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Uncertainty in Climate Science

The Constitutive Elements of Uncertainties in Climate Model Projections

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List of abbreviations and symbols

CA Cellular Automata

CIME Common Infrastructure for Modelling the Earth

CMIP Coupled Model Intercomparison Project

ENIAC Electronic Numerical Integrator and Computer

IAM Integrated Assessment Model

IPCC Intergovernmental Panel on Climate Change

MIP Model Intercomparison Project

ScenarioMIP Scenario Model Intercomparison Project

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1. Introduction

"That there is much uncertainty about the system modeled is precisely one of the main reasons why it is being modeled." (Suárez: 65).

Good news for Belgians: our famous Burgundian lifestyle is being upgraded by an additional regional product. Yes, nowadays, the Belgian wine sector is growing by no less than fifteen to twenty per cent a year, and this way the Belgian monetary nobility knows what to do with its land. This is apparently due to an otherwise unpopular phenomenon: climate change (Moors 2023).

Unfortunately, the Belgian viticulture sector is an exceptional case for which climate change is a blessing. The consequences of the rather abstract concept–an increase in the incidence of extreme weather events, rising sea levels, prolonged droughts, higher temperatures and so on - are less appreciated in many other areas. The *Duin voor Dijk* (Dune for Dike) pilot project is creating denser dunes to protect the dike from water extremes (Blauwe Cluster 2022); this is not pleasant, according to some Belgians, who realise that the monetary value of their coastal residence will plummet if the sea view is lost (Renson 2024). But there are worse things than the loss of the sea sight: in 2020, water suddenly stopped coming out of the tap in Overijse. The culprits were prolonged drought and poor water management (Ysebaert 2020). One year later, the extreme rainfall in Western Europe became the second most expensive natural disaster of that year worldwide with the cost estimated at 38 billion euros, in addition, 240 people died (Van Fleteren 2021).

Naturally, these events are interpreted in terms of climate change (at least by those who are not dogmatic climate deniers) and this is a well-justified belief given the content of the sixth cycle assessment report of the Intergovernmental Panel on Climate Change (IPCC):

> Human influence has likely increased the chance of compound extreme events since the 1950s. This includes increases in the frequency of concurrent heatwaves and droughts on the global scale (high confidence), fire weather in some regions of all inhabited continents (medium confidence), and compound flooding in some locations (medium confidence) (IPCC 2023: 9).

Nevertheless, whether a particular weather event is a consequence of climate change cannot be confirmed. Climate models predict the increasing incidence of extreme weather events, but it remains impossible to project where and when this will manifest with sufficient certainty.

Climate model outputs are plagued with uncertainty; this fact evokes controversy about how they should be interpreted, communicated, and used in decision-making. What do these models tell us and is there a reason to base any policy decisions on their outcomes if these outcomes are so highly uncertain? To warrant our trust in the model outcomes in light of decision-making, the sources of and reasons for the uncertainty should be well-understood.

In this thesis, I will investigate the emergence of uncertainty in climate model projections. More precisely, I am interested in what elements throughout the modelling process are constitutive to the uncertainty in the outcomes and how this uncertainty should be interpreted. This is an epistemological question: I will consider whether trust in the outcomes is warranted, based on a philosophical analysis of the climate modelling process.

At the beginning of my inquiry–with just enough background knowledge about the climate and modelling in science to be sceptical–I had an intuition that climate models could not be adequate. At most, they show that disaster will force, but nothing more. Furthermore, I hypothesised that all uncertainty in the outcomes can be traced back to the original discrepancy between our perception of a thing and the inaccessible thing-in-itself–which also partially clarifies the initial scepticism regarding the truthfulness of the outcomes. On the other hand, given the fact that the global scientific community has not given up on modelling the climate yet, I supposed that my sceptical intuition had to be, at least partially, wrong.

Before diving headlong into the quest for the answer to the research question 'Is the trust in model outcomes warranted?', here is a brief overview of the course of the journey ahead: I will examine climate modelling from three main perspectives: the conceptual, the phenomenological, and the technical point of view. first, I will take a closer look at the concept of model (§ 2.1 & 2.3), system (§ 2.2), and climate (§ 3.1-3.3). Then, I will conduct a phenomenological analysis of the concept of climate to understand how our experience relates to the scientifically constructed concepts and the models thereof (§ 3.4). Afterwards, I will delve into the technicalities of the climate modelling process and examine the construction of single model components (§ 4.1), coupled global earth system models (§ 4.2), and model ensembles (§ 4.3). After each modelling phase, the implications of the employed methods to the uncertainty in the resulting model and model outcomes will be highlighted. Finally, I will bring the findings of the three perspectives together in a concluding chapter (§ 5) and provide an outlook (§ 6).

2. Modelling in science

In this chapter, I will set out some history and philosophical insights about modelling in science. Models have replaced theories at the centre of scientific attention relatively recently: from 1920 onwards, models gained prominence as instruments of scientific inquiry (Frigg 2023: 1). Philosophers started to pay attention to them only in the second half of the twentieth century (Vorms 2018: 172).

