Simulation and Understanding in the Study of Weather and Climate

Wendy S. Parker
Department of Philosophy
Durham University

Abstract: In the study of weather and climate, the digital computer has allowed scientists to make existing theory more useful, both for prediction and for understanding. After characterizing two sorts of understanding commonly sought by scientists in this arena, I show how the use of the computer to (i) generate surrogate observational data, (ii) test physical hypotheses and (iii) experiment on models has helped to advance such understanding in significant ways.

1. Introduction

In 1904, Norwegian physicist Vilhelm Bjerknes published what would become a landmark paper in the history of meteorology. In that paper, he proposed that daily weather forecasts could be made by calculating later states of the atmosphere from an earlier state using the laws of hydrodynamics and thermodynamics (Bjerknes 1904). He outlined a set of differential equations to be solved and advocated the development of graphical and numerical solution methods, since analytic solution was out of the question.

Using these theory-based equations to produce daily forecasts, however, turned out to be more difficult than anticipated. Graphical solution techniques had limited success, and a first attempt to use numerical (finite-difference) methods gave little reason for optimism: it took Lewis Fry Richardson (1922) more than a month to calculate by hand the six-hour forecast for a small region, and the results produced were wildly unrealistic. Writing in 1955, atmospheric scientist Jule Charney characterized dynamical meteorology in the first half of the twentieth century as “a field in which belief in a theory was often more a matter of faith than of experience.…the practicing meteorologist could ignore the results of theory with good conscience” (1955, 798).

The advent of the digital computer in the mid-twentieth century brought new hope for making theory useful. Perhaps accurate numerical weather prediction would be possible after all: the computer could perform rapidly the calculations required by numerical solution techniques, and mathematical models incorporating reformulated ("filtered") versions of the theoretical equations might avoid some of the problems that affected Richardson's forecast.[1] But improving weather forecasts was not the only goal. Scientists also had high hopes for the computer as a device that would allow them to advance their *understanding* of the atmosphere and climate system, in part by allowing them to investigate in new ways the mechanisms by which salient features and phenomena are produced (see e.g. Charney 1951, 1955 and quotes below from Lorenz 1967, 1970).

In the half century since its introduction, the computer has proven valuable indeed for both prediction and understanding in this arena. Often, progress in weather prediction is emphasized, but in what follows I discuss how the computer – especially computer simulation – has helped with the latter goal: understanding. Rather than explore the nature of scientific understanding in general (e.g de Regt and Dieks 2005, Grimm 2006, Strevens 2008, Ylikoski and Kuorokoski 2010), I show how in practice computer simulation can promote two sorts of understanding commonly sought in the study of weather and climate.[2]

In Section 2, I introduce these two sorts of understanding. *Understanding why an event/phenomenon occurs* is achieved when scientists obtain an accurate explanation of the occurrence of that event or phenomenon, while *understanding a complex system/phenomenon* is more open-ended and involves both knowledge and know-how. The next three sections discuss particular ways in which the computer is used to increase, or make progress toward, these sorts of understanding. Section 3 is concerned with the use of the computer to produce simulations that serve as surrogate observational data. Section 4

[1] Richardson himself had identified some of the problems with his attempt and had envisioned improved forecasting by numerical methods with the help of thousands of human "computers", each responsible for performing by hand a limited set of calculations (see Richardson 1922). But this human "forecast factory" was never assembled.

[2] Though my focus is on meteorology and climate science, much of the analysis is likely to apply to the use of computer simulation in other fields as well. For related discussions focusing on other fields, see Bechtel and Abrahamsen (2010) and Ylikoski (this volume). The present paper also dovetails with the more general discussion of simulation and understanding given by Lenhard (2009).

outlines how the testing of physical hypotheses, especially hypotheses relevant to explanation, can be performed with the help of the computer. Section 5 discusses the use of the computer to experiment on models of the atmosphere and climate system, including models that are systematically related in a hierarchy. Finally, Section 6 offers some concluding remarks.

2. Understanding weather and climate

In the study of weather and climate, as in many other scientific fields, understanding is identified as a central aim, though there is little explicit discussion of what the desired understanding consists in. A survey of classic papers, textbooks and research monographs suggests that there are at least two notions of understanding in play in this arena.

One sort of understanding is tightly linked to explanation and has as its target the occurrence of an event or phenomenon, usually defined in terms of a small set of salient or essential properties. For instance, scientists might want to understand why there is an extratropical jet stream – a persistent, narrow region of accelerated air near the top of the troposphere in the extratropical region, or why severe thunderstorms in the central United States sometimes split into two separate storms, or why New York City received a record-setting snowfall last Thursday, rather than a more typical amount of snow. The desired understanding is achieved by scientists when they arrive at (and perhaps also grasp) an accurate explanation of the occurrence of the event or phenomenon.[3] Usually, the explanations sought are causal explanations; the stated aim may be to identify the *mechanism* by which a phenomenon of interest is produced (e.g. Charney 1955, Schneider and Dickinson 1974, Klemp 1987, Markowski 2002), but more generally the goal is to obtain an accurate *causal story* – an accurate account of how a set of causal factors (e.g. forces, processes, conditions) together produces the event or phenomenon to be explained (Parker 2003, 80; see also Cartwright 1983, Ch.4).[4] This sort of understanding will be referred to as *understanding why an event/phenomenon occurs*.

---

[3] Without the grasping requirement, this sort of understanding is similar to de Regt's (2009) *understanding a phenomenon*; if the grasping requirement is included, then it is more similar to Strevens' (2008; 2012) analysis.

[4] Occasionally, something like deductive-nomological explanation is referenced, but it is commonly seen as an inferior sort of explanation. For instance, imagining a perfect numerical simulation of a hurricane, atmospheric scientist Edward Lorenz remarks: "We might still be

Progress toward the goal of understanding why an event/phenomenon occurs is made when scientists obtain what philosopher Peter Railton (1981) calls *explanatory information* – information that reduces uncertainty about the form or content of a sought-after explanation. Since causal explanations are typically desired here, explanatory information can include, among other things: information about causal dependencies; information about the relative contributions of different causal factors; and information about how parts or pieces of a larger mechanism work.

