Learning Without Representation: The Epistemic Role of Models in Climate Science

Gabriel Târziu[1] and Borut Trpin[2]

[1] *LMU Munich, Gabriel.Tarziu@lmu.de*

[2] *LMU Munich, University of Maribor, University of Ljubljana, borut.trpin1@um.si*

Abstract: This paper aims to develop a novel account of how scientific models of complex systems can provide us with knowledge, drawing on insights from climate modelling. We begin by critically examining the prevalent representation-based views of models, which struggle to account for the common practice of using contradictory models and model hierarchies. We then argue that scientific models (especially those of complex systems) are better understood as structures that do not need to represent the target system to be epistemically useful. Instead, their usefulness lies in the fact that they are part of an iterative process of knowledge improvement and restructuring.

Keywords: scientific models, inconsistency of models, hierarchies of models, climate modelling, model-based reasoning, philosophy of science

1. Introduction

Climate science presents us with a plethora of models[1] of different types. We have zero-, one-, two- and three-dimensional energy-balance models, radiative-convective models, dimensionally constrained models, intermediate complexity models, machine-learning-based models, convection-permitting models, surrogate models or emulators, general circulation models (GCMs), and coupled models, which are often used simultaneously in hierarchies of models. An unavoidable question in this context is why climate scientists need so many models. Why do they devote time to building such a great variety of different models instead of concentrating

[1] Unless specified otherwise, throughout this paper we will use (scientific) models to refer to abstract (i.e., conceptual) models, by which we mean all non-physical scientific models.

exclusively on perfecting the most 'realistic' climate models that we have (i.e., the Earth system models)?[2] Why and how is this helpful for learning things about Earth's climate system?

This paper aims to answer this last question in a manner distinct from the representationalist tradition. Our main guiding intuition is that, due to the complexity of the system of interest, its uniqueness, and size, climate scientists are, in many ways, akin to blind mapmakers. By 'blind mapmaker,' what we have in mind is someone who must draw a map without having direct access to the terrain they are mapping. Suppose that, e.g., in their work, this person has to rely only on vague and sometimes unreliable information about a particular landscape – let's call it **L**. Consequently, they can only make informed guesses about what **L** might look like. As expected, this approach carries a significant epistemic limitation: these maps cannot be used in the same way as conventional maps because one cannot *learn from* guesses (no matter how elaborate they may be) the way they learn from maps. Nonetheless, a learning process can take place. To see it, we just have to shift our attention from the maps to the process of (blind) mapmaking. We can imagine, for instance, that our blind mapmaker would resort to a variety of strategies to iteratively refine their map – by 'refine' we don't mean improving representational accuracy, which, given the lack of proper epistemic access to **L**, they cannot properly check. Instead, we mean making their maps useful for specific purposes, such as estimating the time it would take someone to cross **L** from point A to point B. To achieve this, they might build a variety of maps with different degrees of complexity. They could also ask their colleagues to create separate maps of the same terrain and then compare all of them to identify common features. We submit that this is similar to what happens in climate science.

A second important intuition that guides our discussion is that *aboutness does not imply (structural) similarity*. An extreme example is Picasso's Guernica, which is meant to be about the bombing of the Basque town of Guernica during the Spanish Civil War. However, taking this painting as having any kind of structural similarity to the historical events would stretch the concept of similarity beyond its breaking point. This has the important implication that, to the extent that one considers representation to involve some form of similarity (which we believe it should), aboutness cannot be understood solely in terms of representation. This is significant for

[2] Much of the effort in climate science is, of course, concentrated on perfecting the GCMs by increasing their resolution and complexity. We are not questioning that. What we are asking here is why climate scientists consider it important to develop so many other kinds of models besides GCMs.

our discussion because it allows us to say the following: although the maps in the blind mapmaker example are clearly meant to be about **L**, they should not be considered representations of **L**. The reason for this is, of course, different from the case of Guernica, where the focus is on eliciting a strong emotional response rather than accurately depicting historical events. Instead, in the blind mapmaker case, representational failure has to do with the lack of appropriate epistemic access to the system of interest. In contexts such as these, models are about the system by being tools that we can use in the context of an iterative process of knowledge improvement and restructuring. Therefore, when we claim below that climate models don't represent the climate system, we are not saying that they are not *about it*. What we are claiming is that their epistemic role is different than that of regular maps.

A final intuition relevant to our discussion is that *representational accuracy is not necessary for epistemic usefulness*. Consider again the scenario of crossing **L**. Imagine that our mapmaker and their colleagues create three different maps, each leading to the same result: it takes about a month to travel from point A to point B (an estimation they have some reasons to believe to be good). However, the reasons for this conclusion differ: the first map attributes it to the size of **L**, the second to the presence of a mountain range in **L**, and the third to the presence of a river in **L** that blocks the path from A to B and can only be crossed at certain points. If the only concern is the time required to cross **L**, all these maps can be considered equally useful, despite there being no reason to believe any of them is representationally accurate.

Before moving forward with the discussion, it is helpful to say a few words about the view that we are trying to distance ourselves from in this paper, i.e. the representationalist view of models. From a strong representationalist perspective (Bartels 2006; da Costa and French 2003; French 2003; Giere 1999; Pincock 2004; van Fraassen 1980), models play their important epistemic role(s) in science because they bear a mind-independent relation (e.g., isomorphism, partial isomorphism or homomorphism) to their target systems which assures that the information they provide is also valid about the latter. The diversity of models can then be explained by the complexity of the target system, which can hardly be covered by a single model.

The weak (pragmatic/artefactual) representationalist view of models (Bokulich 2013; Currie 2017; Frigg 2022; Frigg and Nguyen 2017, 2020; Knuuttila 2011, 2021a, 2021b; Mäki 2009; Suárez 2004) can be used to come up with a different account of what happens in climate science. According to this view, "no thing is a representation of something else in and of itself"

(Knuuttila 2011, p. 265). Models only gain a representational function if they are used in certain ways, and so the representational relationship holding between models and their target systems should be thought of in terms of what the users' epistemic goals are and what they can accomplish. So, from this perspective, the great diversity of models is explained by the "'division of cognitive labor' among models" (Bokulich 2013, p. 116), i.e., the diversity of epistemic purposes that the climate scientists have in their inquiry pertaining to the climate system.