2.1. A history of modelling in science

2.1.1. The advent of the modelling approach in modern science with Maxwell

According to some, the roots of the word ‘model’ lay in the Latin word ‘modus’ which means ‘measure’. Others, trace it back to the word ‘modulus’ that appeared in the first century BC also meaning ‘measure’, but additionally bearing a particular connotation to the domain of music: it referred to the ‘pitch’ as a measure of time. Around 23 BC, ‘modulus’ is found to be used for the first time in an engineering context[1] (Müller 2009: 638). Throughout history the word ‘model’ has been used in many different contexts, going from models for physical constructions to speaking metaphorically about the model for someone’s behaviour (Müller 2009, 639). What Suarèz calls ‘the modelling attitude’ emerged at the end of the nineteenth century when building models and reflecting on their nature was still done by the same person; science and philosophy of science were no distinct domains of inquiry yet. The ‘philosopher-scientist’ who was arguably most directly ‘culpable’ for introducing the modelling attitude as we know it today was the Scottish physicist Maxwell (Suárez 2024: 19–20). During his education in Scotland, Maxwell was introduced to an important method of inquiry called ‘reasoning by analogy’. The figureheads of this method–Reid, Steward, Hamilton, and Forbes–emphasised the instrumental nature of such analogies; the analogy was merely a tool for inference, not a depiction of reality (Suárez 2024: 26). Furthermore, mainly to reconcile rationalism with empiricism, Scottish academia embraced the idea that (1) mathematical forms of knowledge need to be compared to experience (a posteriori knowledge) and, (2) vice-versa, inductive empirical knowledge is grounded in unreflective presuppositions (a priori knowledge). Therefore, primarily geometry was employed to make mathematical abstractions from experience. These abstractions consisted of comparing an object of experience to an

[1] It referred to the radius of a column in the field of architecture (Müller 2009: 638).

imagined model of this object under changing circumstances (Suárez 2024: 21–22). Maxwell is known for his theory of electromagnetism from which the equations still hold today[2]. However, he inferred these mathematical equations through a semi-mechanistic model of the 'ether' that is not endorsed anymore. The model included 'real analogies'–Maxwell thought they gave insight into the real nature of the processes underlying the phenomenon–and heuristic elements that were merely introduced for coherence (Suárez 2024: 27–28). Maxwell combined Scottish reasoning by analogy with the fruits of his education at Cambridge in mathematical physics: at Cambridge, he cultivated his skills for formalising analogies. This allowed him to develop the model mathematically (Suárez 2024: 30). Furthermore, the idea prevailed at Cambridge that good models were developed based on classical mechanics as the underlying theory, but not in a heuristic way as the Scottish tradition prescribed, but to gain insight into the nature of the 'reality'. At the crossroads of these two traditions, models and their elements became more than heuristic tools for inference (Suárez 2024, 26). Maxwell's peers did not accept the hybrid nature of his model (the combination of elements that would depict the underlying reality with heuristic elements, e.g., the displacement current). Thomson (better known as Lord Kelvin) who worked alongside Maxwell, rejected the theory completely because introducing heuristic elements departed from the ruling mechanistic worldview (Suárez 2024: 30). During the twentieth of his lectures at the Johns Hopkins University in Baltimore, Thomson explained why he thinks these heuristic elements are problematic: "I never satisfy myself until I can make a mechanical model of a thing. If I can make a mechanical model I can understand it. As long as I cannot make a mechanical model all the way through, I cannot understand, and that is why I cannot get the electromagnetic theory." (Thomson (Lord Kelvin) 1884: 270–71)

2.1.2. Controversies regarding the legitimacy of the modelling approach with Poincaré, Duhem, and the Vienna Circle

On the occasion of Kant's Critique of Pure Reason, a major topic of discussion was the connection between logic, mathematics and physics. According to Kant, formal logic–

[2] Maxwell's equations unify the laws of Coulomb, Faraday, and Ampère that describe the phenomena of electricity and magnetism. From Faraday's law – stating that a changing magnetic field instantiates an electric field – and according to the recognition of symmetry in nature, Maxwell hypothesised that the reverse would also hold: a changing electric field instantiates a magnetic field. The combination of the previous laws results in a description of electromagnetic waves as the propagation of alternating magnetic and electric fields that constitute each other's next instance because of their variations. The resulting electromagnetic wave travels through space at the speed of light. Maxwell's equations are part of science education up to this day (Giancoli 2014).

concerned with the form of thought while disregarding its content–can only serve as a *canon*: an instrument to assess the truth of acquired knowledge. To extend the knowledge that we already have with new findings, however, we need a special kind of logic, an *organon* of science (Kant 1998: pt. II). To Kant, this special logic that makes science possible is transcendental logic. It is not entirely clear what the relationship between formal and transcendental logic consists of. Moreover, the nature of the relationship between mathematics and transcendental logic is not clear either: contrary to formal logic, which consists of analytic judgements, mathematics comprises judgements that are synthetic and a priori. Can mathematics serve as an organon of empirical science? The French philosopher Cavaillès considers these remaining ambiguities the source of the different traditions that emerged for providing a foundation for mathematics: intuitionism and formalism (Cortois 1990: 107–9). A third position is logicism–the tradition founded by Russell that conceives mathematics as fully reduceable to logic; all mathematical truths can be reduced to logical truths (Black 1933, 7–8). As an intuitionist, Poincaré holds that mathematics has creative virtue (contrary to formal logic) and therefore forms the organon of science. Syllogistic reasoning, on the other hand, does not allow for the addition of new knowledge, it merely restructures what is given and provides an axiomatic conclusion (Poincaré 1979: 1–3). Poincaré emphasises that the principles of mathematics are empirically inspired, based on experimental laws that have been elevated to absolute truths. Many examples show that mathematics is a system of convention rather than necessity (Poincaré 1979: 158). A popular example is his conceptions of mathematical space that also elucidates why he refines (or substitutes) Kant's a priori forms of intuition–time and space: Poincaré notices that the laws according to which space unfolds itself when we move in it, are learned through repetitive experience (Poincaré 1979: 83–92). The a priori conceptions we need for this are a conception of iteration or repetition (instead of 'time'), and a conception of a continuum (instead of 'space'). Hence, describing space through the Euclidean system is a mere convention; other space systems would be as legitimate if they could be conceived of in terms of iteration and continuity (Poincaré 1979: 94–97). Hereby, even the most abstract mathematical equations get firmly rooted in the most original experience–but retain the capacity to emancipate from the empirical world.