A second sort of understanding is more open-ended and targets complex dynamical phenomena, such as extratropical cyclones and hurricanes, as well as the atmosphere and climate system as a whole. These targets of understanding are perceived as rich objects of study, and it is more difficult to give an account of what the desired understanding of them consists in (e.g. what *understanding the climate system* consists in). It seems to involve both knowledge and know-how, that is, both knowing things about the phenomenon or system, such as facts about its structure and dynamics, and being able to synthesize and apply that knowledge to answer correctly additional questions about the phenomenon or system, especially questions about the effects of interventions on or changes to the system.[5] This second sort of understanding, which is discussed in more detail below, will be referred to as *understanding a complex phenomenon/system*.[6]

In practice, the knowledge that is partially constitutive of this second sort of understanding is often summarized in what scientists who study weather and climate refer to as *conceptual models*. A conceptual model of X is a representation of a set of key elements (parts, features, stages) of X as well as particular relationships (whether spatial, causal, etc.) among those elements.

---

justified in asking why the hurricane formed. The answer that the physical laws required a hurricane to form from the given antecedent conditions might not satisfy us, since we were aware of that fact even before integrating the equations" (Lorenz 1960, 243-244).

[5] Exercising this ability may involve reasoning about the system in a qualitative or rough quantitative way or, when questions are beyond the reach of unaided reasoning, picking out relevant ingredients for simulation studies, etc. This ability to synthesize and apply existing knowledge thus bears some similarity to abilities emphasized by Ylikoski (this volume), de Regt (2009) and Lenhard (2009) in their discussions of understanding.

[6] The two sorts of understanding are different in kind. Whereas the first is concerned with 'understanding why' the second is concerned with 'understanding a system'. Thanks to Henk de Regt for pushing me to clarify this.

Conceptual models in meteorology and climate science typically come in the form of diagrams with associated narrative text. Figure 1, for instance, shows the diagrammatic portion of a conceptual model of the hurricane phenomenon, in this case focusing on a period of time in which the hurricane undergoes eyewall replacement. Conceptual models of parts of phenomena – such as the cold front in an extratropical cyclone – are also common; they zoom in to reveal more detail about particular parts of the larger phenomenon or system. Almost by definition, the content of conceptual models is primarily qualitative, though it is not uncommon for them to make judicious reference to equations in their narrative text. As Figure 1 suggests, often they are constructed with the dual aims of describing and explaining important features of phenomena.

[FIGURE 1 ABOUT HERE]

Understanding a particular complex phenomenon/system, like the atmosphere or climate system, generally does not have a clear point of completion; it is achieved only to a greater or lesser extent. It is increased when a scientific community gains significant new knowledge about the phenomenon or system, or refines existing knowledge, or enhances its ability to synthesize and apply existing knowledge to correctly answer additional questions about the phenomenon or system. In connection with this, note that that uncovering the mechanisms by which salient features of a complex phenomenon or system are produced (i.e. obtaining this knowledge) is one important way of increasing understanding of that phenomenon or system. Hence, the first and second sorts of understanding are not unrelated. Indeed, the first sort of understanding is typically part of the second. Understanding why storm splitting occurs, for instance, is partially constitutive of understanding the supercell as a complex dynamical phenomenon. But understanding supercells is not just a matter of explanation; other sorts of knowledge about supercells – such as descriptive knowledge of their detailed internal composition and structure at different stages of development – also is partially constitutive of understanding of supercells, as is the ability to synthesize and apply such knowledge to answer additional questions about supercells (e.g. would changing feature X of the storm environment enhance storm formation and, if so, why?).

According to philosopher Henk de Regt, even when understanding requires only having an adequate explanation, as in the first sort of understanding discussed above, it implicitly depends on a kind of pragmatic understanding (or know-how) as well. In particular, he argues that it depends on *understanding a theory*, which on his view means being skilled in using the theory to construct suitable models of target systems or phenomena, which in turn are used to develop explanations and/or arrive at predictions (de Regt 2009, 592-593). We might question whether scientific explanation always requires a theory per se, as de Regt's analysis implies, but resolving this matter is not important for present purposes. What is of interest, rather, is that understanding a theory in de Regt's sense seems to be precisely what atmospheric scientists lacked (at least to a significant degree) before the advent of the computer: they had a set of theoretical equations that they believed to apply to the atmosphere, but they were unable to use this theory for many of the explanatory and predictive purposes that interested them.[7] Consequently, the theory was of limited value for understanding the atmosphere and its phenomena at that time.

The computer helped scientists to improve this situation, but how? The computer did not tell scientists which models to construct – it did not tell them how to simplify and idealize the equations of hydrodynamics, thermodynamics, radiative transfer, etc. to arrive at mathematical models that were easier to work with computationally but still realistic enough to be useful (see e.g. the quasi-geostrophic model developed in Charney 1947). But the computer did make it possible to estimate solutions to analytically-intractable equations using numerical methods, something that took ages, and thus was practically infeasible, when calculations were performed by hand. In doing so, it helped scientists to see what followed (or failed to follow) from the physical assumptions reflected in different mathematical models of the atmosphere or climate system. Moreover, because the equations of these models are meant to describe in an approximate way how conditions in the atmosphere or climate system change over time, their repeated solution for small time steps with the help of the computer could produce *simulations*, i.e. representations of the temporal evolution of the atmosphere or climate system.

[7] See, however, de Regt and Dieks 2005 on "PV-thinking" (potential-vorticity thinking) for an example of how simplified theory can be employed in the service of understanding a limited range of atmospheric phenomena.