Although there are important differences between these two broadly conceived views about how models work, they have a lot in common, particularly regarding the way models are used to learn about the world. If we strip away most of the details, we can think about them as being essentially based on the following two central theses:

> **LF** (Learning-From Thesis): Scientists can learn things about the world from studying scientific models.
>
> **IR** (Indispensability of Representation): What makes it possible for models to play this important epistemic role is the existence of a representational relationship holding between them and their target systems.

As we will show, this common core makes these views of models equally vulnerable to two important problems: the problem of inconsistency (due to the use of several inconsistent models) and the problem of hierarchies (due to simultaneous use of models at various levels of comprehensiveness). While these problems may not be insurmountable, they highlight the necessity of exploring an alternative approach.

Our aim in this paper is to provide a new view of how we learn with scientific models, grounded in the modelling practices of climate science, while offering insights applicable to the study of complex systems more broadly. In a nutshell, our account avoids the problems because it denies **LF** and **IR**: we *do not* learn things about the world *from* studying models (except when using physical models) and the learning does not depend on representation. We can learn things *with the models*, though, through a more complicated epistemic process of iterative improvements and reorganisations of our knowledge.

The paper is structured in the following way. The next two sections (2 and 3) will be devoted to discussing the problems of inconsistency and hierarchies in more detail. In section 4, we will introduce our non-representational account of scientific models. We will then show how our account deals with the problems of inconsistency and hierarchies in section 5. We conclude in section 6.

2. Representation and Inconsistency

Consistency is often declared, in the traditional way of thinking about this topic, as an essential aspect of a good scientific theory in two senses, internally and externally (Douglas 2009, pp. 89–94; Kuhn 1977, pp. 321–323). The former sense applies to propositions which belong to some specific theory. If (some) of these propositions are logically inconsistent, then this "implies a fundamental contradiction within a theory, and from a clear contradiction any random conclusions (or predictions) can be drawn, [so] lacking internal consistency is a serious epistemic failing." (Douglas, 2009, p. 94). The problem of inconsistency is not limited to scientific theories; it is also sometimes raised as an objection to specific scientific models. For example, Bohr's atomic model has often been criticised for being internally inconsistent (see Kragh, 2011, for a review).

External inconsistency, i.e., the use of several models based on inconsistent assumptions, is perhaps even more common in scientific practice. In climate science we encounter a great number of GCMs that are different in at least the following two important respects: they use different parametrisations for the subgrid-scale processes and/or they use different equation sets for the dynamic core (e.g., some of them, such as the Goddard Earth Observing System Model, use the fully compressible, non-hydrostatic Euler equations, while others, such as the European Centre Hamburg Model, use the hydrostatic primitive equations). These models are used largely for the same epistemic purposes, such as understanding climate dynamics, making climate change projections, understanding climate change variability, and climate change attribution studies.[3] However, as the climate scientists will confirm, "there is no single agreed-on 'best' model... So, while multiple models could be seen as ontologically incompatible (strictly speaking, they make conflicting assumptions about the real world), and one could argue that scientists have to assess how well they are supported by the data, the community seems happy with the model pluralism" (Knutti et al. 2019, p. 840).

[3] So, what we are dealing with here is not covered by what Weisberg calls "multiple-models idealisation" (MMI), i.e., a kind of idealisation that can be justified by the fact that the models involved in it play various competing representational goals (Weisberg 2007, p. 645).

It is worth pointing out that internal and external inconsistencies of models are particularly problematic if we consider scientific models to be representations of some target system in a similar way as a map is a representation of some area. A map is useful only if it is an (at least somewhat accurate) representation of the world. Hence, if a map shows a forest in the middle of an ocean, then it is internally inconsistent and therefore wrong – no area may be simultaneously covered by a deep sea and a forest. Similarly, if one map indicates that a specific location is a forest and another map claims the same location is an ocean and if we assume that both maps refer to the state of the world at the same time, then at least one (if not both) must be incorrect. This exemplifies how inconsistency in a representational system may be taken as a signal that something is fundamentally wrong with the system.

In practice, however, scientific models often exhibit inconsistencies and yet remain in regular scientific use. For instance, Bohr's model of the atom was abandoned not because of its known inconsistencies but because later, more precise experiments raised questions that the model could not answer (Kragh 2011, p. 349). Why is this the case?

The counter-tradition approach to this issue is to bite the bullet and embrace inconsistency as "a fact of life in science" and not consider it as a "kiss of death" (Davey 2014, p. 3010) or something to be feared. As the literature on this topic shows, philosophers adopting this approach have developed elegant views on how scientists manage to avoid the logical problems associated with the presence of inconsistency in science. Examples include da Costa's and French's partial structures approach and Priest's paraconsistent approach (see, for instance, the papers in Meheus 2002 and the discussion in Vickers 2013).

However, as argued among others by Davey (2014), the counter-tradition is problematic because the examples of inconsistency it relies on to break with the traditional way of thinking fail to support its case. Some involve mathematical errors, others represent intermediary stages on the way to better theories, and still others are cases where scientists are only committed to the claim that a particular model or theory of a system is good for certain purposes, while another model or theory of the same system is good for others. In the last situation, although the models or theories are different ways of representing the world, "when taken together they are better understood as complementary rather than contradictory" (Morrison 2011, p. 344).

We align with Davey on this issue. However, we believe that considering models as complementary rather than contradictory is not valid for climate science. As discussed above, GCMs are usually used for the same purposes in climate science, and it is quite common (see, for instance, the IPCC's assessment reports) to consider most, if not all, of them simultaneously. We believe that the only way to avoid embracing inconsistency (and thus renouncing the traditional way of thinking) in this context is to deny that these models are representations. For this reason, we propose that it is better to think of climate models and models of complex systems in general as guesses (similar to how maps of **L** are guesses) rather than representations.

