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OPINION PIECE

Disclosing the truth: Are models better than observations?

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ABSTRACT: The aphorism, 'All models are wrong, but some models are useful', originally referred to statistical models, but is now used for scientific models in general. When presenting results from a marine simulation model, this statement effectively stops discussions about the quality of the model, as there is always another observation to mismatch, and thereby another confirmation why the model cannot be trusted. It is common that observations are less challenged and are often viewed as a 'gold standard' for judging models, whereas proper interpretations and the true value of models are often overlooked. Models are not perfect, and there are many examples where models are used improperly to provide misleading answers with great confidence, but to what extent does an observation represent the truth? The precision of the observational gear may be high, but what about representativeness? The interpretation of observations is simply another model, but this time not coded in a computer language but rather formed by the individual observer. We submit that it would be more productive to initiate a process where the norm is that models and observations are joined to strengthen both. In the end, neither method is the goal, but both are useful tools for disclosing the truth. Biased views on either observational or modeling approaches would limit us from achieving this goal.

KEY WORDS: Truth · Models · Observations

1. INTRODUCTION

To start with the obvious: A model can never outcompete the precision of a single observation (and if it did, how would we know?). If you deploy your gear in the sea and catch 128 fish, that is your sample. If bottom oxygen is measured to be 1.28 mg l^{-1}, oxygen deficiency is undoubtedly an issue, and within the uncertainty of the instrument, a model is not going to be more correct. On the other hand, what is the effi-

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ciency of your trawl? Is oxygen deficiency a local problem? A model might miss the exact value, but it might be able to tell you to look for the oxygen minimum further to the south, and that the oxygen level was even lower yesterday. A well-constructed model can also make suggestions on what major processes drive changes in time and space, so the answer whether to observe or to model (or both) is not straightforward. In fact, it depends on many factors, including the question asked, the skills of the observer, and what data sources are available to give an informed answer.

However, the questions asked in science are seldom only the request for a representation of a point measurement. Following Lynch et al. (2009), it can instead be stated as such: in science, observations are made on the premise that natural truth is observable and understandable. Both observations and models are approximations of the truth. Neither method is perfect, as both are separated from truth by errors (ε_o and ε_m, respectively) of fundamentally different origin (Fig. 1). It is not the case that observations are truth. Observations are an incomplete sampling in time and space, and much of the truth goes unobserved. Additionally, the method of observation is necessarily imperfect and inserts a wedge between observations and truth. The only thing we can know with some certainty is the mismatch between models and observations, $\delta = \varepsilon_o - \varepsilon_m$. However, $\delta = 0$ does not imply that the error is 0, only that models and observations agree. By combining models and observations, a prediction can be made where the error ε_p is ideally smaller than the other errors (Fig. 1), but the error is still an unknown. This concept is well accepted theoretically but rarely applied in practice. It is still common that models are distrusted or discarded when their results do not match observations, not only by observational scientists, but also by modelers and decision makers. True values of models are often disguised due to the apparent mismatches between models and observations and improper model interpretations. A renewed dialogue is needed to balance our views and to enhance partnerships between models and observations.

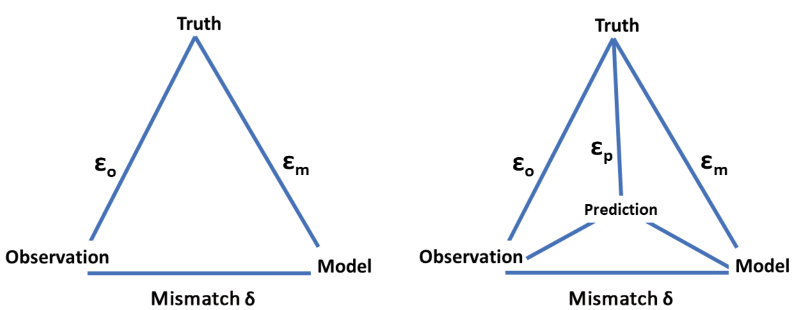

Fig. 1. Left: Conceptual diagram of truth, observations (o) and models (m) with associated departures from each other. Note the distinction between error (ε) and mismatch (δ). Right: Same as left panel but adding prediction and prediction error (ε_p). Redrawn from Lynch et al. (2009; used with permission)