In the next three sections, I discuss in more detail how using the computer to reveal the implications of modelling assumptions and to produce simulations has helped to advance understanding in the study of weather and climate. Given the two sorts of understanding just identified, any of the following would increase, or count as progress toward, understanding: (a) obtaining explanatory information, such as information about causal dependencies or causal relationships; (b) obtaining descriptive knowledge of the structure or evolution of a phenomenon or system of interest – the sort of knowledge that is commonly summarized in conceptual models; (c) enhancing a scientific community's ability to synthesize and apply existing knowledge to answer additional questions about the phenomenon or system. I will suggest that the computer can help with all of these, but I will most often highlight connections with (a).

Before moving on, however, some additional targets of understanding should be mentioned: the occurrence of events and phenomena *in a simulation*; *simulated* complex dynamical phenomena; and *model* atmospheres and climate systems. The mathematical models used to produce simulations in the study of weather and climate include variables that are given physical interpretations – they stand for temperature, pressure, wind speed, etc. Many atmospheric scientists view simulation results as if they were observations of a hypothetical atmosphere or climate system and identify phenomena and events that occur "in the simulation." Often, they seek to understand the occurrence of these simulated phenomena and events, just as they seek to understand the occurrence of real phenomena and events in Earth's atmosphere or climate system; the aim is to explain how the phenomenon or event in the simulation – the "jet stream" or "record snowfall" in the simulation – would be produced by the causal factors *represented* in the simulation. Likewise, atmospheric scientists sometimes seek to better understand a model atmosphere or climate system, or a simulated hurricane, just as they aim to better understand the real atmosphere and climate system and real hurricanes. In general, however, this model-directed understanding is desired as a means to better understanding weather and climate in the real world.

3. Computer simulation results as surrogate observational data

One way to learn about phenomena is to study them observationally, i.e. to collect data regarding their properties using instruments or even the naked eye. Sometimes, these data provide information that leads to significant progress in developing accurate explanations and conceptual models. For example, when there are several competing accounts of the mechanism by which a phenomenon is produced, trustworthy observational data might strongly support one of the proposed mechanisms while indicating that the others are untenable. In such a situation, the observational data provide valuable explanatory information.[8]

Yet obtaining desired observational data in the study of weather and climate can be quite difficult. Routine observations tend to be made at relatively widely-spaced locations and only a few times a day, while many phenomena and events of interest occur on smaller spatiotemporal scales. In addition, some of these phenomena and events – like supercell thunderstorms and hurricanes – involve intense and dangerous conditions. Radar can provide some information about conditions within a supercell from afar, but it is difficult to make in-situ observations of temperature, humidity and other conditions inside such a storm; one must be willing to brave high winds, lightning, heavy rain, hail and perhaps a tornado, and measurements still usually will cover only a relatively limited spatiotemporal domain.

Computer simulations, by contrast, provide values for every variable in the model, at every spatial grid point, for every time step in the simulation. Moreover, simulation results can be examined from the comfort of the computer lab, without risking life and limb and, in many cases, can be obtained for substantially less cost than observational data collected in specialized observing campaigns. So it is not surprising that atmospheric scientists sometimes analyze simulation output in place of real-world data, learning which features of a phenomenon of interest arise in what order in the simulation, how key atmospheric fields (e.g. temperature, pressure, vorticity) are structured at particular time steps, how they change from one time step to the next, etc. (see

[8] What counts as explanatory information for a given scientist, of course, will depend on her background knowledge and cognitive capacities; she must be able to see that the information obtained is relevant to an explanatory goal.

Figure 2 for an illustration).[9] Here, advanced visualization tools, which allow scientists to plot and animate results in ways that make desired information more salient, are especially valuable (see also Winsberg 1999). Just as traditional observational data can aid the development of conceptual models and can favor one proposed explanation over another, so too can simulation results analyzed as surrogate observational data.

The case of supercell thunderstorms illustrates this nicely. Relatively high-resolution simulations of supercells were developed in the early 1980s, drawing on some of the same theoretical foundations used in weather forecasting (i.e. fluid dynamics and thermodynamics) but focusing on a smaller spatiotemporal scale. While traditional observations of the complicated inner workings of supercells were difficult to make, these simulations and their increasingly-sophisticated successors provided "complete kinematic and thermodynamic data both in and around a [simulated] storm" (Klemp 1987, 372). Upon examining and analyzing these data with the help of advanced visualization techniques, atmospheric scientists developed new hypotheses about the mechanisms responsible for salient features of supercells, such as their tendency to propagate to the right of the mean environmental wind (Rotunno and Klemp 1985). In addition, some existing hypotheses about supercell dynamics were called into question because they appeared inconsistent with what was observed to happen in simulations (see e.g. Klemp 1987, 395, and Houze 1994, 294, on the role of the rear-flank downdraft in the transition of the supercell to its tornadic phase), while others were supported by the simulation results.

[FIGURE 2 ABOUT HERE]

In general, conceptual models and explanations developed by analyzing simulation results as surrogate observational data – such as the explanation of storm propagation mentioned above – are treated as *how-possibly* or *how-plausibly* models and explanations, pending further empirical investigation.[10] For instance, a review article on supercells, written shortly after the first wave of

[9] This is what I mean by using simulation results as "surrogate" observational data; they are a surrogate or stand-in for "real" observational data.
[10] See Machamer et al. 2000 and Craver 2006 for further discussion of *how-possibly, how-plausibly* and *how-actually* explanations of the mechanistic variety.

high-resolution simulation studies, draws heavily on these studies but cautions that:

> …although these [simulation] models have demonstrated good qualitative agreement with observed storms, some of the mechanisms derived from the detailed analyses of simulated storms must still be tested against future data that will be obtained from the increasingly sophisticated storm-observing systems. (Klemp 1987, 372)

Fifteen years later, a more specialized review article expresses the same sentiment, but only after attributing to simulation studies "significant advances in our understanding of supercells" (Markowski 2002, 870). By this time, some of the mechanisms derived from detailed analyses of simulated storms had been accepted and, while others remained more hypothetical, they provided starting points for further investigation – starting points that might well have been lacking if atmospheric scientists had not been able to "look inside" simulated supercells, examining their detailed inner workings. It was not possible to do this for real supercells, given the limited availability of observational data, and simply inspecting the theoretical equations used in storm simulations provides little insight into the complex dynamical evolution of supercells. Indeed, as the same review notes, "it is probable that some conclusions drawn from simulation results never could have been made from observations or theory alone" (ibid).

