When to ignore perfect information: how iterative learning can lead to worse decisions

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Abstract

Model-based forecasts have been enabled by recent explosion of data and computational methods and spurred on by decision-makers appetite for forecasts in everything from elections to pandemic response. Using a classic example from fisheries management, I demonstrate that selecting the model that produces the most accurate and precise forecast can lead to decidedly worse outcomes.

Keywords: forecasting, adaptive management, stochasticity, uncertainty, optimal control

Global change issues are complex and outcomes are difficult to predict (Clark *et al.* 2001). To guide decisions in an uncertainty world, researchers and decision makers may consider a range of alternative plausible models to better reflect what we do and do not know about the processes involved (Polasky *et al.* 2011). Forecasts or predictions from possible models can indicate what outcomes are most likely to result under what decisions or actions. This has made model-based forecasts a cornerstone for scientifically based decision making.

By comparing outcomes predicted by a model to future observations, a decision maker can not only *plan* for the uncertainty, but also *learn* which models are most trustworthy. The value of iterative learning has long been reflected in the theory of adaptive management (Walters & Hilborn 1978) as well as in actual adaptive management practices such as Management Strategy Evaluation (MSE) (Punt *et al.* 2016) used in fisheries, and is a central tenant of a rapidly growing interest in ecological forecasting (Dietze *et al.* 2018). But, do iterative learning approaches always lead to better decisions?

In this paper, I will demonstrate that iterative learning or iterative forecasting can also be counter-productive to management outcomes: that in some cases, a manager would be better to ignore new information which could reduce uncertainty over available models. Put another way, the value of information (VOI, as measured by the expected utility given that information minus the utility without it; see Howard (1966); Katz *et al.* (1987)), can actually be negative. This is not a consequence of imperfect information (e.g. observation error) or the result of model over-fitting. The issue is an intrisic consequence of the fact that many models can lead to the same decisions, and no generic solution to the problem exists. However, as this example shows, by better understanding what aspects of model are most and least important to shaping a particular decision, we can at least anticipate the circumstances that make this problem more likely.

Iterative learning approaches such as adaptive management or iterative forecasting are particularly compelling because they address a different reason why seemingly-accurate models can lead to poor outcomes: the problem of overfitting. When models are estimated from the data they seek to describe, the model may over-fit the data, making the data seem even more likely than it would be under the true process (Burnham & Anderson 1998). Over-fit models may underestimate uncertainty and make poor predictions about future outcomes (Ginzburg & Jensen 2004). Because any iterative learning compares models to future outcomes, overfitting those outcomes is impossible. This concept was rigorously formalized by Gneiting & Raftery (2007)'s proof of "proper" scoring rules. By definition, under a proper scoring rule, no probabilistic prediction $Q(x)$ can score better, on average, than that of the underlying process, $P(x)$. Gneiting &

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Raftery (2007) further shows which techniques for evaluating forecast predictions do an do not satisfy this condition, i.e. which cannot be over-fit. Adaptive management is based on equally secure footing because model predictions are again compared to future outcomes not used to fit the model. Instead of scoring and selecting among alternative models, adaptive management considers probabilities over all models (Walters & Hilborn 1978). These two approaches are particularly compelling because they can both reduce uncertainty and avoid over-fitting. My example is not meant to undercut the importance of these approaches. Previous work has long acknowledged the panelope of ways in which iterative learning or other model-based decision making can go astray due to conflicting incentives, implementation errors, or lack of resources for monitoring and updating (e.g. Ludwig *et al.* 1993). Here, the problem is more fundamental.

I illustrate this problem using an example from fisheries management. Fisheries are a significant economic and conservation concern world wide and their management remains an important debate (e.g. Worm *et al.* 2006, 2009; Costello *et al.* 2016). Moreover, their management has been a proving grounds for theoretical and practical decision-making issues which are widely applicable in other areas of ecology and conservation (Ludwig *et al.* 1993; Lande *et al.* 1994), and one that has long wrestled with issues of uncertainty in the context of management decisions (e.g. Clark 1973; Reed 1979; Walters 1981; Ludwig & Walters 1982). While modern fisheries management frequently relies on complex models which may contain scores of parameters to reflect the specific age or stage structure of a specific fish stock (Ricard *et al.* 2011; Ricard *et al.* 2018), I will rely on simple, well-studied models which permit greater intuition and generalization (Levins 1966). Consistent with such previous work (Schaefer 1954; Clark 1973; Reed 1979; Walters 1981; Ludwig & Walters 1982; Costello *et al.* 2016), let us consider the problem of determining the optimal harvest policy given a measurement of the current stock size.

For illustrative purposes, we will focus on the simplest example of model uncertainty, considering two alternative models of equal complexity but differing in the estimated value of certain parameters. While some authors distinguish between model uncertainty and parameter uncertainty, I will refer collectively to any uncertainty that arises from our imperfect knowledge of the system as "model uncertainty," because the distinction is largely a consequence of notation rather something more intrinsic. (For example, two structurally different models, $f(x) = ax$ and $f(x) = ax^2$ can be considered merely different parameterizations of $f(x) = ax^b$, or vice versa.)

