Two Exploratory Uses for General Circulation Models in Climate Science

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In this paper I present two ways in which climate modelers use general circulation models for exploratory purposes. The complexity of Earth's climate system makes it difficult to predict precisely how lower-order climate dynamics will interact over time to drive higher-order dynamics. The same issues arise for complex models built to simulate climate behavior like the Community Earth Systems Model (CESM). I argue that as a result of system complexity, climate modelers use general circulation models to perform model dynamic exploration (MDE) and climate dynamic exploration (CDE). MDE and CDE help climate modelers to better understand the dynamic structure of the general circulation model system and the actual climate system, respectively.

Introduction

Climatologists understand many things about the behavior of Earth's climate. However, the complexity of the climate system makes it difficult to know with precision how it will evolve over time. Earth's climate consists of incredibly complex causal interactions occurring at global scales over long periods of time. To better understand the operations of the climate system, climate modelers run simulations of the climate using general circulation models (GCMs). In this paper, I argue that because there is no general theory that explains how specified climate conditions will evolve over time, modelers rely on GCMs to perform a dual exploratory function. Namely, GCMs are used to explore their own dynamic structure as well as the dynamic structure of the climate system.

Thus, I argue that there are at least two specific ways that general circulation models are used for exploratory purposes. The first of these exploratory techniques I call model dynamic exploration (MDE). MDE often takes the

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form of sensitivity tests, a process whereby climate modelers examine how a model responds to variations in controlled parameters. The models used to simulate the climate system are themselves highly complex systems, as they must be to simulate real-world climate behavior. As such, it is often unclear how the behavior of lower-order model components over time will drive the system as a whole. The second exploratory technique I call climate dynamic exploration (CDE). CDE involves utilizing GCMs to better understand the structure of the climate system itself. In particular, climate modelers observe the behavior of appropriately crafted GCMs to explore how Earth's climate system will evolve under specific conditions. A well-known instance of CDE is the modeling of different emissions scenarios considered by the Intergovernmental Panel on Climate Change (IPCC AR5, 2014). By specifying different rates of carbon dioxide emission across otherwise similar models, climate modelers explore the impact that differing dynamic conditions have on the evolution of the global climate. In utilizing MDE and CDE climate modelers use GCMs to explore the higher-order behavior of a complex system that emerges from specified lower-order dynamics.

In Section 1, I lay out the structure, and comment on the history, of the Community Earth Systems Model (CESM), a fully-coupled global climate model created by the National Center for Atmospheric Research (NCAR).[1] With an understanding of how climate models like CESM are structured, I discuss the exploration of model structure with MDE in Section 2. In Section 3, I consider how modelers use GCMs to explore the dynamics of Earth's climate itself with CDE.

1. The Community Earth Systems Model

Background theory from various scientific fields comes to bear on the climatologists' understanding of Earth's climate. However, it is often the case that these theoretical models can only capture the behavior of such diverse phenomena by simplifying and idealizing the target system. In being broadly applicable, physical theory must misrepresent the real-world target by restricting focus to the causal interactions of a small handful of factors while omitting facts that have a marginal, albeit non-zero, influence on the target system. This motivation is discussed in Weisberg's account of minimal model idealization, where he argues that such minimal models are constructed to include only the causal factors that "*make a difference*" (Weisberg 2007, p. 642; emphasis original). By focusing on the causally relevant factors, minimal models play a crucial role in facilitating scientific explanation. Indeed, while focusing on specific causal patterns within

1. I would like to give special thanks the organizers and co-participants at the 2018 Community Earth Systems Model Tutorial at NCAR for such enlightening discussions on the structure and function of the CESM.

the target system misrepresents that system, in doing so these idealizations improve the scientists' general understanding of the system (Potochnik, 2017, ch. 4). While representing the evolution of Earth's climate over time will necessarily require some forms of simplification and idealization, it does require that the causal contribution of significant climate features be taken into account. As such, climatologists need a tool that can calculate a large number of interactions occurring over a number of timesteps. The Community Earth Systems Model is an example of such a tool.