2. WHAT IS A MODEL?

In science, a model is a simplified (although possibly still complex) representation of an idea, an object, a process, or a system that is used to describe and explain a phenomenon. Models are central to what scientists do, both in their research as well as when communicating their explanations (https://www.sciencelearn.org.nz/resources/575-scientific-modelling). A scientific model is also a way to systematically arrange and utilize the information from observations. Thereby, we can draw conclusions and gain mechanistic understanding that would be difficult to achieve without the model. Models are diverse (Levins 1966, Janssen et al. 2015). Here we will focus on mechanistic marine ecosystem models (MMEMs). These are usually spatially resolved simulation models aiming to replicate a real marine ecosystem, using some sort of numerical time-stepping. Loehle (1983) distinguished between theoretical and predictive models. MMEMs should be both. They should be based on a sound theory, enhance our process understanding, and ideally be able to predict the dynamics of a modeled ecosystem.

There are simple and complex models. Doak & Mills (1994) and Beissinger & Westphal (1998) claimed that models should be as simple as possible, while DeAngelis & Mooij (2003) argued for mechanistically rich models that are less subject to error propagation than simple models in which mechanisms are often aggregated into variables that are difficult to relate to observations. In addition, mechanistically rich models are often necessary to test between alternative hypotheses. In applied science, models of intermediate complexity are gaining growing popularity for balancing model complexity and uncertainty, e.g. being in a 'sweet spot' (Walters 1986, Plagányi et al. 2014, Collie et al. 2016). All MMEMs are observations in a virtual space. Dependent on model structure, it is possible to generate data on variables that are difficult or impossible to observe in the real space. Furthermore, models are the only tool that can be used to study the sensitivity and variability of state variables in what-if scenarios. As such, MMEMs provide great support to management beyond observations (Hyder et al. 2015).

3. WHAT IS AN OBSERVATION?

We understand an observation as a piece of information from a natural system either received through our senses or recorded using scientific tools or instruments. In marine science, observations and data are often misleadingly used as synonyms, even though data include any piece of (quality assured) information. In most cases, a scientific instrument does not directly measure the quantity of interest, but rather something that has been shown to be directly related to it (e.g. fluorescence and chlorophyll). Observations might also be models in themselves, where the measured quantity is a result of either empirically or semi-analytically derived algorithms such as suspended particulate matter from optical or acoustic sensors (Fettweis et al. 2019). Pre-designed sampling strategies need to be accounted for, as the sampling site, timing, frequency, and depth are generally constrained by budgetary, logistical, and scientific needs (e.g. Zingone et al. 2015), and as such, already constitute the observational setup's prior conditions impacting the outcome of the sampling. To fill spatial and temporal gaps, missing values are often substituted using a mathematical model (e.g. Lauvset et al. 2016).

Observations are discrete pieces of information in space and time, and the process of putting these together to describe and explain a phenomenon or system is also a model, a model that is based on the interpretation of all information available to the observer or scientist. Scientists use the available observations to represent an idea, an object, a process, or a system that cannot be experienced directly, to form a conceptual model before reporting the findings. In this way, observations and their interpretation together also form a model, and as scientists belong to different schools, their interpretations of observational evidence thereby represent a large variety in models.

4. ARE MODELS BETTER THAN OBSERVATIONS?

Despite the growing number of observation activities, oceanic observations are still scarce in time and space. Diversification of equipment substantially advances our ability to observe and measure oceanic processes, and standard protocols of observational methods (e.g. Dickson et al. 2007) ensure that observations can be compared across different platforms, times, and areas. The effort required to obtain a single observation is often substantial, and many observations (e.g. of fish and macrobenthos) are often affected by the sampling gear. Thus, availability and quality of observations differ in time and space, as well as for different ecosystem components. Following Oreskes et al. (1994), observations give an incomplete access to a natural phenomenon, while MMEMs offer an incomplete representation or parameterization of processes and components of a natural system. Models will almost always include a basic spatial and temporal resolution on which they operate, while observations often are a compromise between spatial and temporal resolution (e.g. Mills et al. 2003, Petersen 2014, Sheehan et al. 2018, Goni et al. 2019, Zhao et al. 2019). In a highly variable natural system, if observations are focused on single stations or transects with high temporal resolution, it is often difficult to scale them up to longer periods and larger areas. Here MMEMs, with a much higher spatial and temporal resolution, can provide the larger-scale picture, even if they do not include all processes in the oceans with the same degree of detail. Merging observations and machine learning gives an opportunity to further improve models and their parameterization (e.g. Mattei et al. 2018), but there is a need for standard protocols for models to assess quality and to better enable cross-model intercomparison.