Ecological Models

The sustainable harvest decision problem can be stated as follows: The fish stock is observed to be in state X_t at time t, and is then subjected to some harvest H_t before recruiting new fish, subject to stochastic environmental noise ξ_t, to bring the stock to $X_t + 1$,

$$X_{t+1} = f(X_t - H_t, \xi_t) \tag{1}$$

A manager seeks each year to select the harvest quota H_t which will maximize the sum of the utility derived from such a harvest and such a state, $U(X_t, H_t)$, over all time, subject to discount rate δ (Clark 1973):

$$\sum_{t=0}^{t=\infty} U(X_t, H_t)\delta^t \tag{2}$$

For simplicity and comparison with prior work, we will assume a fixed price of fish p with no additional cost on additional harvest, $U(X_t, H_t) = p \min(H_t, X_t)$ (noting that realized harvest cannot exceed the stock size). Without loss of generality we will set the price $p = 1$ and modest discount $\delta = 0.99$.

We further imagine that the function f is not known precisely. Again for simplicity, we restrict ourselves to two simple candidate models f_1 and f_2. Both share the same underlying structure of logistic recruitment (known as the Gordon-Schaefer model in fisheries context owing to groundbreaking work independently by Schaefer (1954) and Gordon & Press (1954)), differing only in their choice of certain parameters:

$$f_i(Y) = Y + r_i Y \left(1 - \frac{Y}{K_i}\right) * \xi_t(\sigma) \tag{3}$$

For simplicity, we will assume $\xi_t(\sigma)$ represents log-normal random noise with mean of unity and log-standard-deviation σ_i for each model. Model 1 is given by $r_1 = 2$, $K_1 = 16$, $\sigma_1 = 0.05$, Model 2 by $r_2 = 0.5$, $K_2 = 10$, $\sigma = 0.075$ (in dimensionless units). Having both the larger growth rate and the larger carrying capacity, Model 1 is clearly the more optimistic of the two choices.

Selecting between Model 1 and Model 2 can thus be considered the simplest illustration of the model uncertainty problem. This is a subset of the more general problem of selecting model parameters, assuming a logistic growth, which itself is a subset of estimating the best structural from (e.g. Ricker, Beverton-Holt, etc). There is no need to consider these more complicated versions of the model uncertainty problem here, since they all inherit the same issue. Reducing the model selection problem to these two models simplifies the presentation and will aid intuition at no loss of generality.

The only additional assumption we will need is that the "true" model is not among the suite of models under consideration. Mathematical models are, at best, approximations of the underlying processes. Ecological processes are much too complex to ever be modeled exactly. For illustrative purposes, we will thus assume the "true" process to be given by Model 3, which is unknown to the decision-maker, but similar enough to at least one of the candidate models might be considered a reasonable approximation:

$$f_3(Y) = Y + r_3 Y^4 \left(1 - \frac{Y}{K_3}\right) \tag{4}$$

with $r_3 = 0.002$, $K_3 = 10$ and $\sigma_3 = 0.05$.

The task of deciding whether Model 1 or Model 2 would be the better choice for decision making is thus perhaps the simplest example of the much studied issue of model uncertainty that we can pose. As in any real world scenario, neither model is the true model, but nevertheless this model set contains a good enough approximation of the true model to make good decisions. However, any of the well-developed approaches for decision-making under model uncertainty will prefer Model 2 over Model 1, despite the fact that the optimal policy under Model 2 leads to much worse outcomes ecologically and economically.

Methods for Managing Under Model Uncertainty

We will use this example to illustrate two alternative approaches for iterative learning over model uncertainty: iterative forecasting and adaptive management. The central difference in the approaches is that iterative forecasting is premised on the ability to score the predictions of alternative models. Iterative forecasting is silent on the issue of what to do with those scores, this is left up to the decision-maker. Adaptive management approaches, by contrast, explicitly seek to integrate probabilities over all candidate models to reach a decision. I consider each in turn.

Statistical approaches: Forecasting under "Proper" Scoring Rules

Like many decision problems, the task of setting a sustainable harvest quota appears to hinge on having an accurate forecast: if we can predict to what size the fish stock will increase next year, $X_t + 1$, and we know the current stock, X_t, then we can sustainably harvest $X_{t+1} - X_t$ without decreasing the biomass over the long term. Selecting a model based on forecast skill is also justifiable on theoretical grounds, since it reduces the risk of over-fitting by comparing model predictions to later observations that were not used to estimate the model (Gneiting & Katzfuss 2014).