The Community Earth Systems Model (CESM) created by the National Center for Atmospheric Research (NCAR) for the wider climate research community began as the Community Climate Model (CCM) in 1983. As a program federally funded by the National Science Foundation, NCAR was created by the US Congress in 1960 to bring together specialists from the numerous fields pertaining to Earth science, from oceanographers to volcanologists, to facilitate collaboration towards an improved understanding of the atmosphere. Since 1983, NCAR has worked to provide researchers the necessary resources for model construction. Their primary organizational mission: "to serve the U.S. academic climate research community through provision, development, and testing of the Community Climate Model (CCM)" (Shackley 2001, p. 124).

Simon Shackley (2001) argues that climate researchers at NCAR are a paradigm example of the epistemic lifestyle commonly found within American climate modeling. Epistemic lifestyles comprise the "set of intellectual questions and problems, and the accompanying set of practices, that provide a sense of purpose, achievement, and ambition to a scientist's work life" (Shackley 2001, p. 114). According to Shackley, climate modelers in the United States differ from climate modelers in the United Kingdom with respect to their epistemic lifestyle. In particular, climate modelers in the UK tend to be "climate seers," emphasizing the sensitivity of the climate system to changing variables and processes. On the other hand, climate modelers in the United States tend to be "climate model constructors," striving to capture the full complexity of the climate system in their climate models. Shackley notes that NCAR, an exemplar of the epistemic lifestyle predominantly found in the United States, houses a small team of three or four scientists operating as climate seers but otherwise consists of researchers dedicated to testing and improving the CESM. With an overwhelming majority of NCAR researchers endorsing the climate model constructor lifestyle, the organizational structure at NCAR has pushed the development of the CESM towards higher spatial resolution and more complex modeling of dynamic processes.

The CESM has thus developed steadily over the past several decades, incorporating a greater number of climate-relevant features in increasingly greater detail. The current version, CESM 2.11, consists of several submodels, each dedicated to representing a particular domain in the global climate regime. These domain-specific submodels include a land model, an atmosphere model, an ocean model, a land ice model, a sea ice model, and models representing river runoff and surface waves. Each submodel is modular, operating independently from the others, but interaction across models is possible through communication with a centralized coupler. The atmosphere model and ocean model are built around a dynamical core that solves the relevant fluid and thermodynamic equations on resolved scales, simulating the general circulation in each domain. These fluid and thermodynamic equations are derived applications of Newton's second law, ensuring that mass and energy are conserved as they flow throughout the system.

At the time of writing, the atmospheric model of CESM is the Community Atmospheric Model 6.0 (CAM6). CAM arose in 2004 from prior generations of the NCAR CCM, with the first CAM (CAM3) comprising the fifth generation of the NCAR atmospheric model. The name was changed to CAM to reflect the role of the model in a fully coupled earth systems model (i.e., the CESM). As such, the development of CAM over the last fifteen years, from CAM3 to CAM6, has included previously neglected dynamic processes (e.g. explicit representations of fractional land and sea-ice coverage in CAM3, the simulation of full aerosol cloud interactions included in CAM5). CAM5 also introduced an interactive chemistry model (CAM-CHEM) capable of simulating biogenic emissions and the deposition of aerosols to snow, ice, ocean, and vegetation. The most recent version of the atmospheric model, CAM6, introduces substantial modifications to the parameterizations for nearly all atmospheric processes, replacing the model dynamics for parameterized processes like cloud macrophysics, shallow convection, and boundary layer turbulence.

