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Adaptability and Revisability in Climate Models

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Abstract

The global climate is shifting rapidly, bringing with it increased risk for climate-related harms to human societies. Climate science is a multi-disciplinary field, requiring experts from diverse specialties to collaborate in order to model complex systems. The complexity and uncertainty of these scientific models raise philosophical questions such as:

- What epistemic, ethical, and social assumptions go into model creation?
- What mathematical and statistical principles are incorporated into their design?
- How is interpretation involved in the selection and analysis of data to generate climate models?

Philosopical issues related to complexity, uncertainty, and the role of values require that modelers evaluate trade-offs. I argue that not only ethical values should be made explicit and taken into account, but also the pragmatic considerations that make models more or less useful for specific purposes. I conclude that effort should be invested into tracking the reliability of climate models and also in making assumptions explicit and revisable.

Introduction

Climate science is a multi-disciplinary field, integrating research from the earth sciences, environmental sciences, and life sciences with the study of energy systems, economic trends, and social policy to understand, explain, and predict the interaction between climate and other natural and social systems. At the core of climate science, experts from diverse specialties collaborate to model complex systems, primarily through computational models and simulations. The nature of the system under study, i.e. the climate, and the sophistication of the tools and methods used to do so leads to substantial complexity and uncertainty in these models and simulations, and consequently in the inferences climate scientists draw. This raises philosophical questions about what types of assumptions are made when creating and interpreting these models and simulations. What ethical, epistemic, political, practical, and aesthetic considerations are made when selecting methods, models, goals, and data? A clear understanding of the assumptions that are incorporated into climate models, as well as diagnosing where and how models are limited can help design social and economic policies that are sensitive to specific areas of uncertainty. In turn, this could better direct research which can improve the utility of models for specific ends.

Beyond the obvious ethical problems of responsibility among nations, corporations, governments, and communities for addressing this problem, there are deeper philosophical and ethical questions about the development of climate models. First among these is whether and when models should value simplicity. In short, there is a tradeoff between precise and accurate prediction on the one hand, and efficient modeling practices that are economically feasible on the other. At one extreme, a model that is parsimonious leaves out too many details and possible interactions to be useful (Baker 2016). At the other extreme, models of excessive complexity can become unwieldy and costly (Helgeson et al. 2021).

This tradeoff between “goodness of fit” and efficiency directly contributes to another concern for philosophers, one that is foundational to what is considered good scientific practice: quantifying uncertainty. Many climate models work on probabilistic representations, and for several reasons uncertainty plays an outsized role in this discipline. The stakes are high, but there are a lot of unknowns, a lot of interactions that are sensitive to initial conditions and slight changes in parameters, and a lot of potential feedback loops between what we know and what we do. Both problems--simplicity and uncertainty quantification--give rise to questions about the ethical and epistemic values that are in play when we select interpretations of data, models of best fit, and the methodologies for constructing them. How we approach and overcome these challenges can have an outsized impact of the utility of the knowledge we produce. In the case of climate change mitigation, the production of highly revisable models should be a primary focus.

Philosophers of science have established themselves to act as both interpreters and tethers to the wider world in this complicated enterprise. Much of the research produced by climate scientists is esoteric; the implications for what they find are wide ranging and difficult to contextualize. Simply put, the world is messy, and the climate is a direct reflection of that tangled reality. Unraveling what climate scientists observe and predict is an endeavor not to be taken lightly, and it carries grave consequences. The received interpretations of climate research become policy, and policies determine how well situated we are to deal with anticipated—or unanticipated—changes in the world around us (Tuana 2010, Tuana 2013, Cartieri & Potochnik 2014).

Simplicity, Complexity, and Probability

That simplicity is desirable in models, calculations, arguments, and proofs has been a central presumption of math, science, and philosophy. William of Ockham, the medieval Franciscan friar and scholastic philosopher, established the principle that if something can be explained without appealing to hypothetical causes or entities, there is no reason to presume the existence of such ancillary entities, a principle known as Occam's Razor (Baker 2016).