I illustrate the process of model selection by strictly proper scoring rules using two scenarios. In Scenario A (passive observation) the fish stock is unharvested and allowed to recover towards carrying capacity (as simulated under our "true" model, Model 3) while comparing the observed stock size in each subsequent time step to the distribution predicted under Model 1 and Model 2 respectively [Fig 1]. The mean, μ_t and variance, σ_t of the forecast are compared against the true observation x_t using a Proper scoring rule of Gneiting & Raftery (2007),

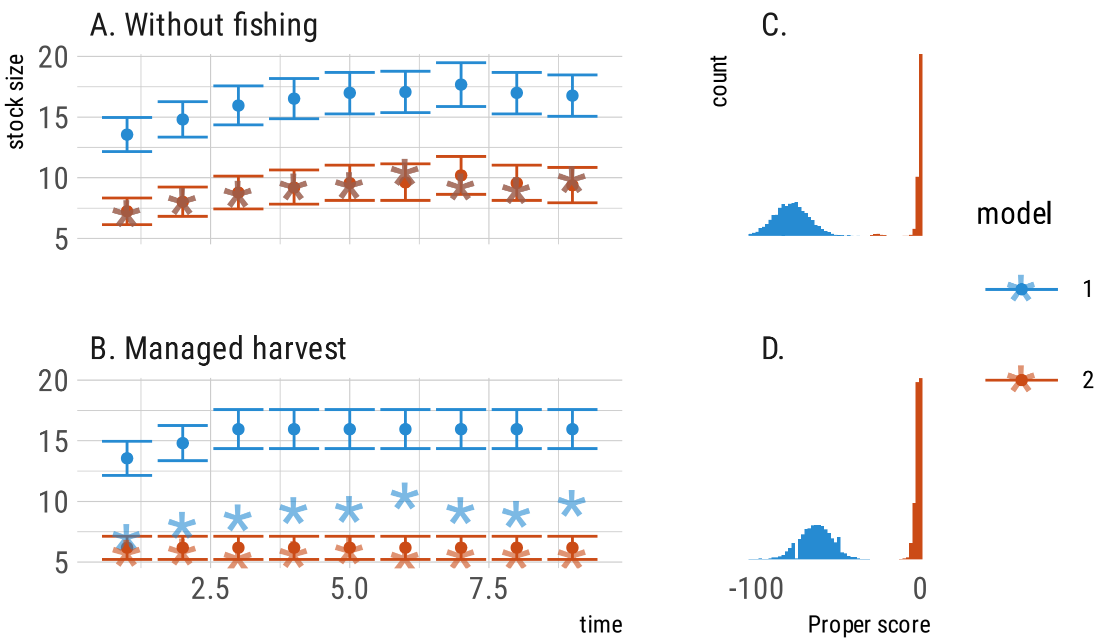

Figure 1: Forecast performance of each model. Panels A, B: Step ahead predictions of stock size under unfished (A) and fished (B) scenarios. Error bars indicating the 95% confidence intervals around each prediction, while stars denote the observed value in that year. Because the models make different decisions each year in the fished scenario, the observed stock size in year 2, 3, etc under the management of model 1 (blue stars) is different from that under model 2 (red stars). Panels C, D: corresponding distribution of proper scores across all predictions (100 replicates of 100 timesteps). Higher scores are better, confirming that model 2 makes the better forecasts.

$$S(x_t|\mu_t, \sigma_t) = -(\mu_t - x_t)^2/\sigma_t^2 - \log(\sigma_t) \tag{5}$$

for each prediction over 100 replicate simulations of 100 time steps each [Fig 1].

In Scenario B (actively harvest), I have first solved for the optimal management strategy for both Model 1 and Model 2 [Fig 1b]. For small noise and concave functions with linear reward structure this can be done analytically (see proof in Reed 1979), or solved more generally by stochastic dynamic programming (see review by Marescot *et al.* 2013, details in Appendix). Under this scenario, replicate simulations of the stock are harvested at each time step using the optimal quota dictated by either Model 1 and Model 2. The resulting stock sizes in the time-step following this harvest are once again compared to the probabilities predicted by each model using Eq (5). Model 2 unequivocally outperforms Model 1 in both scenarios of passive observation and active harvest.

Despite the clearly superior predictive accuracy of Model 2 in both scenarios, the outcomes from management under Model 2 are substantially worse. We can assess such outcomes in less abstract terms than forecasting skill, such as economic value (in dollars) or the ecological value (unharvested biomass). In our simple formulation of the decision problem, the "utility" the manager seeks to maximize is simply the economic value (net present value: the discounted sum of all profits from future harvests, Eq (2)) of harvested fish. This formulation ignores any utility provided by fish that are not harvested, beyond their contribution to future potential harvests. While it is possible to include such contributions directly in the utility function being optimized (e.g. Halpern *et al.* 2013), even without doing so, Model 1 maintains both a higher unharvested biomass and also leads to higher economic returns throughout [Fig 2].