CAM6 typically runs at approximately 100-kilometer horizontal resolution, sufficient to capture much of the relevant large-scale climate phenomena. Relevant processes that occur on scales too small to be resolved are parameterized as subgrid models in order to capture the relevant contribution of the process in each grid cell. While some of these parameterizations are run by CAM6 or POP2, the ocean circulation model, many of them are offloaded to other submodels. For example, the type of land cover in a grid cell will determine how much of the incoming solar radiation is absorbed and converted into heat energy, and how much is reflected back into space. But the surface of the Earth can vary drastically across a single 100x100km grid cell, meaning that land surface variations must be parameterized if we are to adequately approximate surface reflectance. The Community Land Model (CLM) in the CESM accounts for this surface heterogeneity by representing the albedo (light reflected by a body or surface) of the grid cell as a proportional average of the surfaces present in that cell. The CLM begins by representing how much of the surface within a cell is composed of vegetation, city, lake, crop, and glacial surfaces. Once we know the surface composition of a cell, the CLM can calculate its total albedo as a proportional average these surface components' albedo. The CLM does not spatially represent the diverse surface types in a cell but can functionally approximate the influence that surface diversity within each cell would have on local solar reflectance. The functional approximation of parameterization thus collapses the complex dynamic interactions of land surface processes into a small number of parameter values.

As briefly stated before, each of the domain-specific submodels comprising the CESM communicates with the others through a coupler. This communication allows the behavior of the different submodels to influence each other. As such, the centralized coupler functions as a central node of communication for the various submodels of CESM. The coupler controls the flow of time for each of the submodels, synchronizing their execution and ensuring that fluxed quantities are conserved throughout their interaction. It is this interaction facilitated by the coupler that enables climate models like the CESM to best simulate the variety of diverse interactions influencing the state of Earth's climate. For example, the CLM will need to share the calculated albedo values of each cell with the atmospheric model, through interfacing with the coupler. The CLM may in turn receive temperature and precipitation data from the atmospheric model (via the coupler) in order to update the surface properties of each cell. Or, for example, ocean modelers may want an active atmospheric model to constrain temperatures and wind speeds in the lower atmosphere for the purposes of better representing sea surface temperature. In this case, the atmospheric model will send the relevant lower atmospheric output to the coupler at desired intervals, where it will share the output with the ocean model to use in its own calculations. A CESM run that wishes to take advantage of all the modules will have an atmosphere model, an ocean model, a land ice model, a sea ice model, a river model, and a surface wave model all interacting through a central coupler. This will be computationally expensive, taking a larger amount of time and resources, but may be required for some purposes. On the other hand, an atmospheric modeler may only need an active atmosphere model for the purpose at hand, replacing any necessary input from other models with a static dataset. This will be computationally cheap and require relatively less time to perform.

We now have a general understanding of how general circulation models like CESM are structured so as to simulate the behavior of the climate system. The behavior of a general circulation model is governed by a combination of physical dynamics that are explicitly resolved by the simulation and those that are unresolved but approximated by parameterization. The resolved flow of mass and energy throughout the atmosphere and ocean are governed by fluid dynamic equations derived from Newton's second law, making up the dynamical core of atmosphere and ocean models. Unresolved processes occurring at subgrid scales are parameterized as subgrid models. These subgrid models approximate the influence of subgrid phenomena on resolved behavior, altering the properties of relevant grid cells. While modular, the various submodels of the CESM may communicate via a centralized coupler, allowing every part of every submodel to interact with each other. This coupler functions as an intermediary between the submodels, synchronizing their computation while taking relevant outputs from each submodel and providing it as an input for other submodels in calculating their dynamics over time. Coupled climate models like the CESM are, thus, complex model systems designed to represent the complex climate system. With this complexity in mind, we can now consider two ways in which GCMs are used for exploratory purposes.

2. Exploring the Dynamics of Model Systems

Climate models like the CESM are complex structures, made up of numerous components interacting in intricate ways over a large number of timesteps. This complexity bestows climate models with what Johannes Lenhard and Eric Winsberg (Lenhard and Winsberg 2010) call "analytic impenetrability." Analytic impenetrability precludes a modeler from attributing causal responsibility for some behavior or output to a particular model assumption. The interconnectedness of model components, and the resulting causal complexity, makes it impossible to analytically tease out the particular causal influence that each component has on model performance. Indeed, the complexity of the model system arguably makes the entire question of individual component contribution unintelligible. The attribution of causal responsibility for model performance must be a holistic attribution to the model assumptions taken together.