MMEMs can project into the future and inform about the past. As observations are limited to events that have already taken place, hindcast modeling provides an essential piece of the puzzle to understand the present. Hindcast was long the preferred modeling mode, but nowcast/forecast and future projections/predictions are now used widely, e.g. to assess and predict 'good environmental status,' as requested by The European Union's Marine Strategy Framework Directive (https://ec.europa.eu/environment/marine/eu-coast-and-marine-policy/marine-strategy-framework-directive/index_en.htm). MMEMs are probably the best available tool to project and understand the consequences of anthropogenic and climate-driven changes for marine ecosystems (e.g. Piroddi et al. 2015, van Leeuwen et al. 2016), but models should be used carefully and communicated wisely. Beckage et al. (2011) stated that high unpredictability in biological systems effectively prevents the ability of any model to predict the future of ecosystems, and Planque (2016) argued that numerical models might be of limited use to project the future state of marine ecosystems because stochasticity and chaos limit predictability. Naturally, the future states of marine ecosystems are unknown, and long-term projections are subject to large uncertainties. Regardless, scenario-based future projections based on the best available current understanding, can still be useful. The projections resulting from different scenarios and modeling approaches then represent potential realities with associated uncertainties. Through ensemble modeling, more potential realities are generated, which together may be closer to the truth (Araújo & New 2007, Skogen et al. 2014). The joint scientific effort underlying the Intergovernmental Panel on Climate Change (IPCC) is a good example of the usefulness of future projections which has likely been a determining factor of bringing climate action to the international political agenda (IPCC 2014). Decisions about the future are made in the present, and model predictions with their inherent uncertainties (particularly when future states depend on change in human behavior, e.g. future agreements to reduce greenhouse gas emissions) are therefore our best, and in some cases, only source of information to help these decisions. The potential consequences from rejecting future projections based on such arguments might therefore be severe.

MMEMs can estimate what is hard or even impossible to measure. Direct field experiments with chemical tracers are unfeasible in many ways, but stable isotope techniques can be used. However, MMEMs are the most efficient way to trace river nutrients that are advected and modified by biogeochemical processes (Menesguen et al. 2006, Painting et al. 2013, Radtke & Maar 2016, Lenhart & Große 2018) and can be used in support of management decisions (e.g. Lenhart et al. 2010). Monitoring programs are often focused on measuring concentrations (e.g. nutrients, plankton biomass) rather than food web fluxes. The only rate that is routinely measured is primary production, but even that comes with a high degree of uncertainty. Research cruises provide sporadic data on e.g. copepod egg production, grazing, growth, and sedimentation rates. However, it is not possible to measure all fluxes in a food web, and models are required to realistically resolve the emergence of trophic responses in the plankton community (Sailley et al. 2015, Maar et al. 2018). MMEMs can, for instance, be used to evaluate plankton feeding strategies and how this affects nutrient cycles (Sailley et al. 2015), to estimate (organic) carbon budgets and sequestration (Wakelin et al. 2012, Ducklow et al. 2015, Polimene et al. 2016), the controlling factors for productivity (Stock & Dunne 2010), or cascading effects in the planktonic food web due to changes in mortality at higher trophic levels (Maar et al. 2018).

What we observe in natural systems is the integrated effect or outcome of all processes acting at various temporal and spatial scales, and these are difficult or near impossible to disentangle. Observations are good at directly measuring state variables, e.g. abundance and biomass at a particular time and place, but a full investigation of system-wide cause–effect relationships purely from observations is almost impossible if not combined with a modeling analysis. MMEMs allow for a consistent and complete analysis of processes and feedback loops, and for testing hypotheses on the causality for the observed co-variability in a broader sense between ecosystem components. MMEMs can describe a set of key system parameters and variables inside the simulated domain and time, including all related state variables as well as fluxes of matter and energy. Therefore, a growing number of studies use both observations and models to analyze the drivers of a given system (Tett et al. 2013, Marshall et al. 2016).