Had we been able to include Model 3 in our forecast comparisons, it would equal or outperform the forecasting skill of both Model 1 and Model 2 (as guaranteed by the theorem of Gneiting & Raftery (2007)), while also matching or out-performing their economic utility (as guaranteed by the theorem of Reed (1979)). In practice, we never have access to the generating model.

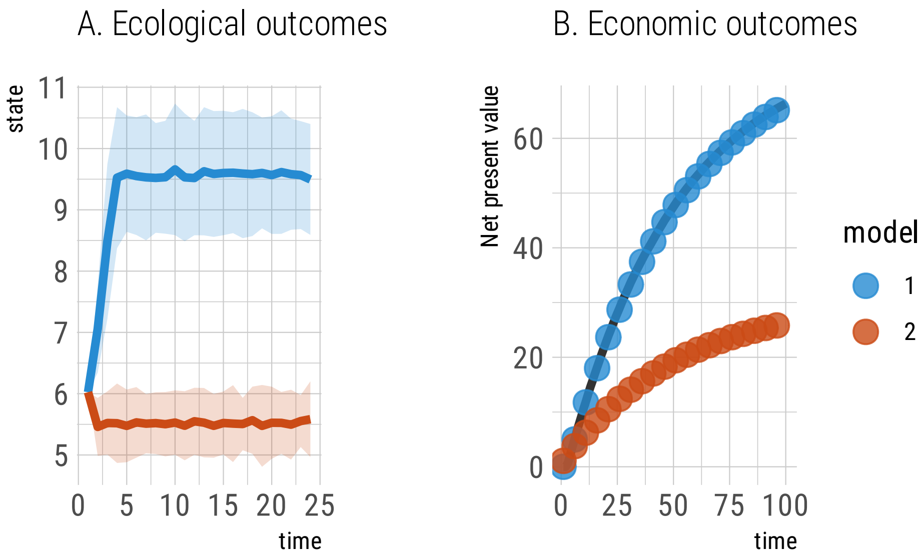

Figure 2: Ecological and economic performance of each forecast. Harvest quotas derived from Model 1 result in a significantly higher fish stock size than under Model 2 (panel A). Economic returns under Model 1 are also substantially higher (panel B)

One obvious limitation in this comparison is that scenario B treats each model as fixed over the entire course of the simulation. It would be possible to generate forecasts for the next n steps, but these forecasts would also be conditional on the management action (i.e. harvest quota) selected at each step. To evaluate two-step-ahead predictions we must consider each possible action under each possible state predicted by the step-ahead forecast, weighted by probability of the state given the model and the probability of the model. This rapidly expanding set of possibilities is addressed by adaptive management for sequential decision problems (e.g. Smith & Walters 1981), which I employ in the next section.

Decision-Theoretic Approaches

Any adaptive management strategy updates posterior distributions over model uncertainty (Ludwig & Walters 1982; Punt *et al.* 2016). Unfortunately, any such adaptive updating leads to worse outcomes than the equivalent non-adaptive strategy, in which model uncertainty is held fixed. I illustrate the application of a passive adaptive management strategy to this simple example, following classic examples for parameter (Ludwig & Walters 1982) or structural (Smith & Walters 1981) model uncertainty. Passive adaptive management for a simple sequential decision problem is straight forward to implement over a discrete set of states and actions using dynamic programming with iterative updates (Smith & Walters 1981, example code in Appendix). To demonstrate that the behavior is not driven by failure to explore sufficiently, (which might be addressed by an active adaptive management), I will assign initial probability that model 2 is true at 1%. After a single iteration of learning, these probabilities are completely reversed, with the manager deciding that model 2 is almost certainly correct [Fig 3]. As before, this results in a management practice with much worse ecological and economic outcomes than would have been realized by a manager who stubbornly clung to model 1 without updating, which achieves a net present value over 100 time steps that only 31% that expected under management using Model 1 alone [Fig 2].

Increasing the space of possible models to cover a whole plausible range of parameters r and K does nothing to resolve this problem. Learning is somewhat slower over the larger range of possibilities, but nevertheless converges towards parameter values with lower growth rates and lower carrying capacity, for which the target biomass is far lower [Fig 3B; details in appendix B]. The manager becomes trapped in vicious cycle as biomass declines further and further, subsequent observations seem more and more consistent with models which most favor over-fishing in the first place. As biomass declines, annual harvests and profits also plunge, and yet our manager becomes only more confident in their decisions.