Thus, as the case of supercells illustrates, the use of simulation results as surrogate observational data can promote both sorts of understanding identified in Section 2. It does this in part by facilitating the development of descriptive and explanatory hypotheses. These hypotheses provide a starting point for further empirical investigation and may eventually be accepted as correct, as when how-possibly or how-plausibly explanations become accepted as *how-actually* explanations in light of subsequent empirical investigation. (The design of such empirical investigation is itself often strongly influenced by what the simulation results indicate, e.g. about where in the storm one should look to find evidence of a particular structure or process.) Without simulation results that stand in for observational data, even how-plausibly explanations for some phenomena might remain out of reach for much longer.

4. Testing hypotheses

A second important way in which the computer helps to advance understanding in the study of weather and climate is by facilitating *tests* of hypotheses relevant to explanation – tests that in many cases would not otherwise be feasible. As Jule Charney put it not long after high-speed digital computers were introduced:

> The radical alteration that is now taking place [in dynamical meteorology] is due not merely to the ability of the machine to solve known equations with known initial and boundary conditions but even more to its ability to serve as an inductive device. … The machine, by reducing the mathematical difficulties involved in carrying a physical argument to its logical conclusion, makes possible the making and testing of physical hypotheses in a field where controlled experiment is still visionary and [physical] model experiment difficult, and so permits a wider range of inductive methods. (Charney 1955, 798-9)

Here, the physical hypotheses of interest concerned the mechanisms responsible for salient, large-scale features of the atmosphere, such as the high- and low-pressure systems that regularly populate the middle latitudes. But the value of the computer for testing hypotheses about climate change was also emphasized early on; even as computer models of the climate system were in their early days, atmospheric scientist Edward Lorenz suggested that "perhaps there should be a center for climatic change hypothesis testing" (Lorenz 1970, 328), where the tests would be carried out with the help of computers.[11]

But how can the computer facilitate hypothesis testing? And what sorts of hypotheses can be tested? According to the Charney passage, the computer facilitates testing by "reducing the mathematical difficulties involved in carrying a physical argument to its logical conclusion" (1955, 798). Put differently, the computer allows scientists to see what follows (or fails to follow) from the physical assumptions reflected in different mathematical models of the atmosphere or climate system – models for which analytical solutions are out of

[11] The climate system is usually defined to include the atmosphere, ocean, land surface and cryosphere. Today's state-of-the-art global climate models incorporate not only atmospheric models similar to those used in weather forecasting, but also representations of these other component systems. Historically, climate modeling grew out of atmospheric modeling, with the first global atmospheric modeling results obtained by Norman Phillips in a project aimed to construct a "dynamic climatology" (see Charney 1955; Phillips 1956).

reach. This allows scientists to test hypotheses about the *sufficiency* of different sets of causal factors (processes, conditions, forces) for producing a phenomenon or event or feature of the atmosphere/climate system, and it can also facilitate tests of hypotheses regarding *necessary* causal factors.

To see why, suppose an atmospheric scientist hypothesizes that *H*: Causal factors $\{c_1 \ldots c_n\}$ are jointly sufficient for producing *P*, a particular phenomenon or event. Even if the scientist cannot say exactly how $\{c_1 \ldots c_n\}$ would produce *P*, she might test *H* by building a mathematical model that accurately represents the mutual interactions among $\{c_1 \ldots c_n\}$ and then checking whether that model entails the occurrence of *P*. Computers help with the latter step, i.e. checking whether the model entails the occurrence of *P*. Of course, typically the computer delivers only approximate solutions to the modelling equations of interest, so it is important to consider whether the occurrence/non-occurrence of *P* in a simulation is a product of errors introduced by the methods used to estimate solutions or by programming mistakes. But when there is reason to think that such errors did not interfere in this way, and that $\{c_1 \ldots c_n\}$ and other important system processes have been adequately represented via the modelling equations, then the simulations produced can provide evidence regarding *H*. In particular, if the simulations produce something closely resembling *P*, then this is evidence for *H*; if they do not produce anything like *P*, then this is evidence against *H*.[12]

In 1970, when Lorenz was writing, hypotheses about climate change mainly concerned the causes of past ice ages and very fundamental questions about the climate system, such as whether there might be more than one semi-stable climate for Earth even when important factors like incoming solar energy and the chemical composition of the atmosphere are held constant. Lorenz describes how the computer could help test the latter sort of hypothesis:

> Meanwhile, it is of interest to ask what would happen if we took the mathematical models which are currently being used to simulate climate, without any modification to accommodate existing climatic change hypotheses, and performed experiments lasting centuries or more. Would climatic changes be revealed? If we include as one hypothesis of climatic

[12] Of course, there is still an empirical dimension to these tests – there is an empirical phenomenon or event or feature to be accounted for. The computer helps with the step in testing that involves deriving a prediction or conclusion from the set of equations.

change the proposition that no processes other than those commonly considered in short-range weather forecasting are needed to bring about changes in climate, we would be testing this hypothesis (Lorenz 1970, 328).

In other words, we would be testing the hypothesis that H: The physical processes represented in 1970-era weather forecasting models are sufficient to produce changes in climate. (Models then used to simulate climate were very similar to the models used in short-range weather forecasting at the time.)