Maxwell's theory and corresponding model were developed in the scientific milieu of the quest for a foundation of mathematics and an organon of science. It seems logical that Thomson was far from the only scientist who took a critical stance regarding Maxwell's electrical theory. Especially sceptical were the partisans of logicism (cf. the logical empiricism of the Vienna

Circle), which was prominent in the French tradition. One of the French scientists–and not accidentally, a member of the Vienna Circle–expressing this frustration was Pierre Duhem. He thoroughly criticised Maxwell's electric theory (Duhem 1902). Moreover, he did not have many good words left for others who claimed to explain physical phenomena mechanically: no self-respecting physicist can endorse that the hypothesis "all phenomena can be mechanically explained" has a meaning, since testing this against empirical reality–*the* criterion for rejection–is impossible given the indeterminacy of the particles' masses and their motions that supposedly cause the phenomenon of interest (Duhem 1980: 97). Duhem took serious offence to Thomson's famous quotation from the Baltimore lectures (see § 2.1.1), to the extent that he calls it 'scandalous' that understanding is considered equivalent to 'imagination'–alluding to the mechanical model that can (or cannot) be constructed for a phenomenon (Duhem 1980: 103).

To explain and to represent is not the same. Duhem believed we should put our faith in the analytic method to explain physical phenomena. Mechanical models are only of use in a practical sense, not logically. A model does not provide a physical theory and hence no explication; they are merely 'nice analogies' (Duhem 1980: 94–103). Poincaré (1979) writes about the devotion of French scientists to a method of exactly formulated hypotheses, strict derivations, and precise conclusions. Maxwell's theory, on the contrary, does not provide the clarification for electromagnetism, he merely shows that it is possible to develop a mechanical model for it. To make matters worse, Maxwell explores electromagnetism by employing contradictory mechanical concepts–without even attempting to reconcile them. The French had difficulties with appreciating the work of their English peers because of this lack of consistency (Poincaré 1979: 220–21). Poincaré seems to have taken a more tolerant stance and writes that however contradictory multiple candidate theories are, they can all have merit as instruments of inquiry (Poincaré 1979: 222).

We see then that Thomson, on the one hand, criticised Maxwell's approach for not being mechanical enough; The French scientists–among whom Duhem–and the proponents of logical empiricism in the tradition of the Vienna Circle on the other hand, criticised Maxwell's theory for being too mechanical as well as arbitrary. Both criticisms seem to emerge from the frustration that the theory of Maxwell does not directly explain the real underlying mechanism of the phenomenon. However, the modelling approach did allow for the extraction of the laws that the modelled phenomena obeyed. In the end, whether phenomena could be clarified by appealing to classical mechanics as corresponding to reality, was a matter of belief; Thomson believed it to be true, Duhem disdained the idea, and Maxwell found a method to extract abstract laws without dedicating himself to any of both opinions.

Is what Maxwell developed for electromagnetism a theory or a model then? We can consider this a two-step process: the model is not a theory yet, but an instrument of inquiry that allows for the extraction of abstract laws, with the potential to become a more general theory. By modelling, we omit to posit a supposed underlying process that would cause the phenomenon in advance. Bailer-Jones (2009: 173–74) maintains that a theory can only be connected to empirical phenomena indirectly, via a model that exists at a lower level of abstraction. The model mediates between theory and phenomenon: the theory can only be applied to the phenomenon via the model, and the theory can only be constructed, inspired by the phenomenon, through the model. We will come back to the relation between theory and model in § 2.3.

2.1.3. Refining the modelling approach with Hertz & Boltzmann

The development of the theory of electromagnetism–and the modelling approach as a method of science–was continued in the German-speaking tradition by scientists such as Hertz and Helmholtz, and later also Boltzmann (Suárez 2024, 29). Helmholtz took Maxwell's mechanical analogies as no more than what Duhem suggested they would be: 'nice analogies'. He added, however, that from these nice analogies, laws could be derived that applied to the phenomena of interest. The German-speaking scientists acknowledged that introducing heuristic elements implied a departure from the underlying mechanistic nature. They did not regard this problematic, however, since "the new approach compensates for the abandonment of complete congruence with nature by the corresponding more striking appearance of the points of similarity." (Boltzmann 1974: 11).

In his introduction to *The Principles of Mechanics* Hertz (1956) describes how inferences from past to future are made:

> We form for ourselves images or images of external objects; and the form which we give them is such that the necessary consequents of the images in thought are always the images of the necessary consequents in nature of the things pictured. [...] The images which we here speak

> of are our conceptions of things. With the things themselves they are in conformity in one important respect, namely, in satisfying the above-mentioned relationship. (Hertz 1956: 1)

So, the only connection of our images to reality is that the inferences based on these images systematically correspond to what we see unfolding. According to Hertz, our thoughts are mere pictures of reality. Because of the limits of our cognitive functions, it is nothing beyond normal that we can only represent parts of reality and never its entirety. Boltzmann argues that we have two options now. (1) We could generalise the original picture to lower the likelihood that it turns out to be incorrect once we compare it to new instances of the phenomenon it depicts. This would imply a more ambiguous picture, contaminating its derivates with uncertainty. (2) Working in the opposite direction, we could make the picture more specific (specialisation): we add features of which we hypothesise that they are determining. If our hypothesis is correct, we can derive the consequences unambiguously from the specialised picture. This approach, however, increases the likelihood that the picture does not fit the new experience (Boltzmann 1974: 225).