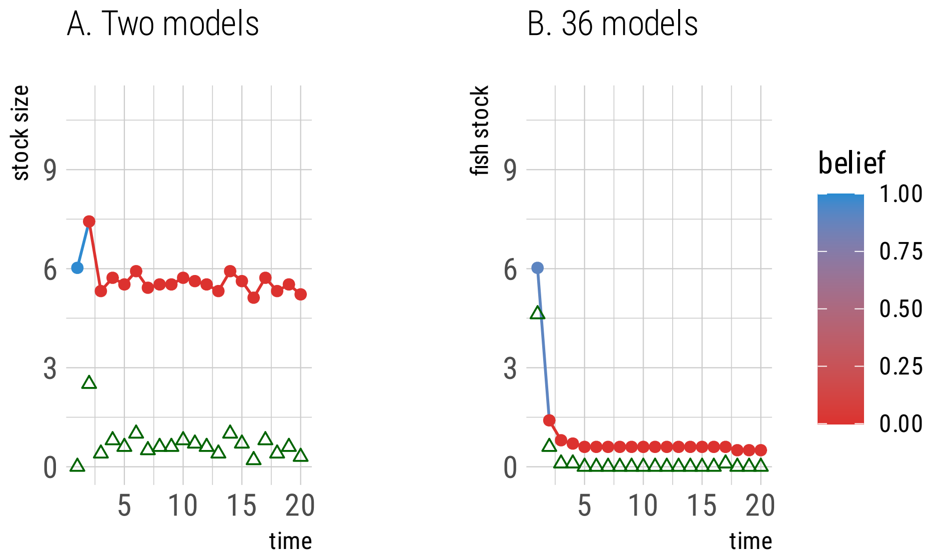

Figure 3: Adaptive management under model uncertainty, color indicating the belief that Model 1 is correct (blue), lines indicating stock biomass over time, green triangles indicating harvest quotas set by adaptive management. Panel A: Each model is assigned an initial prior belief. To ensure that any issues with passive exploration are not the cause of preferring Model 2, the initial belief in Model 2 is set to 1%. Within a single iteration of adaptive management, the belief over models is updated to near certainty in Model 2, resulting in higher harvests and lower stock sizes similar to managing under Model 2 alone, Fig 2A. Panel B: given 36 candidate models over a broad range of parameters, adaptive management leads to models that overharvest even more, leading to even lower stock sizes and lower harvest quotas.

Discussion

Given this simple decision problem in which one of the two models leads to effectively optimal ecological and economic outcomes, current approaches invariably choose the other. Moreover, a decision maker employing an adaptive management or iterative forecasting assessment such as those considered here would have no way of realizing that the outcomes they experienced were in fact sub-optimal. In both approaches, the manager quickly concludes that Model 1 is entirely implausible, while finding that Model 2 is remarkably accurate at predicting future values. This problem is not addressed by re-estimating parameters (equivalently, considering a larger suite of models with all possible K and r values): in fact leads to a model with slightly lower K and even higher level of over-fishing and under-performance than Model 2 (Fig 3B).

The reason for Model 1's seemingly contradictory ability to make good decisions but bad forecasts becomes obvious once we compare both curves to that of the underlying model, Model 3. Plotting the growth rate functions of each model, [Fig 4A], it is hardly surprising that no method exists which would not prefer the closely overlapping Model 2 to the no-where-close Model 1 as the better approximation of Model 3. However, Nevertheless, decisions based on Model 1 are nearly indistinguishable from those based on the true model [Fig 4B], while Model 2 leads to over-harvesting. The explanation comes from noticing that the stock size corresponding to the maximum growth rate under Model 1 (the peak of the curve) falls at almost exactly the same stock size as that of the peak growth rate for Model 3. Meanwhile, the peak of Model 2 occurs at a substantially lower stock size. While the optimal control solution appears to depend only on a step-ahead forecast accuracy (indeed, the SDP solution method used here takes only step-ahead forecast probabilities as input, (Marescot *et al.* 2013)), mathematical analysis showed long ago (Reed 1979) that the optimal solution for this problem depends only on keeping the biomass at the value responsible for the maximum growth rate. This realization is quite general: for most decision problems, simple models will exist under which the optimal decision is the same as it would be for the true model, even when that simple model is wrong in most other ways.

This phenomenon is not unique to sequential decision problems or optimal control solutions. For example, Management Strategy Evaluation (Punt *et al.* 2016) in fisheries seeks to evaluate pre-specified strategies