Before addressing how the models are to be understood in a non-representational sense, let us now turn to the problem of hierarchies, which is especially pertinent in climate science.

3. Hierarchies of Models

Earth's climate is a forced, dissipative, complex, multi-component system composed of a great number of nested and interlinked subsystems, that is also complex and that has a chaotic dynamic and a heterogeneous phenomenology. These characteristics, together with the fact that the climate system is very large and unique (aspects which affect our ability to make adequate observations and to perform experiments on it), make modelling it a very difficult undertaking.

Take, for instance, model evaluation[4] as one of the particularly difficult tasks in climate modelling. One of the most important questions that the climate models are supposed to answer is how much the anthropogenic greenhouse gas emissions will warm our planet, i.e., how severe climate change will be. To quantify the amount of warming to be expected, climate scientists use (among other things, such as the transient climate response and the Earth system sensitivity) the equilibrium climate sensitivity (ECS) which is supposed to measure the global average surface temperature response to a doubling of CO_2 in the atmosphere from the preindustrial conditions and letting the system return to equilibrium. The estimated range of ECS is, according to the IPCC's latest assessment report (AR6), 1.5°C to 4.5°C which is the same as the range estimated in the *Charney Report* 45 years ago (Bony et al. 2013; National Research Council 1979). Given its importance, a lot of research effort has been directed towards improving the estimated range. Unfortunately, this effort did not generate a convergence towards a particular value. Instead, the

[4] For our purpose here, there is no need to work with a clear meaning of 'model evaluation', so we chose to remain vague about what we mean by this. That is why, in the ensuing discussion we will try to avoid taking 'model evaluation' to mean any of the following things in particular: confirmation, verification, validation, or an assessment of the adequacy-for-purpose of a model. For a discussion of the difference between these, see e.g., Baumberger et al. (2017), Oreskes et al. (1994), Winsberg (2018, Chapter 10), Winsberg (2022).

model spread has increased (compared with that produced with older models), with some new models predicting an ECS over 5°C (see, for instance, the discussion in IPCC 2023, Chapter 7).

This raises the question: is there no way of determining which of the models is correct and which is wrong in this regard? The answer is complicated. First of all, we have to keep in mind that ECS is a theoretical construct (the forcing is not real, and the equilibrium is hypothetical because the actual Earth's climate is always in a state of flux) and as such cannot be compared in a *direct* way with something from the system. Secondly, even if ECS had been a real physical quantity, directly measuring it would have been impossible due to the time scale involved (because of the ocean's high heat capacity, it would take a very long time for the climate system to reach a new equilibrium).

Of course, there are ways in which ECS can be estimated from the instrumental records, but these are not more reliable than the ones based on climate models and are also not done without using models (Knutti et al. 2017; Knutti and Hegerl 2008). So, what happens is that, most often, in order to estimate ECS, climate scientists use multiple lines of evidence (e.g., process understanding, paleoclimate data, instrumental records, multi-model ensembles) and a hierarchy of models. This hierarchy is composed of simple models at one end of the spectrum (e.g., the zero-dimensional and the two-zone models used in Bates, 2012), which are used to understand the basic dynamics and the main feedback mechanisms active in the climate system, and comprehensive coupled models at the other end. The comprehensive models are coupled general circulation models which include at least the main components of the climate system (i.e., the atmosphere, the ocean, and the land), the interaction between them, and as many physical processes as possible. Due to their complexity, the use of these models is restricted by computational limitations. In the middle of the hierarchy, we find the Earth system models of intermediate complexity (EMICs) which, although they include more physical processes and interactions than the simple models, can be used for long-term integrations (thousands of years) and so are useful for studying long-term climate dynamics and feedbacks (Plattner et al. 2008).

Why is this important for our discussion? Because it shows that the concern with determining whether models stand in a suitable representational relationship with the target system (whether this is considered relative to a particular purpose or not) is not central for (at least some cases of) model evaluation. In our example, what climate scientists basically end up doing when testing model outputs is nothing more than making inter-model comparisons. The results obtained with GCMs are validated by comparing them with and interpreting them in terms of the understanding provided by simple models and EMICs (Ghil and Robertson 2000, p. 228).

This situation is, of course, not specific to the case of ECS. Claims such as the one below made by Hegerl and Zwiers about climate change detection and attribution are quite common in the climate scientific literature:

> Climate change "detection and attribution requires a model of why climate may be changing to be able to draw conclusions from observations. Models used in the interpretation of observations can range from simple conceptual 'models' to climate models of intermediate complexity, and ultimately to coupled atmosphere-ocean general circulation models and earth system models" (Hegerl and Zwiers 2011, p. 585).

How does this discussion square with a representationalist view of models? To the extent to which it shows that, in performing these important modelling tasks, the climate scientists do not seem particularly concerned with representational accuracy, it can be taken as a source of big problems for the representational views of models. This is because comparing the models with the target system plays only a minimal (if any) role when climate models are used. What our discussion hopefully makes clear is that, because the climate system has all the features listed at the beginning of this section, which make direct epistemic access to it impossible, climate scientists (like in the case of the blind mapmaker discussed in the introduction) had to come up with a different way of performing the modelling tasks than by checking whether the models stand in the suitable relationship with the system. Basically, their solution is to rely on their understanding of the main processes at play in the behaviour of the system. The way this understanding is tested and improved is not by interacting with the system, but by experimenting with a variety of configurations of different levels of complexity.

4. A New (Non-Representational) View of Models

In the previous sections, we identified two key issues associated with the representationalist view of models: inconsistency and hierarchical thinking. The discussion about these problems was not meant to provide a definitive argument against the representationalist position, but to pave the way for our account by highlighting some of its limitations. In this section, we aim to introduce a new account of models that overcomes these limitations. We will do so by comparing a case in which representationalism seems to be the right view about how models are used to learn about the world – namely, the case of physical models – to the way we use models of complex systems, such as those for the general circulation of the atmosphere. By the end of our discussion, we hope to demonstrate that although the representationalist view applies to the way we use physical models, it is not very good for helping us understand how models of complex systems work.