The principle has been widely adopted and restated by scientists and philosophers such as Galileo, Newton, and Einstein, and has been applied to replace supernatural explanations with mechanical ones, to press for the collection of empirical data, to develop efficient methods in mathematics, and to explore the difference between science and philosophy. Opposed to the implicit superiority of simplicity are pragmatists like Quine and Sober, who argued that there are certain epistemic advantages associated with complexity (Baker 2016).

Simplicity in climate models has received a good measure of attention in this regard, with many justifications being made for appeals to both complexity and parsimony. The models which are used for climate research run the gamut from highly idealized to extraordinarily complex, and the epistemic ramifications are not the only reason this question is relevant. Simulation and prediction happen in a rapidly changing world, and modeling practices need to operate efficiently and quickly, while simultaneously providing useful results. The pressure to somehow accomplish both is high.

However, there is a great deal of ambiguity in the language around simplicity in climate modeling. Indeed, simplicity itself evades a straightforward and simple definition in general, and that is doubly true when considered here. Despite the many interpretations of the meaning of simplicity or the kinds of simplicity, this paper will focus on simplicity in terms of mathematical and technical sophistication and practical scope. For instance, there is simplicity as it regards the amount of variability in parameterization, the number of auxiliary assumptions, the reliance of models on interactions between component models and couplers, and the spatio-temporal resolution of the differential equations used. In some models, the 'couplers' themselves are models. This means that many larger complex models are comprised of smaller, simpler models (Parker 2018).

An obvious aspect of simplicity regarding climate modeling is in probability and statistics. Bertrand Russell is quoted as having once said in a 1929 lecture that "probability is the most important concept in modern science, especially as nobody has the slightest notion what it means" (Bell 1945). Probability is a word used often, but what is key to the conclusions we draw from those statements is how we interpret probability. Different interpretations of probability lead to different methods, which in turn introduce different levels of complexity and revisability.

Typically, researchers offer what are called frequentist interpretations of probability (Mann, Lloyd, and Oreskes 2017). Briefly, this is a measurement of the statistical frequency of an outcome in observed or simulated data. When dealing with frequentist probabilities, the measurement commonly encountered is called the p-value. The p-value gives a numerical assessment as to whether an observed frequency in a sample set is statistically significant enough for the researcher to reject the null hypothesis, measured against some pre-determined confidence interval. In other words, it is the probability of giving a false positive (or negative) to a hypothesis test. The null hypothesis usually takes the form of little or no change in the measured quantity, with an alternative hypothesis which suggests that the true value differs from the hypothesized value (Hájek 2019; Mann, Lloyd, and Oreskes 2017). This type of statistical inference is the conventional practice across most of the sciences. For decades, there has been a discussion about the causes for adopting this standard, with accusations of traditionalism or conservatism among scientists standing in the way of the progress of understanding. While the method seems quite entrenched in scientific practice, it only saw widespread adoption in the 1940's (Mann, Lloyd, and Oreskes 2017). This method has significant drawbacks. With enough data, what is and is not statistically significant becomes more obscure, and the significance levels selected for are a matter of convention. In other words, they are arbitrarily selected rather than determined by context and specific conditions.

The meaning of probability changes when considered under a Bayesian framework, which expresses probability as a measure of belief in a given event. The Bayesian methodology takes updates knowledge, such as historical data and past inferences, and couples that with the model results. The researcher then constructs conditional statements which give a more nuanced understanding of the likelihood and usefulness of a hypothesis (Mann, Lloyd, and Oreskes 2017). Notably, this methodology is used more commonly in the biomedical disciplines because it can be more sensitive to the impacts of studied treatments or procedures on patients, where lives are at stake (Mann, Lloyd, and Oreskes 2017). Similarly, climate science deals with predictions that carry weighty consequences for human beings.