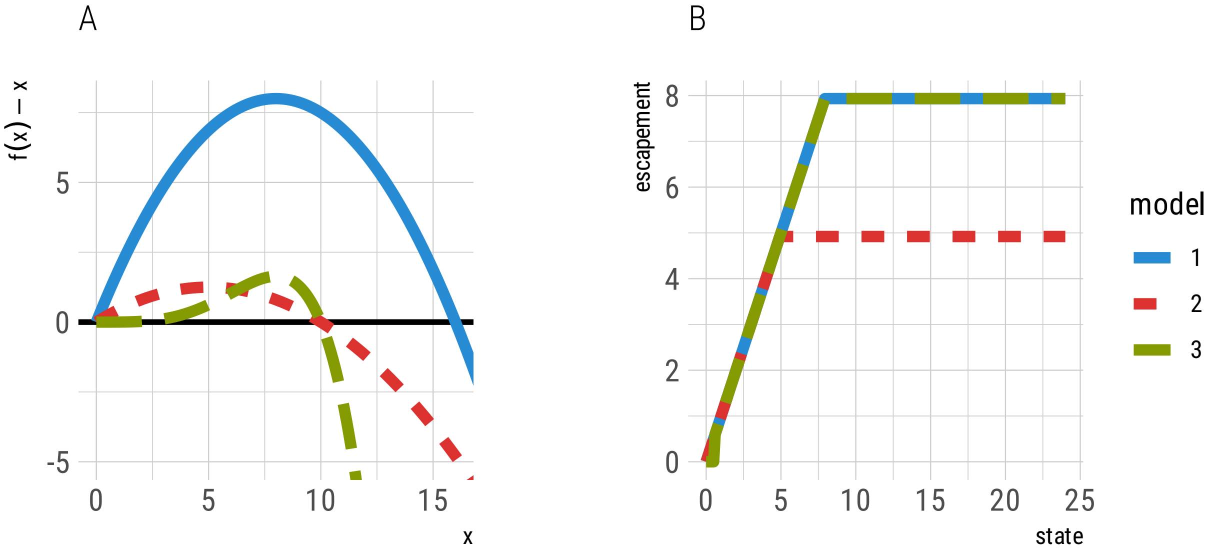

Figure 4: Panel A: Population growth curves of each model. The positive equilibrium of each model occurs where the curve crosses the horizontal axis. Note that while Model 2 is a better approximation to the truth (Model 3), Model 1 better approximates the stock size which leads to maximum growth. Panel B: The optimal control policy under Model 1 is nearly identical to that under the true Model 3, while the optimal policy under Model 2 supresses stock to a much lower escapement level.

rather solve for the best possible strategy through optimal control. This approach is well justified – optimal control techniques such as stochastic dynamic programming illustrated here quickly become intractable for more complex models (Marescot *et al.* 2013) typically used in fisheries stock assessments. Constraining the search to only strategies that impose a constant mortality (defined as harvest per unit biomass, $F = H/B$) means we only have to evaluate those N strategies each iteration, not solve a sequential decision problem. Doing so, we would find the best constant-mortality solution under Model 1 performs much worse than the best constant-mortality solution under Model 2. Does this mean MSE is not susceptible to this issue? No, it does not. It is just as easy to construct an alternative Model 1 with the same properties of leading to nearly optimal decisions while being rejected by any method of iterative learning, such as forecasting or adaptive management. Just as the optimal control policy for a Gordon-Schaefer (logistic) model depends only on parameter K (Reed 1979), the optimum constant escapement policy depends only on parameter r (Schaefer 1954). If Model 1 has a value of r such that it happens to match the best possible constant-mortality solution for the (unobserved) true model, then K can be set arbitrarily high, ensuring the any model selection, forecasting, or adaptive management approach would lead away from Model 1 and towards worse-performing models once again. Many optimization problems share this feature in which the optimal policy depends only on a subset or ratio of model parameters, such that it is usually easy to find a similar Model 1. This example also illustrates the importance of decision constraints – a model that gives very good outcomes when we are free to vary the havest quota each year (the optimal control problem here) may give very poor results under the constraint of constant mortality, and vice versa.

Note that the mechanism shown here has nothing to do with the much more familiar issue of over-fitting, in which a better-fitting model will also lead to worse outcomes (Burnham & Anderson 1998). In fact, an model which has been over-fit will gradually be rejected by either the iterative forecasting or adaptive management approaches shown here, as these approaches continually confront the models with new data to which they had not been previously fit. The ability to avoid over-fitting is one of the greatest appeals of any iterative management strategy. In the example here, both Model 1 and Model 2 have the same structural complexity. The better decision performance of Model 1 is a consequence of capturing the key attribute needed for a good decision, which is perhaps a surprisingly an all-together different criteria than fit. Note that other methods of model selection not considered here, including goodness-of-fit metrics such as r^2 or information criteria (Burnham & Anderson 1998), will all prefer Model 2 over Model 1 for the same reason.

This case cannot be dismissed merely as being dealt a bad hand in having to pick only between Model 1 and Model 2. Model 1 approximates the key feature, giving nearly optimal outcomes. Previous literature has underscored the importance of Knightian "unknown unknowns" two alternative models examined here fail to fully reflect our uncertainty in the underlying dynamics, and the consequences of underestimating model uncertainty are well understood (Wintle *et al.* 2010; Polasky *et al.* 2011). Had we included the true model in the set of possibilities, the techniques illustrated would have had little difficulty in distinguishing it from Models 1 and 2 after sufficient iterations. In practice, we never have the true model, and even a much more thorough suite of candidate models, such as considering any possible values of r, K [Fig 3B], or even among common alternative models with different structural forms, such as Beverton-Holt (Beverton & Holt 1957), Ricker (Ricker 1954), or Shepherd (Shepherd & Cushing 1980), would fail to do any better, since all these models still have symmetric growth rates with a peak growth rate at half the steady-state population size). Models will always be simpler than reality. To insist that this issue can and will be avoided by always including more and better models of the process misses the point.