Abstraction comes down to stripping the picture of the experiential phenomenon of what is (supposedly) not relevant to a higher-level conception we have in mind–a mind-internal model. The specialisation can be applied simultaneously: we can add hypothetical properties that (supposedly) determine the consequents we want to derive from our mind-internal model while making abstractions. Abstractions and specialisations are hypothetical features; Boltzmann believes that without them we "could never go beyond an unsimplified memory mark of each separate phenomenon." (Boltzmann 1974: 225). This condition suggests that the picture in a second instance is informed by what we believe to know already about that kind of phenomenon. What we seem to care about when adding hypothetical features is, as Hertz and Boltzmann told us, that the resulting model fits new experience: the derived mind-internal consequents correspond to the consequents in experience. The features we select should have the highest likelihood of providing a model that satisfies the abovementioned aim. Consider a phenomenon lacking any features that resemble something we have already experienced; arguably, abstractions and specialisations of the original picture would be made at random–with the same likelihood for each element of the set of candidate abstractions and specialisations. When a phenomenon resembles an experience in memory, there exists a background against which the likelihood of hypothetical features increases or decreases. Hereby, the likelihood of the consequents of the mind-internal models fit new experiences.

2.2. Modelling systems

As we will see in § 3.1, 'modelling the climate' is expressed more precisely as 'modelling the climate *system'*. I will elaborate on what it entails for something to be regarded 'a system' in the following paragraphs.

2.2.1. A history of the system

The idea that halfway through the twentieth century received the name 'system' and obtained a corresponding field of inquiry–so-called 'system theory'–has been present in the history of epistemology (at least) since Aristotle wrote: "what is the cause of the unification? In all things which have a plurality of parts, and which are not a total aggregate but a whole of some sort distinct from the parts, there is some cause […]**"** (Aristotle 1933: sec. 1045a). According to Von Bertalanffy (1972: 408), what Aristotle expresses, as well as what is called 'system' is nothing metaphysical; it is a straightforward empirical fact that gets confirmed with every observation we make of a living organism, a social group, or every whole that can be conceived as constituted of parts.

As long as the number of parts is limited and the causal relations between those straightforward, the classical scientific practice that Descartes describes in *Discours de la Methode*–reduce the whole to as many parts as can be discerned and assess their functioning and features in isolation (1637, 8)–can explain the phenomenon (von Bertalanffy 1972: 409). However, this method does not suffice longer when the phenomenon of interest emerges specifically because of the structure of the whole, as abecause of interactions between the parts that have been discerned (and of which Descartes's method abstracts).

At the beginning of the twentieth century, scientists ran into problems when trying to solve the three-body problem of celestial mechanics or when trying to explain phenomena in physiology, psychology (Gestalt), the evolution of species and sociology. It became clear that the constellation of the parts is crucial to the behaviour of the whole, and therefore crucial to the understanding of the phenomenon. The concept 'organisation' gained importance as an explanatory factor for phenomena, as well as jargon such as 'organism' and 'organised entity'. These developments at the beginning of the twentieth century, formed the source for what became 'general system theory' (von Bertalanffy 1972: 410). In a rather practical way, but nevertheless elucidating an important quality, Levine writes that "a system is a device that accepts an input signal and produces an output signal." (Levine 2005: 3).

2.2.2. *The specificities of the system underlying the climate phenomena*

When the state of a system evolves with time, it is called a dynamic system. Often, but not always, dynamic systems can be described by ordinary differential equations. A dynamic system can also be described by partial differential equations when the state variables depend on the change in more than one independent variable. The equations can be linear or non-linear. Linearity means that they obey the superposition principle, comprising additivity (equation 1) and homogeneity (equation 2):

$$f(x_1) + f(x_2) = f(x_1 + x_1) \tag{1}$$

$$a * f(x_1) = f(a * x_1) \tag{2}$$

When the behaviour of the whole is determined by the interactions between the elements, and this 'collective behaviour' breaks with rules that govern the elements in isolation (broken symmetry), the system underlying this behaviour is called 'complex' (Andersen 1972: 393; Ladyman and Wiesner 2020: 3). Although there is no complete overlap, many dynamic systems are also complex. Moreover, many dynamic systems we discern in nature are governed by non-linear differential equations, complicating their analysis (Ladyman and Wiesner 2020: 13).

In the late nineteenth century, Poincaré (1892) inquired into the three-body problem. From the perspective of the classical method that analyses the whole by its parts in isolation, this problem could not be solved. Poincaré elucidated the sensitive dependence of this kind of system on the initial conditions:

> The final goal of celestial mechanics is to resolve the big question of whether Newton's laws alone explain the astronomic phenomena; the only means to achieve this is by making observations that are as precise as possible and by comparing them to the results of the calculation. This calculation can only be an approximation and hence it would not serve any purpose to calculate more decimals than the observations reveal. Thus, it is useless to demand

> a higher precision for the calculations than for the observations; but we cannot ask for less either. (my translation[3]) (Poincaré 1892: I:1)

Hereby, Poincaré is considered the first to have 'discovered' the chaotic dynamic system. However, investigating this kind of system with its many variables and non-linear equations was complicated back in the day. The advent of the computer was a blessing for inquiry into complex systems: the field advanced significantly through the visualisation of complex systems and the enhanced capacity to solve equations numerically (Ladyman and Wiesner 2020, 14).