Some of the greatest motivators for climate research are the effects of climate change on extreme weather events and the potential for rising sea-levels (Anthoff, Nichols and Toll 2010). Both have aggravating effects on further climate changes. The forcing effect these events havecreates feedback loops between extreme weather phenomena and climate patterns. Considering this, we require modeling practices which are revisable under changing parameters and sensitive to the relationship between climate research and the stakes involved (Mann, Lloyd, and Oreskes 2017). It has been demonstrated that increased global temperatures influence the frequency of daily heat extremes (Meehl et al. 2007). This affects the global hydrological cycle (Trenberth 2011) which in turn drives greater likelihood of precipitative events such as extreme rainfall or prolonged dry periods, lower snowfall in polar regions, and increased loss of sea ice. Floods, changing monsoon patterns, and hurricanes have increased in frequency and intensity in recent years (Anthoff, Nichols and Toll 2010; Trenberth 2011). These events also have effects on rapidly shifting coastlines, and sea level rise (SLR) compounds the effect of these phenomena on already vulnerable communities (Anthoff, Nichols and Toll 2010; Diaz 2016; Hooijer and Vernimmen 2021). At the other extreme, droughts and wildfires have become larger, longer, more severe, and more destructive with increasing frequency(Halofsky, Peterson, and Harvey 2020; Meehl et al. 2007; Ruffault et al. 2020). This trend is expected to continue, and research points to a forcing effect these events have on the initial conditions which produce these phenomena in the first place (Halofsky, Peterson, and Harvey 2020; Ruffault et al. 2020).

Considering the complex interactions between climate related disasters and the acceleration of climate related changes, models should be accordingly revisable as new observations and data about shifting dynamics becomes available. One of the ways we might achieve this is a more widespread adoption of Bayesian interpretations and methodologies, but the attitude towards changing philosophies around probability interpretations is not without opposition. Some have suggested that public pressure to attribute causes to climate change and weather phenomena has motivated scientists to draw unwarranted conclusions, and that Bayesian methodologies are more susceptible to this type of faulty infrence (Winsberg 2018). The case against Bayesian interpretations rests on the argument that inference based on projected dynamics with considerable uncertainty is not reliable (Stott et al. 2016). Others suggest that Bayesian interpretations are vulnerable to faulty inference because of the reliance on tuning the models based on their ability to produce the same prior data against which they were tuned (Parker and Winsberg 2018).

Another consideration when adopting a Bayesian philosophy is the possible increased complexity in the modeling process. Additional calculations may be required, and the assessment of interactions between variables and conditional statements requires supplementary analysis (Mann, Lloyd, and Oreskes 2017). These factors can produce added layers of complexity in an already highly complicated research process. However, given the advantages of Bayesian analysis regarding revisability and the stakes involved, it is regarded by some as the more ethical approach, as Michael Mann, Lisa Lloyd, and Naomi Oreskes have concluded (Mann, Lloyd, and Oreskes 2017).

The additional complexity from Bayesian methodologies is one of the potential ways we can increase the revisability of models to improve their utility. Another is using models of fine-grained dimensions. Recently, Nancy Tuana, Casey Helgeson, and others have made the case that simplicity in climate models in the context of computational resources used is most relevant to utility (Helgeson et al. 2021). This includes the method of calibration and tuning, which extends to Bayesian methodologies. Climate modeling is done iteratively. Models are run through computer simulations repeatedly, and the results they generate are then compared to prior observations and historical data. (There are a host of auxiliary assumptions behind the historical data themselves that I will address later.) Often, separate models are run repeatedly, and results are compared and contrasted to give potential ranges of outcomes, in what is called the ensemble method (Parker 2014; Parker 2018; Winsberg 2018). These repeated simulations require time, and usually numerous and powerful computer processors. Access to these processors is limited both by availability and by funds, since renting time on these processors is expensive. The more complex a simulation, the more run-time it needs, and thus the more expensive it is (Helgeson et al. 2021). Simpler models, therefore, are desirable in this regard.