*4.1. Learning **From** Physical Models*

As Ankeny and Leonelli, (2020, p. 6) note, "Model organisms help to create knowledge that can be projected beyond the immediate domain in which it was produced." This observation extends to physical models more broadly. But how do these models function in generating knowledge? More specifically, what are the key characteristics of the epistemic process involved in understanding the world through physical models? Consider the use of *Caenorhabditis elegans* (*C. elegans*) as a model in biology. This nematode, given its simple anatomy (its body is composed of only 959 somatic cells), is extensively used in developmental biology and neurobiology mostly because of the ease with which one can create cell lineage maps that can be subsequently used to identify how specific cells contribute to different tissues and organs.

In justifying the use of *C. elegans* as a model organism, biologists rely (mostly) on the following two empirical hypotheses:

- **H$_1$**: The signalling pathways and molecular mechanisms identified in *C. elegans* are evolutionarily conserved across species.
- **H$_2$**: Complex organisms and different species have homologues for the genes and proteins found in *C. elegans* that perform similar functions.

What these hypotheses are meant to do is to ensure that *C. elegans* can play the role of a surrogate, i.e., that it can be used as "a more manageable experimental setup for studying a phenomenon, where this experimental setup serves as a substitute for another, experimentally less manageable, but physiologically more relevant setup" (Baetu 2016, p. 945). They act as an *epistemic tether* that guarantees that what we discover by studying this nematode is relevant to what goes on with other animals. With this case in mind, we can now explore the epistemic characteristics of learning from physical models:

1. Independence of Target Systems: Physical models either exist and function independently of the target systems or are composed of parts that can exist and function independently of the target systems (e.g., scale models in geosciences). *C. elegans* existed well before biologists decided to use it as a model organism, just as the materials used in geological scale models predate their application in studying mountain formation. The same, clearly, also holds for materials used by atmospheric scientists when constructing the Plumb-McEwan model for understanding the stratospheric Quasi-Biennial Oscillation.

2. Need for Justification: The use of physical models requires justification, often in the form of empirical hypotheses. Since the models are made from preexisting materials or entities, they typically lack a direct connection to the target system. For example, in the absence of hypotheses $\mathbf{H_1}$ and $\mathbf{H_2}$, it would not make sense to use *C. elegans* to model the neural network development in humans. Similarly, the choice of materials in geological models must be justified by ensuring they appropriately scale the relevant forces and processes (Bokulich and Oreskes 2017, p. 896).

3. Epistemic Tethering: The justification for a model ensures that the model is epistemically linked to the target system, meaning it accurately represents the relevant aspects of that system. For example, hypotheses $\mathbf{H_1}$ and $\mathbf{H_2}$ ensure that *C. elegans* serves as a valid model for studying neuronal network development in more complex organisms, including humans. This tethering has two key implications:

(a) *How good a model is* depends on how well it is tethered to its target system, and

(b) a well-tethered model offers *mediated access* to the actual system of interest.

4. Learning From Models: We learn *from* models by studying them, which involves observation, experimentation and analysis. For instance, to discover how growing axons are guided to their correct targets during development in *C. elegans*, biologists use a variety of experimental and observational techniques, such as mutagenesis and fluorescent labelling.

5. Ampliative Reasoning: Model-based reasoning extends our knowledge beyond the model itself. Because physical models operate according to natural laws, independent of our minds, they can reveal unexpected insights. By applying tethering hypotheses, findings from the model can be extrapolated to the target systems, thereby amplifying our knowledge about them. In the case of *C. elegans*, we can use $\mathbf{H_1}$ to infer that whatever we discover about axon guidance by studying this nematode will provide insights into similar processes in more complex organisms, including humans.

Two important things stand out from our discussion of the case of physical models. The first one is that these models can be taken to provide a *window* into how their target systems work and so that we can *learn from them* about the target. The second is that, for the first point to be possible, a good tether has to be in place that can constrain the lessons that we can learn from the model so that they are relevant in connection to the intended target.

What this means is that the **LF** and **IR** theses are indeed valid as far as physical models are concerned: the scientists can learn things about the world from these models and what makes this possible is a special relationship holding between the models and their targets. Hence, the representationalist view about the way models give us knowledge accommodates the case of the physical models very well.

*4.2. Learning **With** Abstract Models*

We will now show that scientific models of complex systems, on the other hand, often defy representationalist views. To illustrate this, consider the early modelling the general circulation of Earth's atmosphere.[5] We suggest to consider this historical example because it is both illustrative and manageable, and because its historical trajectory allows us to understand how the case developed.

Before the early 16th century, Earth's atmosphere was thought to lack a global structure. This view changed with the discovery of the trade winds—consistent east-to-west winds

[5] In discussing this case we are mainly following the detailed historical account presented in Lorenz (1967).

dominating the tropics, blowing from around 30 degrees latitude to the equator. Edmond Halley was the first to attempt an explanation for these winds in his 1686 paper “An Historical Account of the Trade Winds, and Monsoons, Observable in the Seas between and near the Tropicks, with an Attempt to Assign the Physical Cause of the Said Winds.” Halley proposed that the Sun’s heating of the tropics causes the air to become lighter and rise. Because of mass continuity, the rising air in the low latitudes must sink in high latitudes, resulting in a poleward drift at upper part and an equatorward drift in the lower part. Halley believed that the east-to-west direction of the trade winds was due to the air following the Sun’s path. However, his explanation cannot be considered a model of global atmospheric circulation because it was focused solely on wind patterns over the surface of the oceans, not a comprehensive global circulation pattern.

Nearly fifty years after Halley's work, George Hadley proposed the first model of global atmospheric circulation in his 1735 paper, "Concerning the Cause of the General Trade-Winds." Hadley accepted Halley’s ideas about mass conservation and the north-south atmospheric motion but sought a better explanation for the direction of the trade winds. He modified Halley’s view by taking into account the fact that Earth is a rotating object, and that air preserves its absolute angular momentum.[6]

A picture of global circulation may be derived from Hadley’s model: a simple toroidal circulation with warm air rising at the equator due to intense solar heating and mass conservation driving it poleward at upper levels. As the air moves, it tilts eastward because it retains the higher rotational speed of the equator, a result of conserving angular momentum. Upon reaching the poles, the air cools, sinks, and returns toward the equator at lower altitudes. The friction and rotational effects create a more complex flow than Halley’s initial simple equator-to-pole model. Hadley also deduced that the surface eastward-moving winds in the middle latitudes are necessary to prevent the slowing of Earth's rotation due to drag from westward-moving winds at lower latitudes. Friction explains why the observed winds are not stronger. Finally, Hadley’s model predicted westward-moving trade winds in the tropics due to the conservation of angular momentum.