2.2.3. Computer-simulated models

The direct foundations of computer science were established from the seventeenth century on by Leibniz (i.a. the binary system), Babbage (the mechanical computer), Lovelace (the first computer program), Boole (Boolean logic), and Shannon (switching theory underlying digital circuits) (O'Regan 2021, 35–36). Nevertheless, the first generation of digital computers was only developed in the 1940s: e.g., the ENIAC (Electronic Numerical Integrator and Computer) at Princeton, Pennsylvania, in 1946 (O'Regan 2021: 57). From the second half of the twentieth century, computers were employed to analyse complex systems. As we will see in § 3.2, the ENIAC was the first computer used for weather forecasting in 1950. Keller points out that it is also in this post-WOII period that the connotation of the term 'simulation' undergoes a shift from 'deceitful' to "a technique for the promotion of scientific understanding" (Keller 2002: 1). A transformation regarding the means for generating scientific knowledge occurs: Rohrlich situates the new methodological field (that would be called 'computational physics') between traditional theoretical physics and experimental physics, in the sense that computer simulation makes it possible to conduct 'experiments' with theoretical systems (Rohrlich 1990). Keller, however, relativises the novelty Rohrlich ascribes to computational physics: although the new methodology allows for the study of complex physical systems, it does not change the algorithm by which the system is solved–the numerical methods could have been executed with pencil and paper. The progress in the field is caused by the increased accuracy, speed and scale

[3] Original quotation: "Le but final de la Mécanique céleste est de résoudre cette grande question de savoir si la loi de Newton explique à elle seule tous les phénomènes astronomiques; le seul moyen d'y parvenir est de faire des observations aussi précises que possible et de les comparer ensuite aux résultats du calcul. Ce calcul ne peut être qu'approximatif et il ne servirait à rien, d'ailleurs, de calculer plus de décimales que les observations n'en peuvent faire connaître. Il est donc inutile de demander au calcul plus de précision qu'aux observations; mais on ne doit pas non plus lui en demander moins."

at which computers perform the calculations (Keller 2002: 3). Hence, the novelty is not epistemological; computer simulation methods implement other epistemically valuable methods (differential equations, Monte Carlo sampling etc.) for systems that were too complex to calculate by hand with reasonable effort. The novelty corresponds to an abrupt increase in calculation capacity rather than intrinsic epistemic progress. Keller describes how simulation is applied to systems through time: at the beginning, a simulation merely implemented well-formulated theoretical models and elicited their consequences (Keller 2002: 5–6). Later, the theory was adjusted with a view to the implementation's feasibility: empirically derived values were introduced, although they did not directly further the understanding of the processes underlying the simulated phenomenon (Keller 2002: 7). Eventually, the phenomena were even directly simulated, without heeding any underlying laws, let alone theory (should one of these have been devised). This method, called 'cellular automata' (CA), was developed by Wolfram, and eventually also used to model complex dynamic systems (Keller 2002: 9–11). As stated in Keller's citation from Wolfram's *Theory and Applications of Cellular Automata* (1986), Wolfram considers CA the method/model we need to describe complex behaviour in a synthetic way, which was first impeded by the tradition of breaking systems down into their parts (cf. Descartes's scientific approach in § 2.2.1). Keller (2002: 12) explains how the striking success of CA in a vast range of fields seduces scientists into swapping the model for the empirical 'reality'. It is said that CA models do not appeal to theory, but there are some fundamental presuppositions in play: CA simulates a grid in which the cells have states. The states are updated according to a rule (mathematical equation) depending on the state of their neighbouring cells. CA models prescribe micro rules about the transaction of 'information' (the states) to 'agents' (the cells) which results in collective macro-behaviour (Berto and Tagliabue 2023: para. 3.4). Hence, a rule (or law) and the idea (maybe we could even call this theory) that neighbouring agents exchange information, are present.

Müller (2009: 645) writes that a computer-simulated model differs from other models in directly representing the laws that the target (supposedly) obeys, without appealing to another object (a source) that obeys these laws. No other *physical* object is indeed involved with computer-simulated models. A computer-simulated model implements equations that describe laws supposedly applying to the target. However, the computer-simulated model, constituted by implementing theoretical laws, could be considered the source. Inferences about the behaviour of the target are made based on the visualised behaviour, relying on the idea that the source (the computer implementation of the equations or the visualisation) and target obey the same laws.

2.3. Models versus theories

A philosophical review of modelling in science would be seriously deficient if nothing is mentioned about the relation between models and theory. I touched upon this already in § 2.1.2, where we saw that Duhem did not consider a model an explanation exactly because, in his regard, it is not a theory–to Duhem, the essence of a theory is a set of laws that unites different phenomena into ‘a rigorous order’ (Duhem 1980: 103). In that same paragraph, I thought the model a means to construct a theory, following Bailer-Jones. There exists a variety of views on the relationship between model and theory; Frigg and Hartmann (2020: para. 4.) distinguish between two main positions: models as interpretations of theory and models as independent from theory. The former position is applicable when a theory is considered a set of sentences in a formal language and a model is taken to be a structure that organises the sentences of the theory as referring to objects, relations, and functions in a way that they become ‘true’. In that sense, the model is an instance of a more abstract theory. Depending on whether a theory is considered in the syntactic or the semantic sense[4], the instance of the theory (the model) is constructed top-down: the formal sentences are adapted to apply to a specific field, or bottom-up: a theory is conceived of as the overarching result of a set of models. A model can be considered independent of a theory. This independence can take a full-fledged form–the model plays the role of a substitute for a theory–or as partial independence when some relation to an existing theory is present: to explore the theory, to develop the theory, to mediate between theory and target system etc. (Frigg, Roman; Hartmann 2020: 4.2).