The quality of observations is often uncertain, and so is their representativeness. Sandvik et al. (2016) analyzed temperature at the fixed coastal station at Ingøy (71° N, 24° E) with a high-resolution model and concluded that an acceptable deviation ($\varepsilon_o - \varepsilon_m$) was 0.6°C, while Skakala & Smyth (2016) used satellite observations of sea surface temperature and chlorophyll to calculate representative measurement areas for *in situ* networks. Some 50% of the spatial variance in the prey for larval fish occurs at the meter scale, thus extreme care should be taken when using zooplankton observations (Young et al. 2009). Representation error is probably the most important term in a full analysis of uncertainties, and a better understanding of the representation error is the key to more carefully characterizing the truth that we seek from the integration of models and observations. Models also have representation errors due to the model resolution and unresolved processes, but the common assumption that model limitations dominate over observational uncertainty ($\varepsilon_m > \varepsilon_o$) persists, and the role of observational reference limitations are therefore often seen as minor.

There are several other systematic errors that are hard to account for but are important to be aware of. The operation of an instrument might be straightforward, but the level of complexity in operation also provides an indication of the uncertainty, as more complex procedures allow for more unintentional mistakes. Equipment is prone to be lost or cannot be used at sea under rough or extreme conditions, thus observations are often biased towards calm sea conditions. Long-term observational time series are rare gems in marine science, yet they invariably contain equipment changes that often complicate interpretation. Providing a hard surface in a fluid medium is often enough to attract unwanted plants and animals, leading to biofouling and thereby potentially compromising the observations. Observations are often pre-processed before use, and even inter-annual variability might not be preserved after interpolation (Rufino et al. 2019). Particles (like plankton) rarely constitute continuous fields but rather establish patchy patterns with strong gradients due to variable and turbulent currents (Mackas et al. 1985, Richardson et al. 2000, Martin 2003). Observations of such quantities will strongly depend on whether a patch is hit or not, and the representativeness will be a function of the sampling technique and spatiotemporal resolution (Omori & Hamner 1982).

MMEMs can contribute to the efficient design and optimization of observing systems, and observing system simulation experiments (OSSEs) (e.g. Arnold & Dey 1986) have been successfully used to optimize monitoring programs and design observational networks (Fu et al. 2011, Majkut et al. 2014, Charria et al. 2016, De Mey-Frémaux et al. 2019, García-García et al. 2019), and to analyze forecasts with or without assimilating virtual observations (Oke & O'Kane 2011). McGillicuddy et al. (2001) used an OSSE approach to assess the synopticity of observations, e.g. by correcting the station positions for advection from a circulation model. Such efforts will increase the value of observations and enable new applications by connecting and synthesizing sparse observations.

5. CONCLUDING REMARKS

Both MMEMs and observations are approximations of an underlying truth, and while both have strengths and weaknesses, jointly they provide a better representation of the truth. Depending on the model and type of observation, one may be closer to the truth than the other. MMEMs are designed based on our process understanding and typically have their best performance skills at certain spatial and/or temporal scales. One of the important advantages of simulated data is their potential to be disentangled to investigate which driving mechanisms led to the simulated response, and thereby advance our understanding of the natural system. Observations, on the other hand, are snapshots providing information on status, but they cannot inform about the spatial and temporal scales at which the most important drivers act.

According to the philosopher Karl Popper's basic scientific principle no theory is completely correct, but if it can be shown both to be falsifiable and supported by evidence that shows it is true, it can be accepted as truth (Popper 1934). The consequence of this is that no number of positive outcomes at the level of experimental testing can confirm a scientific theory, but a single counterexample is logically decisive. If we consider a mechanistic ecosystem model as a scientific hypothesis, this implies that we can never prove it through validation, and no matter how well it performs, users may focus on its mismatches with observations. Because such a model is not representing the full reality, there will always be mismatches. The question is whether those mismatches are relevant in view of the model objective, as robust comparisons of observations and models require a like-with-like approach using appropriate diagnostics from model simulations to facilitate such comparisons (Cowtan et al. 2015).

One of the main criticisms of Popper's principle is that falsifiability is very strict in its definitions and does not consider the contributions of sciences that are observational and descriptive. The rationale behind this is that in observational research, the experimenter has no control over the composition of the control groups and cannot randomize the allocation of subjects. In addition, the difficulty in isolating what the independent variables are, makes it challenging to identify cause and effect relationships. A paradox is therefore that the principle used to falsify one theory (models) is used in favor of another theory (observations) that the same principle states as pseudoscience.

Both MMEMs and observations are continuously improved in terms of resolution, precision, and accuracy, and tools that are integrating them are being developed. Going forward, it should not be models or observations, but rather models and observations. Using them together generates synergy and allows us to support science better and thereby increase our knowledge and understanding of marine ecosystems to disclose the truth.

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