The analytic impenetrability of complex simulation models is distinct from what Humphreys calls epistemic opacity (Humphreys 2004, 2009). According to Humphreys "a process is essentially epistemically opaque to [cognitive agent] *X* if and only if it is impossible, given the nature of *X*, for *X* to know all of the epistemically relevant elements of the process" (Humphreys 2009, p. 618). A computer simulation is thus epistemically opaque insofar as features of the simulation that are important to its justification are inaccessible to researchers. When computer simulations are epistemically opaque, there are good reasons to reject those simulations as reliable sources of novel information about the world (Guala 2002; Parker 2009a). On the other hand, computer simulations are not epistemically opaque to the extent that epistemically relevant processes are surveyable. To be surveyable is simply to be not epistemically opaque—for all epistemic features important to justification to be accessible to researchers. The surveyability of proofs and calculations, Durán argues, is crucial to the confidence of mathematicians in computational methods (cf. Durán 2018, ch. 4). In distinguishing between different kinds of epistemic opacity, Andreas Kaminski refers to the specific inability of a cognitive agent to survey a computer simulation due to the complexity of its mathematical operations as "internal mathematical opacity" (Kaminski et al. 2018). General circulation models are thus internally mathematically opaque to the extent that researchers are unable to survey the application of the physical dynamics at every timestep within each submodel and between each submodel and the centralized coupler.

Related to internal mathematical opacity, the complexity of a general circulation model will also make it impossible for human cognitive agents to infer how the model system will evolve over time from the initial conditions alone. There are too many deeply interconnected processes running in a full-scale earth systems model for modelers to predict the evolution of the simulation before actually running the simulation. A modeler cannot infer how a model system will develop over time—with its specific initial conditions and dynamics—from an assessment of those initial conditions and dynamics alone. Even for experienced modelers it is not uncommon to discover that a seemingly unimportant adjustment has led the model to behave unexpectedly. Thus, a modeler will need to observe and manipulate model performance in order to learn about how the components of the model interact in guiding the behavior of the system over time. Lenhard (2007) argues that by introducing "a degree of contradiction" into the dynamics of a GCM, Akio Arakawa (1966) was able to provide the model with a long-term stability that previously seemed impossible. That is, the introduction of contradictory foundational dynamics did not destabilize the GCM, but rather stabilized its performance. Thus, I argue that the causal complexity of a climate model produces two related issues: the analytic impenetrability of the model precludes an inference from effect to cause, and inferential impenetrability of the model precludes an inference from initial model conditions to an understanding of model evolution.

Without a general theory relating lower-order phenomena and system-wide climate behavior, climate modelers are left to explore these relations with the use of GCMs. Axel Gelfert (2016, ch. 4.5) describes four ways in which models are used by scientists to perform exploratory functions. Exploratory models can be (1) useful starting points for later inquiry, (2) proof-of-principle demonstrations, (3) possible explanations, and (4) assessments of target suitability. These four forms of exploration can promote, among other things, a tacit model-based understanding "sometimes loosely described as developing 'a feel for' the model (and, by extension, for the behavior of its target system)" (Gelfert 2016, p. 73). General circulation models have certainly been used for the four exploratory purposes that Gelfert presents, helping climate modelers to develop better model-based understanding. However, I argue that models with the structural complexity of modern GCMs can in addition be used to explore the relationship between lower-order model features and higher-order phenomena. In the absence of a theory linking lower-order dynamics and higher-order dynamics, climate modelers may yet develop a feel for the dynamic relations present in some GCM, and by extension an understanding of the dynamic relations in the target system. While I don't take an improved understanding of dynamic relations to be limited to a single kind of understanding, it does promote the "grasping of causal patterns" (Potochnik 2017). In the absence of a general theory bridging lower-order and higher-order climate phenomena, GCMs help researchers to grasp the causal patterns relating the phenomena. This grasping of causal patterns can serve the additional function of helping researchers develop a feel for the target system. As such, GCMs facilitate an additional kind of exploration in line with Gelfert's original set of exploratory purposes. Complex simulation models like GCMs allow researchers to explore what higher-order phenomena emerge from lower-order dynamics. Thus, I suggest a novel exploratory use for complex models that target complex systems.