There are many processes that can be approximated or ignored in a highly idealized model. Often, such a model is still able to describe the interaction we are interested in without necessarily needing to be a precise fit for the phenomenon in the world being modeled. For instance, the Danish Arctic Ice Sheet model (or DAISM) is an extremely simplified representation of a complex landscape. It represents the arctic ice sheet as a half spheroid placed over a shallow conical structure of land (Helgeson et al. 2021). This is an area larger than the continental United States, represented as idealized geometrical shapes. However, the results we are interested in from it are related to snow accumulation and ice melt, and this model can serve that purpose well without demanding much processor time (Helgeson et al. 2021).

As models increase in scope to include further parameterizations such as a more complete accounting of the carbon cycle, additional phenomena such as dynamic vegetation, or previously ignored or approximated interactions like microphysical effects of aerosols on cumulus clouds, the models quickly become very elaborate (Schmidt and Sherwood 2015). These require increasingly complicated statistical techniques and computational methods to 'couple' the different component models used to produce simulations, which are then typically 'tuned' using a handful of variables deemed relevant to the inquiry at hand (Parker 2018; Schmidt and Sherwood 2015; Winsberg 2018). There is therefore an epistemic tradeoff in climate modeling between the scope and the resolution, which is to say that models designed to explore or predict climate events on global or hemispheric scales modified or tuned for expediency or computational efficiency tend to have less value for impact assessment or risk analysis on specific localities or for isolated events (Diaz 2016; Schmidt and Sherwood 2015).

The Dynamic Interactive Vulnerability Assessment (DIVA) model is an integrated, aggregated, granular database on coastal segments detailing impacts on flooding, erosion, wetlands, estuaries, and associated analyses. It serves as an example of a model which offers the possibility of modeling on a global scale with the potential for fine grained resolution. Models such as this are necessarily complicated, and do not escape the challenges complexity brings to researchers, but they offer a great degree of utility to researchers when it comes to offering predictions and assessments important to stakeholders (Diaz 2016). This aptly demonstrates the ironic and paradoxical trade-off between simplicity and complexity. There is utility in a model being more complex, and utility in a model being simpler.

However, with added complexity comes the additional aspect of resistance to tuning or calibration. As previously stated, models are programmed into computer simulations, and the results generated are then checked against prior data. The models are then tuned to more closely approximate prior conditions given the appropriate inputs. Once they have been tuned to a satisfactory level, they can be fed inputs for present or predicted future parameters (Helgeson et al. 2021; Parker 2018). Bayesian methods require additional runs of the simulation to build out posterior distributions, thereby increasing complexity and, by extension, cost in time and money. Therefore, complex models inhibit the researcher from being able to accumulate enough simulation runs to develop these distributions, distributions which are necessary to perform a desirable accounting of uncertainty and track its propagation in model projections (Helgeson et al. 2021).

Uncertainty and Quantification

Uncertainty is often divided into two categories, *aleatoric* and *epistemic*. The former is sometimes also called ontological uncertainty, and it arises from the stochastic nature of the phenomena being modeled. Climate modelers do not always have a comprehensive theoretical model for systems, and some processes have internal variability. A climate modeler's inability to predict the exact weather in Rochester, NY on some given day next July is not due to a fault of the climate projections, but a feature of the variability in the weather. So, atmospheric climate models have an irreducible uncertainty which arises from the randomness built into the model. This randomness is generated by a lack of ability to quantify or model stochastic processes in a way in which they become adequately determined.

Epistemic uncertainty follows from factors such as errors in or dearth of data, from lack of knowledge about which initial conditions to seed a model with, and from idealization of the models. For example, if a researcher were to construct a counterfactual model of Earth without human activity in order to investigate anthropogenic climate change, there would be elements that would need to be approximated with 'best guesses,' the researcher would have to intuit which initial conditions to seed the respective models with in order to generate a reasonably simulated Earth, and there would be a great deal of idealization of the component systems in order to present a relevant and useful scenario from which to draw comparisons. The reflectivity of the Earth, called the albedo, is often calculated as if the planet were a sphere with a uniform reflectivity across its surface. It is given a number between 0, representing a black body which reflects no solar radiation, and 1, which represents a body that is perfectly reflective. In that case there are a whole host of idealizations going on, but the calculations made are still useful for their prescribed purposes (Winsberg 2018).