Previous work has acknowledged that iterative learning may not always be feasible and that it may not always be beneficial, but has failed to recognize the possibility that it can potentially be detrimental. For example, active adaptive management is premised on the observation that future observations may be too uninformative to distinguish between alternatives (Walters & Hilborn 1978). Others have also noted that even big improvements in predictive accuracy could have negligible improvement on the decision outcomes, which motivates quantifying the Value of Information (VOI) (Katz *et al.* 1987). But in both cases, the worse outcome is wasted effort. In the scenario considered here, the VOI is negative: any learning over the proposed model uncertainty leads to lower expected net utility than not learning.

The only way to avoid this trap is to *forego learning* with each new observation, to avoid iterative updates. It may seem that the adaptive management approach fails because posterior probabilities are updated according to Bayes rule. Like iterative forecasting, this favors models which better predict the data, despite the fact that under the adaptive management approach, the overall optimization is conditioned on actual utility and not model fit. However, this issue is not easily avoided. For example, so-called greedy optimization techniques that favor actions with higher immediate reward do even worse in this context, since such an algorithm would obviously maximize the immediate harvest and therefore collapse the stock. Only by comparing the net utility derived from management under model 1 for many iterations to the net utility derived under model 2 after many iterations can we deterime that model 1 leads to better outcomes. This raises several questions. Do such methods of learning and reducing model uncertainty ever lead us towards worse long-term outcomes in the real world? If so, How would we know, and what should we do about it?

Do models which give nearly optimal performance while at the same time making wildly wrong predictions really exist? It is tempting to argue that Model 1 is a kind of unicorn, a mythical creature existing only in theory. But that is a difficult assertion to prove. Examples of serious forecasts that widely fail to predict future observations abound wherever forecasts are common, from elections to economics to environmental change (e.g. Tetlock & Gardner 2015). If there is no shortage of bad forecasts, then could any of them be useful? The premise that model need not perfectly capture reality to be useful is at the very heart of modeling. Model 1 successfully captures the one key feature driving decisions in optimal harvest control problems: the stock size at which the maximum growth rate occurs [Fig 4A]. Capturing only the essential aspects as simply as possible is the goal of any model building exercise. Thus it should be no surprise that a model can drive good decisions while making poor predictions. It is also important to note that in many cases, any models being used in decision-making are not necessarily being subjected to the rigorous evaluation and updating steps proposed by adaptive management (Walters & Hilborn 1978) or iterative forecasting (Dietze *et al.* 2018). This makes it more likely that such models could persist in practice until now. While iterations that revise this models will no doubt improve decision outcomes in many case, it is worth bearing in mind from the example here that such a connection is not guaranteed.

If these unicorns do exist in real world management, then what do we do about them? I believe this is an open question, but that our first step must be to recognize it as such. We have seen that the problem cannot be resolved by more data, and is not the result of overfitting. Nor is "creating more models" the answer: when we have a model that is good enough to get optimal results, we cannot always insist on more models. We have also seen how not updating our uncertainty estimates, or doing so less frequently, can reveal a unicorn model before it is discounted by further iterations. Approaches such as iterative forecasting or adaptive management that can reduce model uncertainty over time remain promising and important techniques, but because value of information can be negative, we must revise model uncertainty only cautiously. More importantly, we have seen that the intuition offered by decision theory [Fig 4] can help us better understand what features of a model are essential to decision outcomes and what are not. Conversely, models which appear to lead to accurate predictions (like Model 2) can result in outcomes that are far from optimal. Building on such understanding, it may possible to identify strategies for learning that are more agnostic to the details of the model that are not important, or perhaps not reliant on model-based predictions at all. How that is done is an open question.

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References

Beverton, R.J.H. & Holt, S.J. (1957). *On the Dynamics of Exploited Fish Populations*. Chapman; Hall, London.

Burnham, K.P. & Anderson, D.R. (1998). Practical Use of the Information-Theoretic Approach. In: *Model Selection and Inference*. Springer New York, New York, NY, pp. 75–117.

Clark, C.W. (1973). Profit maximization and the extinction of animal species. *Journal of Political Economy*, 81, 950–961.

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, 657–660.

Costello, C., Ovando, D., Clavelle, T., Strauss, C.K., Hilborn, R., Melnychuk, M.C., *et al.* (2016). Global fishery prospects under contrasting management regimes. *Proceedings of the National Academy of Sciences*, 113, 5125–5129.

Dietze, M.C., Fox, A., Beck-Johnson, L.M., Betancourt, J.L., Hooten, M.B., Jarnevich, C.S., *et al.* (2018). Iterative near-term ecological forecasting: Needs, opportunities, and challenges. *Proceedings of the National Academy of Sciences*, 115, 1424–1432.