In the face of model complexity, modelers must explore a model's behavior under a variety of specific conditions to develop an understanding of the model. I call this "model dynamic exploration" (MDE). MDE is required early in the life of a model when the parameters of the model have yet to be calibrated. Model parameters will be calibrated in response to the exploration of how particular parameterization schemas cause the model to behave. MDE is thus a crucial aspect of tuning complex simulation models. However, MDE is not limited to the early life of a model. In developing GCMs MDE can often take the form of a sensitivity test, where a modeler takes interest in how some feature or features of the model will respond to variations in some other feature. For example, an ocean modeler may want to know how sensitive sea surface temperatures are to changes in insolation (that is, incoming solar radiation) within a particular run of the CESM. As such, the modeler can run a coupled ocean-atmosphere model under a wide range of insolation conditions. Incoming solar radiation currently averages about 340 W/m^2, but the modeler may choose to run an ensemble of models with radiation values between 250–500 W/m^2. The modeler may then observe how sea surface temperatures represented in the model vary in response to insolation change.

It's important to note that parameter variations need not fall into the range of plausible, or even nomologically possible, values for the sensitivity test to be useful. Modelers performing sensitivity tests are not initially interested in accurately representing the target climate system. A modeler can vary insolation values between 250 and 500 W/m^2 even if many of the values in that range are implausible for contemporary or historical purposes. The modeler is primarily exploring the dynamics of the model system in order to better understand how specific features of the model are related, not for the immediate purpose of accurately representing some climate system. This exploration helps modelers to better understand the models they are using and the contexts in which a particular model will and will not be useful.

In our example, the modeler is specifically interested in exploring how sea surface temperatures depicted in the model vary in response to changes in insolation. Upon inspection of the ensemble results, the modeler may discover that sea surface temperatures respond too much or too little to varying insolation. Background climatological theory may suggest a range of plausible responses that the model does not reproduce, implying that some of the model dynamics are inadequately represented. On the other hand, model performance may fall within the expected range for a subset of insolation values, suggesting that the GCM adequately approximates the influence of solar insolation on sea surface temperatures when insolation values are within that subset.

Observing model performance is our best means for developing a deeper understanding of the models we use to simulate the climate. Thus, it is often worthwhile to run a GCM under a range of similar yet diverse conditions in order to explore the interdependencies present in the model. An assessment of the underlying equations and initial conditions of the model will not reveal these interdependencies, leaving modelers with no alternative but to explore model performance.

3. Exploring the Dynamics of Climate Systems

Of course, climate modelers are not merely interested in exploring the structure of their own complicated research tools. While it is often necessary to investigate the behavior of a GCM to better understand the model, this is ultimately so that the model may be later used to investigate the actual climate. This brings us to the second novel form of exploration in which general circulation models are useful: climate dynamic exploration (CDE). CDE is a process by which climate modelers utilize GCMs to explore the way that the elements of the climate system interact over time, driving the higher-order behavior of the climate system.[2]

For a climatologist to use GCMs to explore the dynamics of the actual climate system, the GCM must bear the right relationship to the target system. In line with a view she previously defends regarding evolutionary theory (Lloyd 1987), Elisabeth Lloyd argues that climate modelers, in accordance with the semantic view of scientific theory, utilize sets of models to explain empirical phenomena.[3] Under the semantic view of theories, models and their target systems are homomorphic, sharing a common structure. Thus, for a GCM to tell us something about the climate system, it must be structured to capture the behavior of the climate system. Of

2. While the kind of exploration depicted in CDE is not likely to be limited to climate science, and it is most likely that CDE is a particular application of a more general target dynamic exploration to climate science, I will restrict my discussion in this paper to the particular application.