Elements of aleatoric uncertainty in a model might be moved into the second category were we able to build more exact models or become better acquainted with the systems that give rise to it. This draws out an interesting duality in aleatoric uncertainty, in that there are systems which are inherently chaotic, whose randomness will never be fully predictable, and systems which we treat as such because we do not understand them well enough to do otherwise. For instance, one of the more poorly understood phenomena is cloud dynamics, which lacks a working comprehensive theoretical model (Winsberg 2018). Workarounds for this might be to create a model of atmospheric dynamics which is fine-grained enough that cloud dynamics no longer need to be accounted for. Ideally, however, we would figure out a way to accurately understand and model what is going on. If we could do so, that would move the uncertainty of cloud dynamics from the first camp to the second, from inherent randomness to epistemic uncertainty.

Another challenge to understanding uncertainty quantification is the distinction between variability and uncertainty. These are two concepts often used interchangeably in conversation, but for a modeler there is a significant difference. Variability refers to the range of values a given prediction or measurement might take across different points in space and time, while uncertainty refers to our inability to know the exact value of some quantity. The first is traditionally quantified with a distribution of frequencies across numerous instances, and the second by probability distributions around the uncertain value of the quantity in a singular sense. However, both contribute to uncertainty.

Uncertainty quantification is done primarily in two ways. One is the previously mentioned calculation of forward propagation of uncertainty through a modeling process (Helgeson et al. 2021). This means researchers take into account uncertainty that arises from particular elements in the modeling process and how that uncertainty gets carried forward through subsequent steps to ultimately add to the uncertainty of the results. This includes consideration of uncertainty in parametric data, volatility inherent in the actual variables researchers feed into their models, errors in calculation, and algorithmic uncertainty. This last component comes from the inherent deficiencies in modeling phenomena through partial differential equations. These algorithms for solving the mathematical models of change in the stochastic phenomena cannot be calculated to perfect certainty (Winsberg 2018).

Uncertainty in the parameters of the model is particularly prevalent in climate science, as historical data which are used to construct the models in the first place come from diverse sources: soil sediment sampling, tree rings, speleothem analysis, ice cores, and historical records, among others (Schmidt and Sherwood 2015; Winsberg 2018). Often these proxies are radically different from one another, occurring on different timescales and in sporadic and diverse geographic locations (ice cores from polar regions, tree rings from old growth forests, stalagmites from isolated caves, etc.). As such, these proxies can provide spotty background information, and require radically different methods of quantification and collection (Parker 2018). Furthermore, the quality of the data can be questionable due to the lack of certainty around the methods of collection historically (Winsberg 2018). Some of these historical records contain no description of the methods used to collect the data, which can itself be an important consideration. For example, different methods for collecting sea water for temperature measurements produce statistically significant differences (Winsberg 2018). In the 19th century, regular buckets were used to collect samples. Around the turn of the century, the preferred method became a type of canvas bucket, which eventually was replaced by specialized collection receptacles which in very few ways resemble what we might think of as buckets. Each of these apparatuses gives different temperature readings on the same sample (Winsberg 2018). With incomplete or unclear historical records on methods of collection, researchers must build a certain degree of uncertainty into the historical data they use to construct models and for comparison purposes. This includes making numerous auxiliary assumptions and can necessitate further simulation and approximation to incorporate this historical data into the modelling framework (Schmidt and Sherwood 2015; Winsberg 2018).