For a more recent example, consider a hypothesis about the causes of late twentieth century global warming, H_1: Estimated changes in natural forcing factors are sufficient to produce most of the global warming observed to occur during the second half of the twentieth century; changes in greenhouse gas emissions and other human-related factors need not have contributed much. To test H_1, scientists might run today's state-of-the-art climate models, allowing natural forcing factors (i.e. changes in solar output and volcanic aerosols) to vary in accordance with twentieth century estimates but holding fixed all anthropogenic forcing factors. Of interest would be whether global warming similar in magnitude to that observed during the latter half of the twentieth century occurred in the simulations. In fact, such simulations have been produced, and they do not show warming similar to that observed to occur during the second half of the twentieth century (see Figure 3b). Insofar as natural forcing factors and important climate system processes are adequately represented in today's climate models, this finding is evidence against H_1.[13]

[FIGURE 3 ABOUT HERE]

By contrast, simulations produced with state-of-the-art climate models that include representations of both anthropogenic and natural forcing factors do show changes in global mean temperature that (roughly) match those estimated from twentieth century observations (see Figure 3a). Insofar as the identified forcing factors and important climate system processes are adequately represented in today's climate models, this finding supports hypothesis H_2: These anthropogenic and natural forcing factors are sufficient to produce

[13] Here, I mean adequately represented for purposes of discerning the major causes of late twentieth century global warming; a model might be adequate for this purpose but not, say, for giving precise quantitative predictions of long-term regional and local changes in climate.

(roughly) the changes in global mean temperature observed to occur over the course of the twentieth century. Moreover, to the extent that there is also good reason to think that all major natural forcing factors have been identified, the two sets of simulations together also support H_3: Anthropogenic forcing factors are necessary to account for observed twentieth century global warming.

As the examples illustrate, the conclusion that simulations results provide evidence of the sufficiency or necessity of a set of causal factors rests on some significant assumptions, for instance, that the causal factors of interest, as well as important system processes, are adequately represented in the models used. In the case of hypotheses about necessary factors, there is also the assumption that all of the plausible candidate factors have been identified. The difficulty in justifying these assumptions will vary from case to case. Some of the easier cases are those in which hypotheses concern the sufficiency of a relatively small set of causal factors for producing *P,* and something resembling *P* does appear in the simulations. For instance, early investigations found that phenomena resembling extratropical cyclones, the large low-pressure systems that bring poor weather in the middle latitudes, would develop in simulations made with simple atmospheric models that represented a reduced set of causal factors (see Charney 1955, 800-801), supporting the hypothesis that those factors are sufficient for cyclogenesis.[14] On the other hand, with a system as complex as the climate system, about which there is substantial but still rather limited knowledge, it is not easy to argue persuasively that all candidate causes of a climate phenomenon have been identified, which is required when testing whether a particular causal factor is necessary. The rejection of H_1 above is resisted by some individuals precisely on the grounds that there may be other important natural forcing factors – such as cosmic rays – that are not represented, or not represented adequately, in today's models.[15]

So how does using computers to test hypotheses about necessary and sufficient causal factors advance understanding? Once again, the clearest links

[14] Charney concluded that these simulation studies had determined the actual cause of cyclogenesis (see Charney 1955, 801), but this conclusion would seem unwarranted, since existing rival hypotheses had not been tested.

[15] It is beyond the scope of this paper to examine past and ongoing scientific debates about additional natural forcing factors. Such debates do, however, merit further attention from philosophers of science and scholars in STS. For more on the assumptions made in contemporary detection and attribution studies, see Solomon et al. 2007, Parker 2010 and Petersen 2012.

have to do with explanation: testing these hypotheses sometimes provides explanatory information. Learning that a set of causal factors is sufficient for producing phenomenon *P* indicates that a causal or mechanistic explanation of *P* in terms of those causal factors should be possible; one can then being pursuing such an explanation.[16] Learning that the set of factors is not sufficient for producing *P* can prevent one from wasting time trying to find such an explanation. Moreover, learning that particular causal factors are necessary for producing *P* can strongly constrain the space of possible explanations of *P* (e.g. the range of mechanism descriptions) that should be taken seriously.

5. Experimenting on models / exploring hierarchies

The atmosphere and climate system are made up of numerous nonlinear and interactive processes, making it difficult to infer causal relationships by simply observing these systems in action. By experimenting on a computer simulation model of the atmosphere or climate system in various ways – "turning off" particular physical processes, varying the values of parameters, etc. – and comparing the simulations produced with and without these interventions, scientists investigate the contributions of the manipulated processes and parameters in producing (simulated) phenomena of interest. For instance, a scientist might include more realistic topography in a climate model in order to learn whether this *makes much difference* to the amount of (simulated) annual precipitation that falls over the United States or to other outcomes of interest. What is learned in this way about dependencies in the model can provide a starting point for identifying the mechanisms by which real-world phenomena are produced and for reasoning about the effects of particular interventions. In this way, it can promote both sorts of understanding identified in Section 2.

In fact, a closely related approach to advancing understanding of the atmosphere and climate system was explicitly recommended when the digital computer first came on the scene. The idea was to start with simplified models that represent in an idealized way a reduced set of causal factors thought to be particularly important in shaping system behavior, and then gradually increase the models' complexity by including representations of additional causal factors and/or by representing previously-included factors more realistically (see e.g.

[16] There is no guarantee that such an explanation will be correct, of course, but at least one's efforts are directed in a potentially fruitful way.

Charney 1949, Phillips 1956, Lorenz 1960; see also Dahan Dalmedico 2001). By observing how the simulated atmosphere or climate system changed with the addition of each new causal factor, such as frictional drag or a primitive hydrologic cycle, scientists could develop a storehouse of information about dependences in simpler models, which would serve as a resource for constructing explanations of the behavior of more complex models and of the real atmosphere and climate system.[17]

In other words, understanding was to be advanced by constructing and experimenting on *a hierarchy of models of increasingly complexity*, not by running the most comprehensive and "realistic" computer simulation model possible. The latter was considered unlikely to help much with the goal of identifying the causal contributions of different factors:

> The total behavior of the [atmospheric] circulation is so complex that the relative importance of various physical features, such as the Earth's topography and the presence of water, is no more evident from an examination of numerical solutions than from direct observations of the real atmosphere. (Lorenz 1967, 134)

On Lorenz's view, "it is only when we use systematically imperfect equations or initial conditions that we can begin to gain further understanding of the phenomena which we observe" (1960, 244). Doing so can show us how things would be different – in the simulated system and perhaps in the real system – if particular factors were absent or changed.