3. Climate modelling

In this thesis, I will focus on the emergence of uncertainty in climate model projections. Climate modelling is the state-of-the-art way to gain insight into what we call ‘the climate’.

[4] Carnap distinguishes three conceptions of language: the pragmatic view (focussing on the use of the sentences), the semantic view (focussing on the referents of the sentences, the meaning), and the syntactic view (focussing on the abstract structure and the logical relationships between the sentences). This distinction is applied to make sense of theories: the syntactic view conceives the essence of a theory as a logical structure of abstract sentences phrased in metamathematical language, the semantic view grants a privileged position to the meaning of the sentences and the (persisting) role of modelling to theory, and the pragmatic view makes sense of the concept of theory in the light of its non-formal components (Winther 2021: para. 1.1).

Frigg and Hartmann (2020: para. 4.2) consider climate models to fall under the kind of model that serves as a mediator between theory and the target system, in virtue of being (partially) independent of both sides. For complex cases such as climate models, the line between what is theory and what is model becomes blurry, corresponding to the idea that models are instances of 'more general' theories, which is a gradual notion and hence does not provide a clear criterion to distinguish between both.

Nevertheless, climate modelling offers a vocabulary, methods, and an overall framework for investigating climate phenomena and how they relate to other phenomena. Particular aspects of climate models amount to or thwart uncertainty and have been scrutinised in the last decades. Before delving into the epistemic consequences of the technical particularities, I will briefly outline certain fundaments of climate science that are indispensable for understanding the workings of a climate model and the emergence of uncertainty related to it.

3.1. Introduction to the climate and the climate system

In everyday life, we understand the term 'climate' as the patterns of weather conditions that appear typical for a certain region over a long period. However, what is meant by 'climate' scientifically–or at least, what it *should* mean–requires philosophical inquiry. Frigg, Thompson, and Werndl (2015: 953) distinguish two main ways of defining 'climate': the climate as a distribution over time, and the climate as an ensemble distribution. The former definition points to the distribution of the values of climate variables over a certain period. The latter assumes the probability distribution of the climate variables at a certain moment in the future. Both types of definitions come with their corresponding problems. They conclude that the least problematic definition among the candidates is climate as "the finite distribution over time of the climate variables arising under a certain regime of varying external conditions (given the initial states)." (2015: 955). Unlike the definitions relying on ensemble distributions, this definition does not pose problems in defining the present and past climate. The definition also considers the external conditions as they are, namely, varying instead of constant. A remaining problem with this definition of climate is that it is still unclear over which period we should evaluate the values of the climate variables. However, these authors argue that it suffices to adapt the time interval to the purpose of the research (2015: 955). This idea stands in contrast to the fixed evaluation period of thirty years–determined by the World Meteorological Institute[5]–taken up in the definition of the IPCC for the sixth cycle assessment report:

> Climate in a narrow sense is usually defined as the average weather, or more rigorously as the statistical description in terms of the mean and variability of relevant quantities over a period ranging from months to thousands or millions of years. The classical period for averaging these variables is 30 years, as defined by the World Meteorological Organization. The relevant quantities are most often surface variables such as temperature, precipitation and wind. Climate in a wider sense is the state, including a statistical description, of the climate system. (IPCC 2023: 2222)

The IPCC definition refers to 'the climate system' of which the 'climate' would be a state and covers a wider notion than the average weather. The IPCC defines 'climate system' as follows:

> The global system consisting of five major components: the *atmosphere*, the *hydrosphere*, the *cryosphere*, the *lithosphere* and the *biosphere* and the interactions between them. The climate system changes in time under the influence of its own internal dynamics and because of *external forcings* such as volcanic eruptions, solar variations, orbital forcing, and *anthropogenic* forcings such as the changing composition of the atmosphere and *land-use change*. (IPCC 2023: 2224)

We can interpret the relation between these definitions by considering 'climate' initially as a phenomenon of experience, namely, the pattern that can be discerned in the subsequent weather conditions over longer periods, in a certain region. Currently, we understand the emergence of this phenomenon by positing a system of components that bring the phenomena about by interacting with each other. We call the system we posit the 'climate system' and consequentially, a state of this system is the climate at a certain instance of time and space. The IPCC conceives of the climate system as composed of five subsystems: the atmosphere, the hydrosphere, the cryosphere, the lithosphere, and the biosphere. The atmosphere is the gaseous shell encapsulating the solid earth; the hydrosphere comprises all that is water in liquid form, both at the surface and subterraneously; the cryosphere comprises all water in solid form; the lithosphere is the upper shell of solid earth; and the biosphere consists of all the biomass–living or dead–that pertains to ecosystems on the land, in the water and the air (IPCC 2023: 2219,

[5] The World Meteorological Organisation states that periods of thirty years should be used to calculate a climatological standard normal. This period was decided on at the beginning of the twentieth century after heavy international debate about what averaging period would be sufficiently long to allow convergence of the long-term averages (World Meteorological Organization 2007). In light of climate change, the suitability of the thirty years was revisited and retained (World Meteorological Organization 2017: 8–9).

2225, 2234, 2237). The IPCC definition is explicit about the interactions between the components being a part of the climate system–contrary to the 1975 definition of the World Meteorological Organisation. Emphasis on the interactions has been steadily increasing since then (McGuffie and Henderson-Sellers 2005: 5).