3. Elisabeth Lloyd's 1987 work on evolutionary models articulates in detail how the semantic view accounts for the use of ecological and evolutionary models. I would like to thank her for bringing to light the connection between her work on climate modelling and her work on ecological and evolutionary modelling (Elisabeth Lloyd, personal communication, August 10, 2018).

course, given that parameterizations are known to misrepresent the target system in important respects, we should not expect GCMs to accurately represent all aspects of the climate's behavior (Parker 2009b, 2020). Rather, as Parker argues, GCMs can sacrifice representational accuracy in parameterizing their dynamics insofar as they are still adequate for their intended purpose.

Still, GCMs must bear some structural similarities to their target climate system for them to be useful for climate modeling purposes, and Lloyd presents four ways in which GCMs can be shown to bear such similarities. Lloyd argues that there are four methods for confirming GCM homomorphism: Model Fit, Variety of Evidence, Robustness, and Independent Support (2009). A climate model is confirmed when it accurately predicts or retrodicts observational data (Model Fit), and further confirmed when it accurately predicts or retrodicts multiple independent observations (Variety of Evidence). Aspects of a model can also be confirmed when multiple, heterogeneous models with a common structure produce the same robust result (Robustness), or when independent evidence exists for the reliability of parameters, parameterizations, and general theory (Independent Support). Lloyd's four methods of confirmation are important across model purposes, exploratory and otherwise, for supporting the homomorphism of the GCM and the climate system.

With regard to CDE the adequacy of the GCM may be assessed in light of model fit and variety of evidence when the GCM aims to represent the actual climate during times for which we have observational evidence. However, when CDE is used to consider climate dynamics for counterfactual conditions, or during unobserved future times, climatologists may only have access to the confirmation methods of robustness and independent support. For example, when GCMs are used to model counterfactual natural (non-anthropogenic) forcings for comparison with models that include anthropogenic forcings, real world observations (IPCC 2019) and the variety of the evidence are of no help in assessing the model fit to the counterfactual target system. Rather, independent understanding of the climate system is required to constrain the values for non-anthropogenic forcings.

Performing CDE requires that modelers represent the foundational physical equations guiding the evolution of the climate system at resolved scales, important dynamic features occurring at unresolved scales as parameterizations, and the relevant boundary conditions. These physical dynamics, parameterizations, and relevant boundary conditions are independently supported applications by a combination model-independent theory and empirical observation.

The fluid and thermodynamic equations composing the dynamical core of the atmospheric and ocean models are derived from Newton's second law, which has enjoyed a large share of empirical support in numerous and diverse thermodynamic and fluid dynamic contexts. These equations conserve mass and energy across the system in accordance with well-supported physical principles. As such, the adequacy of Newtonian mechanics for modeling fluid and thermodynamics provides independent support for their implementation in GCMs. However, Newtonian equations derived to the continuous Navier-Stokes equations must be discretized to be useful for modeling purposes. Discretizing techniques, like the finite-volume discretization method (Herrington et al. 2019) adopted by the CESM, allow for the tractability of the otherwise unsolvable equations. Such methods are supported insofar as they satisfactorily approximate the output of continuous equations. That is, through model fit with observation.