Each of these sources of uncertainty feeds into later stages of modeling. It is the challenge for researchers doing uncertainty quantification to track this uncertainty, to create a sub-model for the uncertainty itself, and to give a reasonable account of how it shifts the predictions and results of the model overall for the purpose of gauging its utility (Helgeson et al. 2021; Parker 2018; Winsberg 2018).

The second type of uncertainty quantification has to do with calibrating a model to determine goodness of fit, which has also been mentioned previously. Experimental results are compared to simulation results, and discrepancies are identified between the observational data and the results. The model is then varied in a systematic to account for the perceived biases. This mode of uncertainty quantification is also affected by the uncertainty of the historical data to which it is compared. Typically, a model's effectiveness is determined by its ability to reproduce historical data given the appropriate starting conditions. If we want to test a model for global temperatures, we feed it data from some past epoch and let it run a simulation. If the model can approximate the changes in the average temperature we know from our historical sources, we judge the model to be more useful than one which cannot reproduce the historical results. However, uncertainty in historical data can be a concern when measuring goodness of fit this way (Winsberg 2018).

Another problem for calibration is the possibility of feeding flawed assumptions into the model (Pielke and Ritchie 2021). Researchers are often under social or professional pressures to ensure their models give results that do not stray too far from the wider consensus of their peers (Winsberg 2012; Winsberg 2018). Eric Winsberg has proposed that there may be subtle tweaking of models so that the model is not rejected out of hand for giving results that are perceived as too radical or too different from the body of research at large. Winsberg seems to suggest that this causes a repression of new research or evidence which might challenge the status quo of modeling in the discipline at large. The concern is that the certainty with which climate scientists make claims is unwarranted, and such confidence may not be justified (Winsberg 2012; Winsberg 2018).

Roger Pielke has pointed out the flawed socioeconomic assumptions in the Intergovernemental Panel on Climate Change (IPCC) scenarios, which contemporary climate models continue to be based on (Pielke and Ritchie 2021). The projections produced under these flawed assumptions about future use of land resources, fossil fuel use, and particulate pollution, among other things, continue to be used by governments globally to drive policy and planning (Pielke and Ritchie 2021). Some of these assumptions include scenarios where coal use continues to increase for decades, when it has already slowed, or other assumptions which fail to account for economic value being placed on sustainable methods of production (Pielke and

Ritchie 2021). Without models that disrupt the consensus, we cannot investigate which of our assumptions might be flawed, or where our models might be deficient. Further, Pielke notes the conclusion of many of these scientists that producing models which tend towards a "single 'best guess' or 'business as usual' scenario is neither possible nor desirable" (Pielke and Ritchie 2021).

It is apparent that much of the uncertainty in climate models is structural. It is generated by methodological choices, such as the mathematical methods used, and by the uncertainty in the instruments of measurement for background data. Minimization and accurate quantification of uncertainty are key concerns for researchers who want their work to be useful to policymakers and stakeholders (Helgeson et. al 2021). However, tuning models and producing projections require researchers to decide between tradeoffs. Models cannot be tuned for one purpose without becoming less efficient or useful for another. Methods of quantification take different factors into account, weight these factors inconsistently, and make distinct procedural decisions, all of which can lead to vastly different outcomes.

Values, Evaluation, and the Ethical-Epistemic Coupling

Climate modelers have dual commitments in practice. There is, on one hand, the drive to create models which can explore climactic mechanisms, in order to identify causal relations or correlative patterns in climate data. On the other, there is a commitment to produce models which serve specialized purposes, such as giving socially and economically useful predictions for the impact of sea level rise on coastal communities. Because of the immediacy of climate related disaster, researchers are obligated to ensure their models and simulations reflect the realities of the world they are studying, not just mechanically but in terms of reliable and useful analysis and predictions. This draws attention to the purpose researchers have in mind during the process of model development and selection. Models can serve a primary function of discovery, or they can serve a primary function of utility. These ends are not always exclusive, but there seems to be some tension in the practice of climate modelling, as these two ends do not always converge. Researchers must make judgements about methods, datasets, and where to focus development; where there are judgements, there are values.