How does using this model compare with case of the physical models discussed earlier? Let us consider the following points:

[6] More precisely, Hadley talked about the conservation of velocity instead of absolute angular momentum.

1. Dependence on Target Systems: Unlike physical models, abstract models do not have an independent existence; they are created to serve an epistemic purpose related to a target system. Hadley's model, for example, was created specifically to explain the occurrence of the trade winds in the tropics. The model creatively organised knowledge available to Hadley at that time and made it relevant to the question of interest to him.

2. No Need for Justification: Since they are explicitly created in connection to a target system, abstract models do not need a justification for their use as models of those systems. For example, Hadley's model has no need for hypotheses like those used when applying *C. elegans* model. For abstract models, the focus is on model creation rather than justification.[7]

3. Epistemic Tethering: Unlike physical models, abstract models do not rely on epistemic tethers for their validity. The creation of Hadley's model, for instance, may be reconstructed as following four phases of finding a solution to a mathematical problem distinguished by Polya, (1945, pp. 5–6): (i) understanding the problem (what exactly is required), (ii) seeing how various items are connected (how the unknown is linked to the data) and making a plan about how best to approach the problem, (iii) carrying out the plan, and finally (iv) looking back and reviewing the solution. Hadley could only rely on little physics (Newton's theory was known at that time, but the scientific community lacked a proper understanding of the conservation of angular momentum[8] and the Coriolis effect was not yet known) and little data about the system (e.g., there was no knowledge of the fact that the atmosphere is layered). Remarkably, this limited knowledge was enough for him to construct an abstract structure in which the unknown (the trade winds) was connected to the known. This was a highly creative process on Hadley's part in which tethers played no part. This point has two important implications:

(a) *How good a model is* in helping us learn about a target system is no longer judged by how well it is tethered to that system but by how effectively it leverages existing knowledge. This

---

[7] The importance of the construction process for the epistemology of models is, of course, emphasized in previous work – most prominently perhaps by Morgan and Morrison (1999). Our approach is different because we are not interested in the role of theories in model construction or in making clear that models are constructed to serve specific epistemic purposes by making use of various representational tools Knuuttila (2021b, 2021a). Our aim is to argue that, if we look at how models are constructed, it becomes clear that representation plays no role.

[8] As already mentioned, Hadley made use of the conservation of velocity in his explanation of the deflection of the air from the simple north-east path.

includes the strength of the connections between the known and unknown, the model's success in fulfilling its intended epistemic purpose, and its alignment with observations available at the time of its creation. Edward Lorenz, (1967, p. 60) echoes this view, stating that a model should be valued if it exhibits sound dynamical reasoning and consistency with contemporary observations. He argues that a model of general circulation must account for the transport of angular momentum, energy, and water between latitudes (Lorenz 1991, p. 10). Hadley's model meets these criteria,[9] making it dynamically consistent and epistemically valuable, even though it was later found to be incorrect.

(b) However, abstract models like Hadley's offer *no direct access to the actual system* of interest. Unlike physical models, the knowledge used to build these abstract models is not sufficiently constraining to reveal how the world truly works. As Lorenz notes (1967, p. 60) in connection to what happens in atmospheric sciences, our understanding of the equations governing atmospheric motion and boundary conditions is too incomplete to restrict model construction. Consequently, different assumptions can lead to vastly different circulations, making it difficult to claim that these models provide direct access to the real system.

4. Learning With Models: Unlike physical models, abstract models do not simply allow us to learn *from* them but rather *with* them. Although we do not have the space here for a detailed discussion on how abstract models facilitate learning about the world (which we reserve for another paper), it is important to clarify that these models are not governed by natural laws and do not function independently of our minds. Consequently, we cannot learn about the target system by merely experimenting with the model and observing its behaviour under different conditions. Instead, learning with abstract models involves a complex process of iterative knowledge improvement, facilitated by the model's use.

Consider an example from meteorology in the 19th century. Observations revealed that the eastward-moving winds in the middle latitudes blew from the southwest, contrary to the northwest direction predicted by Hadley's model. In response, several meteorologists proposed new models, but the most significant was independently developed by William Ferrel and James Thomson around 1857-9. They introduced the concept of centrifugal force—a crucial factor that Hadley's

[9] Except, of course, for the water transport requirement. But this, given the knowledge available at that time, can be considered irrelevant.

model had overlooked—and emphasised the importance of the pressure gradient. Incorporating these elements into the model of general circulation led to the realisation that air returning from the poles, slowed by friction near the ground, would lack the necessary centrifugal force (the north-south component of the Coriolis force) relative to the air above it. As a result, the air would begin to drift back towards the poles, eventually forming a new atmospheric cell, now known as the Ferrel cell, which circulates in the opposite direction to the Hadley cell and is not driven by thermal forcing.

As Edward Lorenz (1967, p. 65) notes, "Just as there was little observational evidence in Hadley's day to contradict his scheme, so there was little evidence in Thomson's day to contradict his." This highlights a key aspect of learning with abstract models: once a model serves its epistemic purpose and aligns well with observations, there is not much more that can be done with it. This differs from physical models, where new and unexpected insights can continually be drawn through by studying the model.

The history of atmospheric circulation modelling continued to evolve, particularly with improved observations of higher atmospheric levels and growing evidence of large-scale asymmetries in circulation. However, this brief overview suffices to illustrate our point: with abstract models, learning is achieved progressively through a constant restructuring of our knowledge to solve specific epistemic problems that are generated by our interaction with the world. Hadley, Ferrel, Thomson, and later researchers like Jeffrey, Starr, and Bjerknes all used the knowledge available to them to refine their models in response to new observations and problems.