The climate system comprises large-scale stable patterns, such as the convection zones and the thermohaline circulation, as well as positive and negative feedback loops, with enforcing and dampening effects respectively (Ladyman and Wiesner 2020: 35). The processes comprised in the climate system happen on different time scales. For example, carbon turnover happens on a short timescale in the cycle driven by the metabolism of organisms: absorption and respiration of carbon dioxide (CO_2) from and to the atmosphere and ocean; slow carbon turnover is the process in which carbon compounds are taken up in geological formations, among which the turnover into crude oil. In a certain sense, we couple slow to fast carbon turnover by the extraction of fossil fuels (Ladyman and Wiesner 2020: 36).

3.1.1. A closed system with thermodynamically open subsystems

Thermodynamically speaking, the components of the climate system are open systems: they exchange heat, momentum, and mass. (IPCC 2001: 89). The system is 'driven' by factors outside the system such as solar irradiation, plate tectonics, and mantle dynamics (Ladyman and Wiesner 2020: 35). Changes in the behaviour of the system can be the result of changes in these external drivers (also called external or radiative forcings) such as volcanic eruptions, solar variations, changes in Earth's orbit, and anthropogenic changes in the composition of the atmosphere or land use (IPCC 2023: 2229). Contrary to the subsystems that exchange mass, the impact of the external drivers is accounted for in the form of energy alone; no matter is exchanged between the external source and the components of the climate system. This means that the climate system, as the amalgam of open subsystems, is conceived of as a closed system (2001: 91).

The principal driver of the climate system is the incoming solar energy. The system is in equilibrium when the average net radiation at the top of the atmosphere is zero. Instead of the stratosphere, the tropopause is taken as the top of the atmosphere given its transient response to changing average radiative forcing because of the thermal inertia of the oceans (2001: 90–91). Volcanoes and anthropogenic activity are not considered part of the climate system; consequentially, their impacts on the climate system are accounted for as radiative forcing.

Besides radiative forcing, changes in the state of the climate system can be attributed to internal variability–the interactions between the various components of the climate system (2001: 91).

3.1.2. A dynamic system in transient balance

The climate system is a "dynamic system in transient balance" (McGuffie and Henderson-Sellers 2005: 22). The system is 'dynamic' because the values of the variables that describe the system are time dependent. The system is in 'balance' since the values for the state variables oscillate around certain averages. It concerns a 'transient' balance since certain events can induce a change in the current equilibrium after which the system evolves towards a new equilibrium. When the system is pushed out of its equilibrium state, a transient state is induced: a dynamic state between the moment of disturbance and the moment that the system settles back into the same or another equilibrium state. The transient climate response (TCR) and the equilibrium climate sensitivity (ECS) are key concepts in climate modelling that are related to the so-called response theory of dynamic systems (McGuffie and Henderson-Sellers 2005: 72).

3.1.3. A complex and chaotic system

The climate system is a complex dynamic system described by non-linear partial differential equations. It also exhibits chaotic behaviour–sensitive dependence on the initial conditions.

A climate model is a scientific representation of the climate system or, at least, a part of it. Climate models consist of a set of equations that aim to describe the state of the climate system–the distribution over time of a set of climate variables–by representing the underlying processes conditioned by varying circumstances (Frigg and Hartmann 2020; McGuffie and Henderson-Sellers 2005; IPCC 2023: 181).

3.2. A brief history of climate and weather modelling

In the broader context of the development of the modelling approach, climate models were developed based on weather models. In 1904, the Norwegian physicist Vilhelm Bjerknes (2009) presented a mathematical model of the atmosphere comprising a set of six non-linear partial differential equations: the three Navier-Stokes equations, the continuity equation that expresses the conservation of mass, and the two first laws of thermodynamics; and one equation of state: the ideal gas law–the equation of state for the atmosphere (2009: 664). He suggested that it would be possible to forecast the weather by solving this set of seven equations as an initial value problem for the atmosphere (Gramelsberger 2009: 671). Lewis Fry Richardson developed a method to solve the model equations proposed by Bjerknes and published the results in his book *Weather Prediction by Numerical Process* (1922). He solved the differential equations numerically over a grid that divides the continuous atmosphere in discrete units and at specific points in time. Before computers got involved, weeks were needed to manually compute a forecast of just a couple of hours. Even when in 1950 the method was executed by the meteorology group under Von Neumann at Princeton using the ENIAC, the computations took 24 hours for a 24-hour forecast; they could barely keep up with the weather itself (Lynch 2007: 3436; Charney, Fjörtoft, and Neumann 1950).

In 1955, Philips explicitly applied numerical techniques to predict atmospheric circulations for the next month–remarkably far into the future compared to what had been put to the test before. This could be considered the first climate model, or at least the first intention to apply the numerical weather forecasting method to a general circulation model of the atmosphere for long-term predictions(Lewis 1998: 41; Phillips 1956). Following Philips' initial impetus, many research groups started to develop general circulation models of the atmosphere, including as many of the understood processes as possible. In 1969, at the Geophysical Fluid Dynamics Laboratory (GDFL) at Princeton, Manabe and Bryan (Manabe and Bryan 1969) developed the first coupled global circulation model: the atmospheric model includes the temperature of the upper ocean layer as a boundary condition, and the ocean model includes the influx of heat, water and momentum computed by the atmospheric model as boundary conditions (1969: 787).