When there is discussion about values in the context of scientific practice, there is often an ambiguity about the word value itself. When we talk about value and values (in the sense of virtues) in science we are explaining or discussing commitments to epistemic or ethical principles. Epistemic value extends to a theory or model's reliability in giving predictions, something eminently important in climate science. Social and ethical values are beliefs and principles held by practitioners or the public at large, and the pressures exerted by this type of value on model selection and causal attribution may have a forcing effect on the methodologies of researchers, which in turn has implications for the epistemic qualities of the models these researchers produce (Parker 2014; Parker and Winsberg 2018; Vezér et al. 2018; Winsberg 2018).

Conventionally, many scientists have held the view that ideal science is free from pressures induced by non-epistemic values, or at least should be practiced in way that works towards that end (Douglas 2009). Proponents of Bayesian reasoning contend that social, ethical, and political values play less of an influential role in Bayesian inference than standard methods of hypothesis selection (Parker and Winsberg 2018). Yet, the Bayesian analysis does not escape from the Duhem/Quine problem and inductive risk (Winsberg 2018). Heather Douglas, among others, has pointed out that selecting hypotheses and models requires researchers to consider the inductive risk involved (Douglas 2009; Cartieri & Potochnik 2014; Parker and Winsberg 2018). Eric Winsberg and Wendy Parker have also pushed back on the traditionally received view that climate modelling and science in general can be value-free, but they make a second, more novel contention. They have argued that models cannot be divorced from the non-epistemic value choices which influence model development (Parker 2014; Parker and Winsberg 2018; Vezér et al. 2018; Winsberg 2012; Winsberg 2018). However, interestingly, researchers need not concede that the value-ladenness of climate models is necessarily a fault. The coupling of ethical values with epistemic ones can help researchers better inform decision-makers when human costs are involved (Bessette et al. 2017; Cartieri & Potochnik 2014; Tuana 2010; Tuana 2013; Tuana 2020). Ethical and social values can help direct researchers when evaluating a model's utility, and they are the point of engagement for decision-makers and stakeholders (Bessette et al. 2017; Cartieri & Potochnik 2014; Tuana 2010; Tuana 2013; Tuana 2020).

The roles simplicity and uncertainty quantification (UQ) play in all of this are central to understanding the practical value of specific models. It is through UQ that researchers can give a metric to both the likelihood of a particular outcome and the range of possible values for some given quantity, such as the aforementioned sea level rise. Likelihood and variability are understandable to non-scientists, i.e., most policymakers and stakeholders. Human life and economies depend on reliable quantification and communication of uncertainty in climate modeling stakeholders (Cartieri & Potochnik 2014; Tuana 2010; Tuana 2013; Tuana 2020; Winsberg 2012). Simplicity lends itself to the cost-effectiveness of research. Models which are simplified to give projections on relevant phenomena for the sake of policymaking, impact analysis, or risk assessment are evaluated based on adequacy for purpose and need not always be so complex. This allows for more runs, larger pools of simulated observations, and a wider array of models presented in ensembles (Helgeson et al. 2021). On the other hand, the more fine grained the resolution of a model and its simulated results, the more well-informed decision-makers might be when considering climate change mitigation strategies. It seems intuitive that more complex models with more component systems, each of which can be tuned individually, would be more flexible under revision, even if the process itself becomes more complicated.

Understanding the complicated history of climate data sets and models for the purpose of UQ requires an examination of the influence of social and economic values on the researchers themselves, the schools and disciplines they were educated in, the institutions within which they practice, and the bodies they report to. All these factors may influence the methodological choices and priorities of modelers (Parker and Winsberg 2018; Winsberg 2018). The history of individual component models should be tracked as well. Because of the complexity of the systems under study and the modularity of component models, many of these modules are used in different models with divergent goals and different background assumptions. There are possible epistemic consequences for modelers when building complex assemblies out of existing component models that have been developed under different assumptions or for different purposes. The component models may have been constructed by different teams, at separate times, with varying expertise, training, or epistemic commitments. The computer driven aspect of these models means much of the programming is done by software engineers and computer scientists, who bring with them their own assumptions, idiosyncrasies, and foibles. Indeed, the very idea of what modularity means may be different between the climatologist directing the model development and the programmer building the code. These component models can contribute to the epistemic uncertainty of the simulation because of non-epistemic choices made during their development (Parker 2014; Parker and Winsberg 2018; Vezér et al. 2018; Winsberg