So have atmospheric scientists followed the hierarchies-of-models approach to advancing understanding? That is, have collections of systematically-related models been carefully developed and intensively studied, to provide a foundation for explaining the observed behavior of the atmosphere and climate system and for reasoning about how weather and climate would be different if conditions were changed in various ways? Only to a limited extent, it would appear. While significant progress via a hierarchy-of-models approach was made early on, in recent decades a tremendous increase in computing power

[17] This strategy calls to mind uses of "false" models in biology identified by William Wimsatt: "An oversimplified model may act as a starting point in a series of models of increasing complexity and realism" and "An oversimplified model may provide a simpler model for answering questions about the properties of more complex models that also appear in the simpler case, and answers derived here can sometimes be extended to cover the more complex models" (1987, 30-31).

and a growing interest in predicting future climate change has led atmospheric scientists to focus their efforts on the development of more and more comprehensive and detailed models, without attending carefully to how they relate to other models and without investing comparable effort in understanding simpler ones.

This state of affairs has not gone unnoticed. Recently, atmospheric scientist Isaac Held (2005) expressed concern over the growing gap between what can be simulated with today's climate models and what is understood about the climate system and its dynamics. He calls for renewed efforts to develop "hierarchies of lasting value" – sets of systematically-related "elegant" models, the careful study of which can provide a foundation for understanding the real atmosphere and climate system.[18] Constructing hierarchies of lasting value will not be easy, he suggests. Unlike molecular biologists, who in their quest to understand human biology at the molecular level are provided by nature with a ready-made, evolutionarily-connected hierarchy of model organisms, ranging from bacteria to fruit fly to mouse to man, atmospheric scientists must construct their hierarchies from scratch; nevertheless, they should try to identify "the *E.coli* of climate models" as well as models of intermediate complexity that they take "just as seriously as do the biologists who map out every single connection in the nervous system of the snail" (ibid, 1610 & 1614). Despite the challenges associated with a hierarchies-of-models approach, on Held's view, "there are no alternatives if we want to understand the climate system and our comprehensive climate models" (ibid, 1610).[19]

As noted above, experimenting on a computer model of the atmosphere or climate system can provide explanatory information and can aid and inform reasoning about the effects of particular interventions on the real system. Exploration of a hierarchy of models of the atmosphere or climate system involves extensive experimentation on models, with similar benefits. Moreover,

[18] By "elegant" models, he means ones that include only what is necessary to "to capture the essence of a particular source of complexity" in the atmosphere or climate system (Held 2005, 1613).

[19] While this is a strong claim, it is difficult to see how else desired understanding of these complex systems would be achieved, given humans' cognitive limitations. Of course, particular questions about the atmosphere and climate system might be answered in other ways – e.g. by experimenting on a single model. But understanding the atmosphere or climate system (in the sense of *understanding a complex phenomenon/system* as discussed in Section 2) aims at more comprehensive knowledge and know-how.

in the long run, such exploration/experimentation can create a familiarity with the behavior of model atmospheres and climate systems, and with the ways in which different causal factors shape their behavior, that can enhance scientists' ability to synthesize and apply existing knowledge to answer additional questions about their real counterparts (i.e. can help to develop this know-how).[20,21] Exploration of a hierarchy of systematically-related models is, and is explicitly recognized to be, a long-term strategy for advancing understanding of the atmosphere and climate system – a strategy that involves leveraging knowledge about and experience with simpler models to make progress in understanding more complex models and systems.

6. Concluding remarks

In the half century since its introduction, the computer has helped to transform the study of weather and climate. Its impact has been felt not just in weather prediction, where dramatic increases in forecast skill have been achieved, but also in basic research that aims to advance understanding of weather and climate phenomena and of the atmosphere and climate system as a whole.

Three ways in which the computer has helped to advance understanding in this arena were identified above. First, the computer has been used to produce simulations that supply surrogate observational data, aiding the development of conceptual models and explanations. Second, it has been used to facilitate tests of explanatory hypotheses, especially hypotheses about the causal factors that are necessary or sufficient for producing a phenomenon of interest. Third, the computer has been used to experiment on models, including models related systematically in a hierarchy; this not only can reveal information that aids the search for explanations but also can create a familiarity with the behaviour of model atmospheres and climate systems that enhances one's

[20] Here, I refer to the know-how involved in carrying out qualitative reasoning about the system, or in deciding which process to represent, and in what manner, in a mathematical model of the system, etc., given the goal of correctly answering some additional question about the system (see Section 2).

[21] As Lenhard (2009) suggests, with experimentation on models, one may develop "the ability to recognize … qualitatively characteristic consequences of modelling assumptions even though the modelling dynamic remains partly opaque" (p.173).

ability to synthesize and apply existing knowledge to answer additional questions about these systems.

The discussion also revealed, however, some limitations or caveats on these uses of the computer to advance understanding. For instance, conceptual models and explanations developed by analyzing simulation results as surrogate observational data are treated as *how-possibly* or *how-plausibly* models and explanations, pending further empirical investigation; they are not, nor should they be, immediately accepted as *how-actually* models and explanations. Likewise, testing hypotheses about the sufficiency or necessity of sets of causal factors requires some significant assumptions – for instance, that the causal factors of interest, as well as important system processes, are adequately represented in the models used – and these assumptions are sometimes difficult to justify.

Despite these limitations and caveats, the computer is now firmly established as an important tool for advancing understanding in the study of weather and climate. This paper provided a preliminary overview of some of the ways in which the computer is used to advance understanding in this arena. These practices involving simulation, both in the study of weather and climate and in other fields, merit additional attention from philosophers of science and scholars in STS; further analysis and detailed case studies can shed more light on how use of the digital computer is enriching and transforming the quest for understanding in science.