5. Non-Ampliative Nature of Model-Based Reasoning: Abstract models are mental constructs based on the knowledge available at the moment of their creation and are subject to the laws of thought (i.e., to logic and whatever mathematical framework, if any, one uses to formulate them). As such, they function pretty much like any mathematical solution to a problem by organising our knowledge in such a way that the unknown can be linked (in a regulated way) to the known. This is significant because it means that what you get out of these models cannot exceed what you put in: the models merely help us understand the implications of our knowledge. In other words, model-based reasoning is nonampliative in the case of abstract models. Hadley’s model, for instance, explored the implications of the framework he developed but did not yield new information about atmospheric dynamics beyond its initial scope. Experimenting with abstract

models (or using the models in an exploratory way as discussed for instance in Fisher et al., 2021, and Massimi, 2019) is, from our perspective, nothing more than exploring the implications of different ways of structuring our knowledge.

In our view, then, abstract models should be primarily understood as tools for organising and structuring knowledge to extract useful implications, where "useful" is context-dependent and tied to the specific needs of the scientific community in relation to a target system. Unlike representationalist views, which suggest we learn directly from models, our perspective suggests that we learn *with* models through an iterative process of knowledge improvement and restructuring. This distinction means that the "learning from" (**LF**) thesis, which applies to physical models, does not hold for abstract models. Since **LF** does not apply in our framework, **IR** also loses its place. Moreover, as argued earlier, the knowledge used to construct abstract models is not sufficiently constraining to fulfil the role that **IR** demands.

Thus, for abstract models and their role in helping us understand the world, the following theses are more fitting than the representationalist approach:

> **LW** (Learning With thesis): Scientists can learn things about the world *with* the help of scientific models (but not directly *from* them!).
>
> **DR** (Dispensability of Representation): No special relationship (besides what we get from the knowledge used in the process of model construction) between models and target systems is needed to make it possible for models to play this important epistemic role.

Before moving on, we want to address one potential worry, namely that our account may not be as non-representational as we take it to be. There is no denying, for example, that Hadley's model is *about* the general circulation of the atmosphere. It is meant to "stand for" that system. This may be perceived as a source of problems for the way we are positioning our account because, as is generally accepted in the literature: "Representation as 'standing for' is embedded in representationalism" (Knuuttila 2011, p. 263). If this is taken to convey what representationalism is all about, then we have no choice but to concede: our account falls into the representationalist camp. However, framing things this way makes it hard to conceive the possibility of there being any other camps. What we want to make clear is that the discussion in this paper is not necessarily aimed at representationalism in general, but at a very specific view about how using models to learn about the world is to be understood (i.e., the view characterised by the **LF** and **IR** theses).

5. How Does the New View Deal With the Problems?

We began this paper by highlighting the overwhelming complexity of climate scientific modelling, given the great number and diversity of models that climate scientists use to study Earth's climate system. This diversity has even left some climate scientists puzzled, prompting them to ask: "Have we at once become Borges's cartographers as well as denizens of Babel?" (Jeevanjee et al. 2017, p. 1760). From an epistemological perspective, this situation raises a significant problem: How can we use this great diversity of (at least most of the time) mutually inconsistent models to learn something about the target system? In other words, what epistemic utility can the information that we receive from a plurality of mutually inconsistent models of a physical system actually have?

Consider, for example, the state-of-the-art coupled climate models like the Goddard Earth Observing System Model and the European Centre Hamburg Model. Both are designed to serve the same epistemic purposes, yet they have very different configurations and offer varying predictions about future atmospheric conditions—such as differing values for Equilibrium Climate Sensitivity (ECS). How, then, can these models be useful for learning about the climate system?

As we have argued in this paper, this problem becomes particularly challenging if we adhere to a representationalist view of modelling—where we expect to learn directly from models as accurate representations of target systems. However, if we adopt the perspective on models and learning proposed in this paper, these issues are easily resolved. The key insight is that we do not learn *directly from* the models themselves but rather *with* their help. The diverse knowledge structures employed in modelling are not inconsistent because they are not intended to serve as surrogates for the target system. Therefore, they should not be judged by how accurately they represent that system. Instead, these models are tools designed to enhance our knowledge through continuous restructuring, aimed at solving specific epistemic problems that arise from our interaction with the world. Each model helps in organizing our knowledge with respect to the problem at hand. However, since our knowledge is not sufficiently constrained (as we tried to make clear above, this happens in the case of complex systems due to the lack of proper epistemic access to the systems), we can end up with different configurations based on the same knowledge (by, e.g., employing slightly different assumptions). This approach makes the models complementary in improving and restructuring our knowledge, rather than contradictory, as we do not use models to directly learn what the target system is like.

The use of model hierarchies is also easily explained. Remember that from our perspective modelling is similar to solving mathematical problems. In mathematics, when faced with a difficult problem, a common approach is to first find a similar simpler problem and solve it. By solving this simpler version, we can then gradually move on to more complex settings. The solution to the simpler problem provides a foundation for improving more complex configurations, as well as a means to evaluate them and identify potential sources of errors. This is mirrored in climate science, where results from simpler models can be used to verify, for example, whether uncertainties in climate sensitivity are related to convective parameterisations or some other factor.

The picture we are trying to paint here is that there are (at least) two fundamentally different types of models: physical models and abstract models, each functioning in distinct ways. Physical models operate as representationalists suggest all models do. These models are often easier-to-handle configurations or chosen for other practical reasons, and they serve as proxies for a target system, studied with the aim of learning about that system. The key to their effectiveness lies in what we call "epistemic tethers"—a set of hypotheses that ensure the model shares relevant features with its target. These tethers allow us to extrapolate findings from the model to the actual system. Crucially, physical models do not encounter the problems discussed earlier in sections 2 and 3. When epistemic tethers are well chosen, different models do not yield conflicting results and thereby avoid inconsistency. To use our previous example, because (as it seems) hypotheses $\mathbf{H_1}$ and $\mathbf{H_2}$ are true, what we learn about the neural network development from *C. elegans* is consistent with what we learn from *Drosophila melanogaster*, *Danio rerio*, *Xenopus Laevis*, and other species. If this would not have been the case, it would mean that either $\mathbf{H_1}$ or $\mathbf{H_2}$ is false and so that *C. elegans* cannot be used as a reliable model for understanding the molecular mechanisms underlying neuronal network development in more complex organisms.

