershing, A.J., and Maps, F. 2013. The paradox of the "paradox of the plankton". ICES J. Mar. Sci. J. du Conseil, fst049.

Sider, D., and Brunschön, C. 2007. Theophrastus of eresus. On Weather Signs, Leiden, the Netherlands.

Stumpf, R.P., Tomlinson, M.C., Calkins, J.A., Kirkpatrick, B., Fisher, K., Nierenberg, K., et al. 2009. Skill assessment for an operational algal bloom forecast system. J. Mar. Syst. **76**(1): 151–161. doi: 10.1016/j.jmarsys.2008.05.016.

Tommasi, D., Stock, C.A., Pegion, K., Vecchi, G.A., Methot, R.D., Alexander, M.A., and Checkley, D.M. 2017. Improved management of small pelagic fisheries through seasonal climate prediction. Ecol. Appl. **27**(2): 378–388. doi: 10.1002/eap.1458. PMID: 28221708.

Zhang, F., Sun, S., Jin, X., and Li, C. 2012. Associations of large jellyfish distributions with temperature and salinity in the yellow sea and East China Sea. Hydrobiologia, **690**(1): 81–96. doi: 10.1007/s10750-012-1057-5.