References

Bechtel, William, and Adele Abrahamsen. 2010. "Dynamic Mechanistic Explanation: Computational Modeling of Circadian Rhythms as an Exemplar for Cognitive Science." *Studies in History and Philosophy of Science A*, doi:10.1016/j.shpsa.2010.07.003.

Bjerknes, Vilhelm. 1904. "Das Problem der Wettervorhersage, betrachtet von Standpunkt der Mechanick und Physic." *Meteorologische Zeitschrift* 21: 1-7.

Cartwright, Nancy. 1983. *How the Laws of Physics Lie.* Oxford: Oxford University Press.

Charney, Jule G. 1947. "Dynamics of long waves in a baroclinic westerly current." *Journal of Meteorology* 4: 135-162.

Charney, Jule G. 1949. "On a Physical Basis for Numerical Prediction of Large-Scale Motions in the Atmosphere." *Journal of Meteorology* 6: 371-385.

Charney, Jule G. 1951. "Dynamical forecasting by numerical process." Pp. 470-482 in *Compendium of Meteorology*. Boston: American Meteorological Society.

Charney, Jule G. 1955. "Numerical Methods in Dynamical Meteorology." *Proceedings of the National Academy of Science* 41(11): 798–802.

Craver, Carl F. 2006. "When mechanistic models explain." *Synthese* 153: 355–376.

Dahan Dalmedico, Amy. 2001. "History and Epistemology of Models: Meteorology (1946–1963) as a Case Study." *Archive for the History of the Exact Sciences* 55: 395–422.

de Regt, Henk W. and Dennis Dieks. 2005. "A Contextual Approach to Scientific Understanding." *Synthese* 144: 137-170.

de Regt, Henk W. 2009. “The Epistemic Value of Understanding.” *Philosophy of Science* 76(5): 585-597.

Grimm, Steven R. 2006. “Is Understanding A Species of Knowledge?” *British Journal for the Philosophy of Science* 57: 515-535.

Hegerl, Gabriele C. et al. 2007. “Understanding and Attributing Climate Change.” Pp. 663-745 in Solomon et al. 2007.

Held, Isaac. 2005. “The Gap between Simulation and Understanding in Climate Modeling.” *Bulletin of the American Meteorological Society* 86(11): 1609-1614.

Houze, Robert. 1994. *Cloud Dynamics*. San Diego: Academic Press.

Houze, Robert et al. 2007. “Hurricane Intensity and Eyewall Replacement.” *Science* 315(5816): 1235-1239.

Jewitt, Brian F. and Robert B. Wilhemson. 2006. “The Role of Forcing in Cell Morphology and Evolution within Midlatitude Squall Lines.” *Monthly Weather Review* 134: 3714-3734.

Klemp, Joseph B. 1987. “Dynamics of Tornadic Thunderstorms.” *Annual Reviews of Fluid Mechanics* 19: 369-402.

Lenhard, Johannes. 2009. “The Great Deluge: Simulation Modeling and Scientific Understanding.” Pp. 169-186 in *Scientific Understanding*. Edited by Henk W. de Regt, Sabine Leonelli and Kai Eigner. Pittsburgh: University of Pittsburgh Press.

Lorenz, Edward N. 1960. “Maximum simplification of the dynamic equations.” *Tellus* 12: 243-254.

Lorenz, Edward N. 1967. *The Nature and Theory of the General Circulation of the Atmosphere.* Geneva: World Meteorological Organization.

Lorenz, Edward N. 1970. “Climatic Change as a Mathematical Problem.” *Journal of Applied Meteorology* 9: 325-329.

Machamer, Peter K., Darden, Lindley, and Carl F. Craver. 2000. “Thinking about Mechanisms.” *Philosophy of Science 57*: 1–25.

Markowski, Paul M. 2002. “Hook Echoes and Rear-Flank Downdrafts: A Review.” *Monthly Weather Review* 130: 852-876.

Parker, Wendy S. 2003. *Computer Modeling in Climate Science: Experiment, Explanation, Pluralism*. PhD Dissertation. Pittsburgh: University of Pittsburgh.

Parker, Wendy S. 2010. Comparative process tracing and climate change fingerprints. *Philosophy of Science* 77(5): 1083-1095.

Petersen, Arthur C. 2000. Philosophy of Climate Science. *Bulletin of the American Meteorological Association* 81(2): 265-271.

Petersen, Arthur C. 2012. *Simulating Nature*, 2nd edition. Boca Raton: CRC Press.

Phillips, Norman A. 1956. “The general circulation of the atmosphere: a numerical experiment.” *Quarterly Journal of the Royal Meteorological Society* 82: 123-164.

Railton, Peter. 1981. “Probability, Explanation, and Information.” *Synthese* 48: 233-256.

Richardson, Lewis F. 1922/1965. *Weather Prediction by Numerical Process.* New York: Dover.

Rotunno, Richard and Joseph B. Klemp. 1985. “On the rotation and propagation of simulated supercell thunderstorms.” *Journal of the Atmospheric Sciences* 42: 271-92.

Schneider, Stephen H. and Robert E. Dickinson. 1974. “Climate Modeling.” *Reviews of Geophysics and Space Physics* 12: 447-493.

Solomon, Susan et al. (eds.) 2007. *Climate Change 2007: The Physical Science Basis.* Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. New York: Cambridge University Press.

Strevens, Michael. 2008. *Depth: An Account of Scientific Explanation*. Cambridge: Harvard University Press.

Strevens, Michael. 2012. No understanding without explanation. *Studies in History and Philosophy of Science A.* http://dx.doi.org/10.1016/j.shpsa.2012.12.005.

Wimsatt, William C. 1987. “False models as means to truer theories.” Pp. 23-55 in *Neutral Models in Biology.* Edited by in Matthew Nitecki and Antoni Hoffman. London: Oxford University Press.

Winsberg, Eric. 1999. “Sanctioning Models: The Epistemology of Simulation.” *Science in Context* 12(2): 275-292.