Ginzburg, L.R. & Jensen, C.X.J. (2004). Rules of thumb for judging ecological theories. *Trends in Ecology & Evolution*, 19, 121–126.

Gneiting, T. & Katzfuss, M. (2014). Probabilistic Forecasting. *Annual Review of Statistics and Its Application*, 1, 125–151.

Gneiting, T. & Raftery, A.E. (2007). Strictly Proper Scoring Rules, Prediction, and Estimation. *Journal of the American Statistical Association*, 102, 359–378.

Gordon, H.S. & Press, C. (1954). The Economic Theory of a Common-Property Resource: The Fishery. *Journal of Political Economy*, 62, 124–142.

Halpern, B.S., Klein, C.J., Brown, C.J., Beger, M., Grantham, H.S., Mangubhai, S., *et al.* (2013). Achieving the triple bottom line in the face of inherent trade-offs among social equity, economic return, and conservation. *Proceedings of the National Academy of Sciences*, 110, 6229–34.

Howard, R. (1966). Information Value Theory. *IEEE Transactions on Systems Science and Cybernetics*, 2, 22–26.

Katz, R.W., Brown, B.G. & Murphy, A.H. (1987). Decision-analytic assessment of the economic value of weather forecasts: The fallowing/planting problem. *Journal of Forecasting*, 6, 77–89.

Lande, R., Engen, S. & Saether, B.-E. (1994). Optimal harvesting, economic discounting and extinction risk in fluctuating populations. *Nature*, 372, 88–90.

Levins, R. (1966). The strategy of model building in population biology. *American Scientist*, 54, 421–431.

Ludwig, D., Hilborn, R. & Walters, C. (1993). Uncertainty, Resource Exploitation, and Conservation: Lessons from History. *Science*, 260, 17–36.

Ludwig, D. & Walters, C.J. (1982). Optimal harvesting with imprecise parameter estimates. *Ecological Modelling*, 14, 273–292.

Marescot, L., Chapron, G., Chadès, I., Fackler, P.L., Duchamp, C., Marboutin, E., *et al.* (2013). Complex decisions made simple: A primer on stochastic dynamic programming. *Methods in Ecology and Evolution*, 4, 872–884.

Polasky, S., Carpenter, S.R., Folke, C. & Keeler, B. (2011). Decision-making under great uncertainty: environmental management in an era of global change. *Trends in Ecology & Evolution*, 26, 398–404.

Punt, A.E., Butterworth, D.S., Moor, C.L. de, De Oliveira, J.A.A. & Haddon, M. (2016). Management strategy evaluation: Best practices. *Fish and Fisheries*, 17, 303–334.

Reed, W.J. (1979). Optimal escapement levels in stochastic and deterministic harvesting models. *Journal of Environmental Economics and Management*, 6, 350–363.

Ricard, D., Minto, C., Jensen, O.P. & Baum, J.K. (2011). Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. *Fish and Fisheries*, 13, 380–398.

Ricard, D., Minto, C., Jensen, O.P. & Baum, J.K. (2018). RAM Legacy Stock Assessment Database v4.44.

Ricker, W.E. (1954). Stock and Recruitment. *Journal of the Fisheries Research Board of Canada*, 11, 559–623.

Schaefer, M.B. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Bulletin of the Inter-American Tropical Tuna Commission*, 1, 27–56.

Shepherd, J.G. & Cushing, D.H. (1980). A mechanism for density-dependent survival of larval fish as the basis of a stock-recruitment relationship. *ICES Journal of Marine Science*, 39, 160–167.

Smith, A.D.M. & Walters, C.J. (1981). Adaptive Management of Stock–Recruitment Systems. *Canadian Journal of Fisheries and Aquatic Sciences*, 38, 690–703.

Tetlock, P.E. & Gardner, D. (2015). *Superforecasting: The art and science of prediction.* First edition. Crown Publishers, New York.

Walters, C.J. (1981). Optimum Escapements in the Face of Alternative Recruitment Hypotheses. *Canadian Journal of Fisheries and Aquatic Sciences*, 38, 678–689.

Walters, C.J. & Hilborn, R. (1978). Ecological Optimization and Adaptive Management. *Annual Review of Ecology and Systematics*, 9, 157–188.

Wintle, B.A., Runge, M.C. & Bekessy, S.A. (2010). Allocating monitoring effort in the face of unknown unknowns: Monitoring and the unknown unknowns. *Ecology Letters*, 13, 1325–1337.

Worm, B., Barbier, E.B., Beaumont, N., Duffy, J.E., Folke, C., Halpern, B.S., *et al.* (2006). Impacts of biodiversity loss on ocean ecosystem services. *Science (New York, N.Y.)*, 314, 787–90.

Worm, B., Hilborn, R., Baum, J.K., Branch, T.A., Collie, J.S., Costello, C., *et al.* (2009). Rebuilding global fisheries. *Science (New York, N.Y.)*, 325, 578–85.