Why are representationalists then not also right about abstract models of complex systems? We believe that this is because unlike physical models, abstract models do not act as direct representations of the target system. Hence, a representationalist account about what the learning process is all about makes abstract models appear as very problematic tools for learning about the world (due to the problem of inconsistency). Moreover, the view fails to adequately explain modelling practices such as the one encountered in climate science (due to the problem of hierarchies).

6. Conclusion

Abstract models of complex systems serve as tools for structuring and organising knowledge. They facilitate an iterative process of knowledge improvement rather than offering direct insights into the target systems. Our account offers a novel perspective on what learning with abstract models entails—one that, we believe, aligns more closely with the practices observed in climate science and does not render these models as problematic epistemic tools. This approach not only resolves the two main problems for representationalists (inconsistency and model hierarchies), but also supports a more accurate and practical understanding of how models contribute to scientific inquiry.

Although our discussion has been motivated by challenges in climate scientific modelling, the insights apply more broadly to abstract models of complex systems. For example, consider the use of abstract models in social sciences. In social sciences, agent-based models are used to simulate complex social processes, like the evolution of norms or organisational adaptation (Epstein 2012). These models abstract away many details to focus on specific interactions and processes, offering insights into patterns and trends rather than precise predictions. Similarly, in engineering, the use of models to simulate traffic flow (Aleksander and Paweł 2020) allows for iterative improvements and optimisation, even though these models do not capture every detail of the real-world systems they represent.

Rather than going further into how our account applies to modelling practices beyond climate science, we return to our central question: How do models give us knowledge? We hope to have established that abstract models give us knowledge not through accurate representation, but rather in a manner that is more akin to mathematical problem-solving: through an iterative process that focuses on uncovering patterns and improving understanding of the target system.

References

Aleksander, R., & Paweł, C. (2020). Recent advances in traffic optimisation: systematic literature review of modern models, methods and algorithms. *IET Intelligent Transport Systems*, *14*(13), 1740–1758. https://doi.org/10.1049/iet-its.2020.0328

Ankeny, R., & Leonelli, S. (2020). *Model Organisms*. Cambridge University Press. https://doi.org/10.1017/9781108593014

Baetu, T. M. (2016). The 'Big Picture': The Problem of Extrapolation in Basic Research. *The British Journal for the Philosophy of Science*, *67*(4), 941–964. https://doi.org/10.1093/bjps/axv018

Bartels, A. (2006). Defending the structural concept of representation. *Theoria*, *21*(1), 7–19. https://doi.org/10.1387/theoria.550

Bates, J. R. (2012). Climate stability and sensitivity in some simple conceptual models. *Climate Dynamics*, *38*(3–4), 455–473. https://doi.org/10.1007/s00382-010-0966-0

Baumberger, C., Knutti, R., & Hirsch Hadorn, G. (2017). Building confidence in climate model projections: an analysis of inferences from fit. *WIREs Climate Change*, *8*(3). https://doi.org/10.1002/wcc.454

Bokulich, A. (2013). Explanatory Models Versus Predictive Models: Reduced Complexity Modeling in Geomorphology. In V. Karakostas & D. Dieks (Eds.), *EPSA11 Perspectives and Foundational Problems in Philosophy of Science* (pp. 115–128). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-01306-0_10

Bokulich, A., & Oreskes, N. (2017). Models in Geosciences. In L. Magnani & T. Bertolotti (Eds.), *Springer Handbook of Model-Based Science* (pp. 891–911). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-30526-4_41

Bony, S., Stevens, B., Held, I. M., Mitchell, J. F., Dufresne, J.-L., Emanuel, K. A., et al. (2013). Carbon Dioxide and Climate: Perspectives on a Scientific Assessment. In G. R. Asrar & J. W. Hurrell (Eds.), *Climate Science for Serving Society* (pp. 391–413). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-007-6692-1_14

Currie, A. (2017). From Models-as-Fictions to Models-as-Tools. *Ergo, an Open Access Journal of Philosophy*, *4*(20201214). https://doi.org/10.3998/ergo.12405314.0004.027

da Costa, N. C. A., & French, S. (2003). *Science and Partial Truth*. New York: Oxford University Press. https://doi.org/10.1093/019515651X.001.0001

Davey, K. (2014). Can good science be logically inconsistent? *Synthese*, *191*(13), 3009–3026. https://doi.org/10.1007/s11229-014-0470-x

Douglas, H. E. (2009). *Science, Policy, and the Value-Free Ideal*. Pittsburgh: University of Pittsburgh Press. https://doi.org/10.2307/j.ctt6wrc78

Epstein, J. M. (2012). *Generative Social Science: Studies in Agent-Based Computational Modeling*. Princeton University Press. https://doi.org/10.1515/9781400842872

Fisher, G., Gelfert, A., & Steinle, F. (2021). Exploratory Models and Exploratory Modeling in Science: Introduction. *Perspectives on Science*, *29*(4), 355–358. https://doi.org/10.1162/posc_e_00374

French, S. (2003). A Model-Theoretic Account of Representation (Or, I Don't Know Much about Art…but I Know It Involves Isomorphism). *Philosophy of Science*, *70*(5), 1472–1483. https://doi.org/10.1086/377423

Frigg, R. (2022). *Models and Theories*. London: Routledge. https://doi.org/10.4324/9781003285106

Frigg, R., & Nguyen, J. (2017). Models and Representation. In L. Magnani & T. Bertolotti (Eds.), *Springer Handbook of Model-Based Science* (pp. 49–102). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-30526-4_3

Frigg, R., & Nguyen, J. (2020). *Modelling Nature: An Opinionated Introduction to Scientific Representation* (Vol. 427). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-45153-0