Parameterizations represent a host of important but unresolved climate-relevant processes. While submodel parameterizations can be developed with an eye to more sophisticated theoretical models, their adequacy as simplifications will require adequate performance in light of relevant observations. Many parameterization submodels are thus calibrated to approximate the influence of subgrid processes in accordance with empirically observed relations. For example, a land model may represent the albedo of a grid-cell as the proportional average of the albedo of its constituent land-types. Doing so requires that climatologists empirically calibrate the albedo of various land types in accordance with measured values. Once these values are empirically derived from observation they can be incorporated into the land-model for the purpose of better approximating a grid cell's surface reflectance. Thus, submodel parameterizations are supported by model-independent theory and their ability to reproduce model-independent observation.

Meanwhile, boundary conditions for GCM simulations of the twentieth and twenty-first centuries are supported by independent empirical observation. Satellites, radiosondes, simple thermometers, barometers, udometers, and the like are used to measure a variety of features of Earth's climate, going back as far as the 1800s. Sea surface temperature boundary conditions in CAM between 1850 to 1981 (Hurrell et al. 2008), for example, are derived from adjusted and gridded in situ temperature measurements of sea surface water collected in buckets behind moving ships (Folland and Parker 1995). Empirical observations constituting the instrument record thus constrain the boundary conditions for contemporary climate simulation.

On the other hand, GCMs used for paleoclimate purposes rely on proxy measures to get a handle on what the relevant boundary conditions were in the distant past. Popular proxy climate measures like tree rings, oxygen isotopes, biomarkers, and pollen are particularly useful when instrumental data is lacking for the relevant time period. Since the growth of a tree displays clearly discernible annual patterns, and this growth is sensitive to temperature and moisture conditions, the analysis of tree rings can provide a dendroecological account of past climate trends. It has been shown that the isotopic composition of the shells of planktonic foraminifera reliably varies with temperature, making the oxygen isotopes preserved in those shells a useful proxy for sea surface temperatures. The kinds of biochemicals produced by such organisms are also susceptible to environmental conditions, making the preserved chemical fossils they leave behind an indicator of what those ocean conditions were like. Similarly, the pollen of land flora is well preserved in the sediment record, making pollen that can be reliably tied to a particular kind of plant very useful for constraining the local climate at the time of deposition.

The fundamental dynamic equations, parameterizations, and boundary conditions make up the model assumptions necessary to capture the relevant features of the climate system. If a GCM does not adequately capture the relevant features of the climate, then it is not adequate for climate dynamic exploration in that case. This is primarily what distinguishes climate dynamic exploration from model dynamic exploration: ensuring the external validity of model assumptions.[4] Climate dynamic exploration requires that the model be validated, such that researchers establish the adequacy of the relationship between the simulation model and the empirical world (Oberkampf et al. 2003). If the model assumptions do not adequately capture the features relevant to the purpose at hand, then the model cannot reliably be used to study the target climate system (Parker 2009b, 2020). If a GCM does capture the relevant structure of the climate system, then we can use its performance to explore the dynamics of the actual climate. That is, we can explore the dynamics of the climate system by observing the dynamics of the model system once the GCM has been validated, or shown to be externally valid, for its intended purpose; this process requires establishing that the model bears the relevant structural similarities to the target system via Lloyd's methods of confirmation. Only by establishing the external validity of a GCM can an exploration of the model permit an exploration of the target climate system.

It may be apparent by now that climate dynamic exploration is always a kind of model dynamic exploration. Climate modelers explore the target climate system by way of exploring how the lower-order dynamics of the general circulation model govern its higher-order behavior. CDE is an instance of MDE in as much as it utilizes the evolution of the general circulation model to explore the

4. Eric Winsberg (2010) argues that it is the emphasis on establishing the external validity of simulation that distinguishes model simulation from traditional experiment, which focuses on establishing the internal validity of the experiment.

evolution of its target climate system. That the model must bear the right similarities to the target climate system means, however, that one is not free to explore the GCM by way of adjusting the parameters in any which way. We may thus distinguish between MDE in cases where the model is the target of exploration, with less concern for precisely how the model might later be used to represent some real-world target, and cases of MDE where the exploratory choices are guided by some specific application to the world.