2012; Winsberg 2018). Without such examination, experts cannot begin to account for the sources of epistemic uncertainty in the climate models which they scrutinize.

For example, we can look to recommendations by theorists on the role ethicists and non-traditional experts can play in helping to build better models for driving policy and strategy. Because of the many layers of uncertainty and the variability of the natural processes under study, the condition that policymakers must operate in regarding climate mitigation strategies is called ‘deep uncertainty’ by decision theorists (Helgeson 2020; Vezér et al. 2018). Confronted by distinct projections, widely varying confidences, and lack of background information, decision makers have incomplete access to knowledge of possible outcomes or the impact of individual choices. Structuring model development, prioritizing specific quantities or aspects of phenomena or systems for study, and desired utilities for the findings of the research can all be taken into consideration to help policymakers make decisions in the face of deep uncertainty and risk (Helgeson 2020; Vezér et al. 2018). These are non-epistemic concerns, but their enmeshment with the process of model creation, hypothesis selection, data interpretation, and model evaluation means these values have very nuanced interactions with the epistemic process. Wendy Parker and Eric Winsberg contend that this intertwining is so complete that total separation of the models (especially those which involve a great deal of computer driven simulation) from their non-epistemic influences is impossible (Parker 2014; Parker and Winsberg 2018; Winsberg 2018).

The time for the ‘ivory tower’ intellectual who dreamily pontificates on an abstract and distant world is over. Unrealistic proclamations of idealized scientific practice free from outside influence are outdated and unproductive. Acknowledging and tracking the influence that values have on the selection of hypotheses and models is critical, whether the purpose of models is exploration, predictive analysis, impact assessments, policies, or action plans. Failure to do so amounts to ‘bad science.’

Conclusion

This is but a mere glimpse of the challenges in climate modeling. Attempting to inventory the various questions and problems facing researchers is a daunting task. Whether from epistemic tradeoffs between simplicity and totality of representation, differing methods for interpretations of probability, quantifying uncertainty, or the coupling of epistemic and ethical values, there are a lot of nooks and crannies where we might find distributed epistemic agency. That is to say: the beliefs, conjectures, and conclusions which scientists explore, adopt, or reject via climate models and simulations are influenced by these attributes of the modeling and simulation processes, rather than purely by their relation to the real phenomena. Because of the high stakes, climate scientists and their collaborators have an obligation to be aware of how secondary or tertiary influences, such as methodological choices or non-epistemic values, affect their modeling practices.

Therefore, it is a logical extension of that awareness to conclude that a model selected for adaptability to purpose and changing background information serves the ends of climate researchers better than some other model. On this view, models which can be easily fitted or tailored to both the particular phenomena under study and the epistemic and non-epistemic concerns of the researcher make ideal candidates for selection. This is arguably a more robust criterion for selection than simple computational simplicity. Interpretations of probability and other mathematical and methodological conventions and choices are important to track and understand because they give scientists insight into the process of how their beliefs are created, shaped, and refined. This goes double for the non-epistemic values that are injected into and intertwined with model creation and simulation.

This ambition calls for a comprehensive perspective, one which philosophers of science seem uniquely suited to provide. Much of climate modeling already takes place among teams with diverse disciplinary and personal backgrounds. Fostering this diversity and expanding the role of philosophers in the collective conversation allows for more acute observation of and accounting for the ways these trade-offs, methodological choices, interpretations, and values can shape and shift beliefs.

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