Ghil, M., & Robertson, A. W. (2000). Solving Problems with GCMs: General Circulation Models and Their Role in the Climate Modeling Hierarchy. In D. A. Randall (Ed.), *General Circulation Model Development* (pp. 285–325). London: Academic Press. https://doi.org/10.1016/S0074-6142(00)80058-3

Giere, R. N. (1999). Using Models to Represent Reality. In L. Magnani, N. J. Nersessian, & P. Thagard (Eds.), *Model-Based Reasoning in Scientific Discovery* (pp. 41–57). Boston, MA: Springer US. https://doi.org/10.1007/978-1-4615-4813-3_3

Hegerl, G., & Zwiers, F. (2011). Use of models in detection and attribution of climate change. *WIREs Climate Change*, *2*(4), 570–591. https://doi.org/10.1002/wcc.121

Intergovernmental Panel on Climate Change (IPCC). (2023). *Climate Change 2021 – The Physical Science Basis*. Cambridge University Press. https://doi.org/10.1017/9781009157896

Jeevanjee, N., Hassanzadeh, P., Hill, S., & Sheshadri, A. (2017). A perspective on climate model hierarchies. *Journal of Advances in Modeling Earth Systems*, *9*(4), 1760–1771. https://doi.org/10.1002/2017MS001038

Knutti, R., Baumberger, C., & Hirsch Hadorn, G. (2019). Uncertainty Quantification Using Multiple Models—Prospects and Challenges. In C. Beisbart & N. J. Saam (Eds.), *Computer Simulation Validation. Simulation Foundations, Methods and Applications* (pp. 835–855). Cham: Springer. https://doi.org/10.1007/978-3-319-70766-2_34

Knutti, R., & Hegerl, G. C. (2008). The equilibrium sensitivity of the Earth's temperature to radiation changes. *Nature Geoscience*, *1*(11), 735–743. https://doi.org/10.1038/ngeo337

Knutti, R., Rugenstein, M. A. A., & Hegerl, G. C. (2017). Beyond equilibrium climate sensitivity. *Nature Geoscience*, *10*(10), 727–736. https://doi.org/10.1038/ngeo3017

Knuuttila, T. (2011). Modelling and representing: An artefactual approach to model-based representation. *Studies in History and Philosophy of Science Part A*, *42*(2), 262–271. https://doi.org/10.1016/j.shpsa.2010.11.034

Knuuttila, T. (2021a). Imagination extended and embedded: artifactual versus fictional accounts of models. *Synthese*, *198*(S21), 5077–5097. https://doi.org/10.1007/s11229-017-1545-2

Knuuttila, T. (2021b). Models, Fictions and Artifacts. In W. J. Gonzalez (Ed.), *Language and Scientific Research* (pp. 199–220). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-60537-7_7

Kragh, H. (2011). Conceptual objections to the Bohr atomic theory — do electrons have a "free will"? *The European Physical Journal H*, *36*(3), 327–352. https://doi.org/10.1140/epjh/e2011-20031-x

Kuhn, T. S. (1977). *The Essential Tension: Selected Studies in Scientific Tradition and Change*. Chicago: University of Chicago Press. https://doi.org/10.7208/chicago/9780226217239.001.0001

Lorenz, E. N. (1967). *The nature and theory of the general circulation of the atmosphere*. Geneva: World Meteorological Organization.

Lorenz, E. N. (1991). The general circulation of the atmosphere: an evolving problem. *Tellus B*, *43*(4), 8–15. https://doi.org/10.1034/j.1600-0889.1991.t01-3-00003.x

Mäki, U. (2009). MISSing the World. Models as Isolations and Credible Surrogate Systems. *Erkenntnis*, *70*(1), 29–43. https://doi.org/10.1007/s10670-008-9135-9

Massimi, M. (2019). Two Kinds of Exploratory Models. *Philosophy of Science*, *86*(5), 869–881. https://doi.org/10.1086/705494

Meheus, J. (Ed.). (2002). *Inconsistency in Science*. Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-017-0085-6

Morgan, M. S., & Morrison, M. (Eds.). (1999). *Models as Mediators*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511660108

Morrison, M. (2011). One phenomenon, many models: Inconsistency and complementarity. *Studies in History and Philosophy of Science Part A*, *42*(2), 342–351. https://doi.org/10.1016/j.shpsa.2010.11.042

National Research Council. (1979). *Carbon Dioxide and Climate: A Scientific Assessment*. Washington, D.C.: National Academies Press. https://doi.org/10.17226/12181

Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. *Science*, *263*(5147), 641–646. https://doi.org/10.1126/science.263.5147.641

Pincock, C. (2004). A New Perspective on the Problem of Applying Mathematics. *Philosophia Mathematica*, *12*(2), 135–161. https://doi.org/10.1093/philmat/12.2.135

Plattner, G.-K., Knutti, R., Joos, F., Stocker, T. F., von Bloh, W., Brovkin, V., et al. (2008). Long-Term Climate Commitments Projected with Climate–Carbon Cycle Models. *Journal of Climate*, *21*(12), 2721–2751. https://doi.org/10.1175/2007JCLI1905.1

Polya, G. (1945). *How to Solve It: A New Aspect of Mathematical Method*. Princeton, NJ: Princeton University Press.

Suárez, M. (2004). An Inferential Conception of Scientific Representation. *Philosophy of Science*, *71*(5), 767–779. https://doi.org/10.1086/421415

van Fraassen, Bas. C. (1980). *The Scientific Image*. Oxford: Oxford University Press. https://doi.org/10.1093/0198244274.001.0001

Vickers, P. (2013). *Understanding Inconsistent Science*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199692026.001.0001

Weisberg, M. (2007). Three Kinds of Idealization. *Journal of Philosophy*, *104*(12), 639–659. https://doi.org/10.5840/jphil20071041240

Winsberg, E. (2018). *Philosophy and Climate Science*. Cambridge University Press. https://doi.org/10.1017/9781108164290

Winsberg, E. (2022). Computer Simulations in Science. In E. N. Zalta & U. Nodelman (Eds.), *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University.