After implementing the requisite dynamic equations, parameterizations, and boundary conditions, modelers can run the model to explore how these features of climate system behave. While many assumptions have been made about the structure of the climate system in generating the model, novel higher-order patterns and behaviors will emerge during model performance. As a result of inferential impenetrability some of these patterns and behaviors will be unanticipated. It is these emergent climate phenomena and their influence that modelers are exploring when they run general circulation models. Climate modelers are investigating how specified lower-order dynamics interact at global scales over significant periods of time to influence system wide behavior. Indeed, that the use of general circulation models in climate science largely consists of CDE suggests that exploration is not always merely an intermediary stage in scientific modeling. Exploration can be introduced early in model development and persist as a distinct mode of research.

As an example, suppose that we are interested in the global distribution of a particular species of planktonic foraminifera. The global distribution of a particular foraminifera (single cell organisms with shells) species may be one of many higher-order features we consider when modeling the Earth's climate. Suppose that we are particularly interested in how that species will respond to a 100ppm increase in atmospheric CO_2. We construct a general circulation model to address our question, knowing that it must incorporate the ways in which atmospheric CO_2 influences the surface water conditions, including temperature, salinity, the prevalence of predators, and nutrient availability. To adequately model the relevant factors will at least require coupled atmospheric, oceanic, river runoff, land ice and sea ice models. The atmospheric model will model the influence of the carbon-infused atmosphere, feeding insolation and temperature values to ocean and land models. The ocean model will represent ocean circulation and the distribution of temperature, salinity, and relevant biochemistry. Our species of interest is expected to occupy ocean surfaces of within a particular temperature-salinity range, in some proportion to nutrient availability. However, changes in salinity, temperature and nutrient availability will also result from river runoff and the melting of land and sea ice, so it will be important to model their contribution to surface water conditions.

As such, the global distribution of our target foraminifera is a higher-order pattern emerging from the interaction of a variety of lower-order dynamics across various submodels, the interaction of which we explore with our climate simulations.

Climate modelers may also choose to explore the effect that higher-order phenomena have on more localized aspect of the climate system. For example, because the presence of ice cover in the Arctic is so significant to global climate sensitivity, climate modelers regularly explore the influence that twenty-first century warming will have specifically on the Arctic (e.g. Wunderling et al. 2020). In this case, modelers implement the requisite dynamics, parameterizations, and boundary conditions, then run the model. The model produces higher-order patterns as usual, and these higher-order patterns are inferentially impenetrable from initial conditions. Being interested specifically in the condition of the Arctic during the duration of the simulation, the modeler will focus on how these higher-order patterns (emerging from lower-order dynamics) effect ice-loss in the Arctic. Thus, climate modelers may also explore the effects of higher-order climate dynamics on a more local aspect of the climate system.

CDE is a process whereby modelers explore the higher-order climate behavior that arises from specified lower-order dynamics. As a result of inferential impenetrability, running general circulation models is the best means available for exploring emergent climate patterns and behaviors. For this exploration to be successful, however, model dynamics, parameterizations, and boundary conditions must adequately represent the relevant features of the climate system. To learn about the real-world climate system by assessing GCM performance, the GCM must capture the relevant independently supported lower-order dynamics.

4. Conclusion

In this paper I have argued that climate modelers take advantage of two exploratory practices in studying complex systems, model dynamic exploration (MDE) and climate dynamic exploration (CDE). MDE allows climate modelers to better understand the relationship between established lower-level dynamics and the evolution of the model system over time. CDE helps modelers to understand the complicated dynamics of the real-world climate by way of assessing general circulation models. It is likely that modelers working with models of comparable causal and spatiotemporal complexity outside of climatology take advantage of similar forms of model exploration, but I leave this for future discussion. However, it is certain that both MDE and CDE are important forms of exploratory model use for climate modelers working to develop an understanding of the dynamics governing Earth's climate system into the twenty-first century.

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