Ylikoski, Petri, and Jaakko Kuorikoski. 2010. “Dissecting explanatory power.” *Philosophical Studies* 148: 201-219.

Ylikoski, Petri. This volume. Agent-Based Simulation and Sociological Understanding.

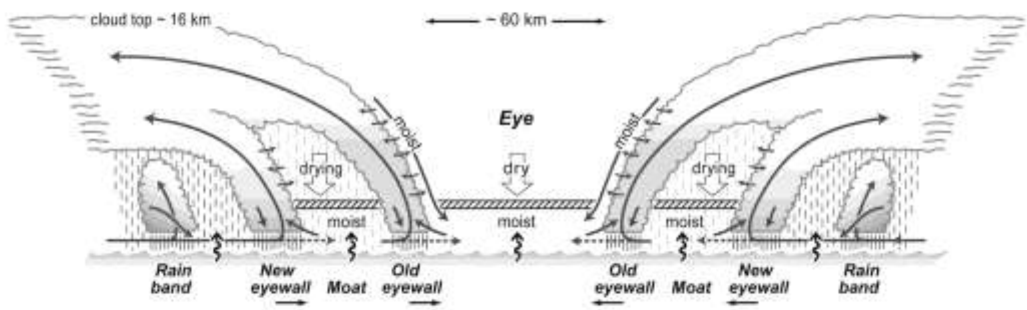

Figure 1. Diagrammatic portion of a conceptual model of a hurricane undergoing eyewall replacement (From Houze et al. 2007, Figure 4; see original caption and accompanying text for further details).

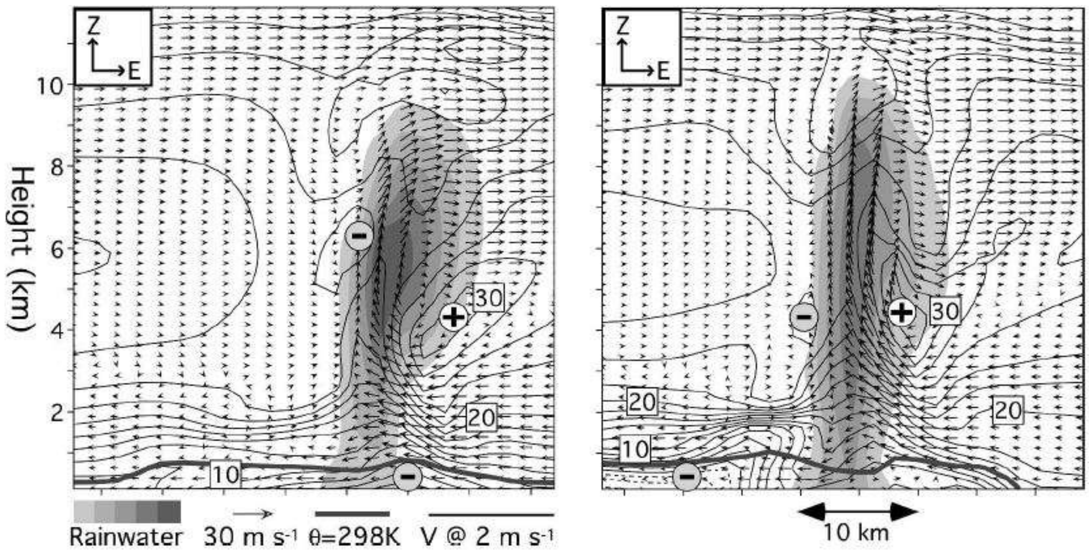

Figure 2. Vertical cross section of conditions 75 minutes into a simulation of convection when the convection is isolated (left) and along a frontal boundary (right). The plot shows rainwater density (shading), wind speed and direction in the plane (arrows) and normal to the plane (contours), locations of prominent minima and maxima (+/-), and the location of the 298°K potential temperature isotherm (dark grey line). (From Jewitt and Wilhelmson 2006, Figure 12)

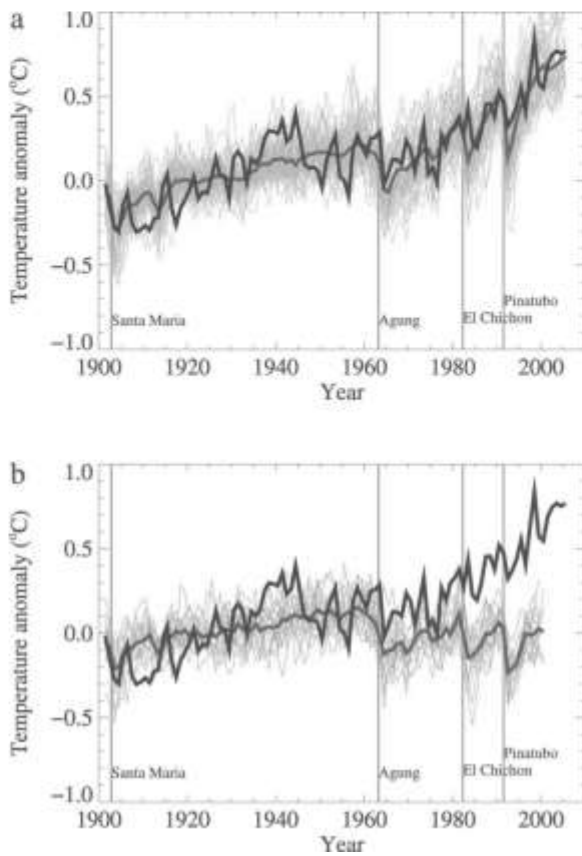

Figure 3. Global mean surface temperature anomalies over the 20th century from observations (black) and from simulations (thin light grey) when the simulations include (a) both natural and anthropogenic forcing factors and (b) natural forcing factors only. Anomalies comprising a given time series are calculated relative to the global mean surface temperature for that simulation (or from observations) during the period 1900-1950. The heavier grey line shows the average anomaly in the simulations. (Adapted from Hegerl et al. 2007, Figure 9.5)