3.3. Climate models and weather models

Although climate models are based on the numerical implementation of the same differential equations as models for weather forecasting, they are crucially different: climate models are not weather models that have evolved over longer periods. A weather model considers the local geographical conditions such as elevation, exposure, and the presence of rivers and water bodies. It considers the most recent and spatially precise atmospheric conditions–e.g., the latest temperature, pressure, humidity, cloud cover, wind speed and direction for a specific location. Therefore, weather models operate on spatio-temporal scales of mere kilometres and hours. The weather is ideated as the phenomenon resulting from an underlying weather system, described by a set of partial differential equations; the weather projections comprise the variability of this system, propagated from the initial conditions. Because of the chaotic nature of the system (the high sensitivity of the system equations on the previous state), the accuracy of the forecast is highly dependent on the precision of the initial conditions; it inevitably drops dramatically after a couple of days (Bauer, Thorpe, and Brunet 2015: 50). We will see in § 4.3.3 that the variability we want to record to make accurate weather predictions is exactly the variability we desire to omit when making climate projections.

With a climate model, we aim to predict a 'coarse-grained' variant of the weather on seasonal timescales and longer: the precise temperatures at certain moments of the day, at precise locations, are replaced by average temperatures over longer periods or temperature trends compared to a baseline; in specific regions or at certain latitudes. Climate projections aim to predict the probability distribution of the weather, not the weather itself (Vitart and Robertson 2019: 6). To make such projections over periods of a decade or a century, the aspects of the system that only cause day-to-day variations must be ignored in the light of this new purpose: a climate model is evolved over a lower spatial resolution–e.g., 100 km compared to 100 m, a magnitude difference of 10^5–which improves the accuracy of results on higher temporal scales (2019: 7). Furthermore, the model employed must consider the aspects of the system that make a difference in the long term but are not causing significant changes over a couple of days: climate models comprise equations that describe the dynamics of the ocean, ocean ice and land surface besides the atmosphere alone. The resulting model is a so-called earth system model (ECM) consisting of several coupled global circulation models (2019: 7–8).

3.4. The construction of 'the climate'

3.4.1. A phenomenological analysis of the climate

I adhere to Kant's revelation that we cannot access 'the thing in itself'. Our perception of 'reality', what would be out there independent of us, is mediated by our senses; they inevitably leave a particular flavour on the resulting representation we discern (Kant 1998: para. A30). This idea poses an epistemological problem: what can be legitimately claimed about the world if we do not have direct access to it? Husserl addressed this question with his transcendental idealism, a conception of the relationship between the phenomenon and the mind-independent world or 'reality'. To Husserl, the perception of a phenomenon at a certain moment in time is an intentional act (*noesis*, a meaning-giving act of consciousness) comprising a correlate (*noema*, the ideal content of this act) (Husserl 1982: vol. I, paras 80, 88–93)

The intentional act as a fundamental unit happens at a given moment; hence, approaching the weather phenomenologically is more straightforward than doing so for the climate. If we consider our perception of the weather as an intentional act, then what we discern as 'the weather' is its ideal content. The experience of the climate, on the other hand, requires 'the presence' of more than only the weather at an instance of time; it should be the experience of a certain consistency in the weather patterns within a region. If what we refer to as 'climate' is also an ideal content of an intentional act, then this act should be directed to more than the weather at the very moment. Husserl illustrates the role of time-consciousness with the apprehension of a melody. In the present instance, it is apprehended as one object with a duration and not simply as single tones. In the intentional act, the subsequent phases are apprehended through 'retention' and 'protention' processes. They extend the consciousness of the previous tone in the past and evoke the idea of a supposed subsequent tone (Husserl 1991: paras 7–13, 40).

Has the experience of the climate the same structure as the experience of a melody? Husserl considered retention the kind of process that targets 'what has just been' (Husserl 1991, para. 12). Clearly, this does not apply to the climate, which is conventionally evaluated at timescales of thirty years, as we have seen in § 3.1. A more fruitful approach could be to consider the processes of memory and anticipation with subsequent fulfilment or frustration. I was born and raised in Belgium, where I am used to the weather patterns throughout the year. What led to the ideation of the climate through experience happened to me for the first time when I lived in the Southern part of Chile for about nine months: the temperature, precipitation, humidity, and winds occur in different patterns; the weather changes move along a different path. Recently, I experienced what led to the ideation of climate again: being in Belgium, I am surprised by the amount of rain in the past months. The climatological report of the Royal Meteorological Institute of Belgium confirms my experience: the winter of 2024 has been the third wettest winter since the first observations in 1833 (Koninklijk Meteorologisch Instituut (KMI) 2024: 2).

I infer from these anecdotes that the experience of a rupture in the expected patterns (frustration) calls for an object that clarifies this variability: different temperatures and precipitations over hours and days are understood as 'the weather'; changes over months, with a certain return period, are addressed by ‘seasonality’; regional variability in the weather patterns is explained by the idea of climate zones. Recently, new variability has entered: even though we stay put, the patterns change in a way that does not show a return period. The object we posit to make sense of that experienced change is climate change.[6] In this understanding, the climate is not what we experience, but a second-order object, a concept tailored to make sense of the variability in the object posited instantaneously. Hepach (2023: 204) would agree; moreover, he would say that the process of imagination plays a key role in my positing of the climate as a response to the extreme precipitation event in Belgium.

Scepticism about the legitimacy of a phenomenology of the climate exists in the field of climate science (because it is a scientifically constructed object that can only be learned about through media devices), as well as in other disciplines (because the climate is not a universally shared object) (Hepach and Hartz 2023: 214; Schneider and Nocke 2014: 12). Nevertheless, authors developed phenomenological analyses for this invisible phenomenon: Knebusch takes climate as “a cultural relationship established progressively between human beings and weather.” (Knebusch 2008: 5). By this, he means that we experience climate by experiencing the weather, through second-order objects such as seasonality, when locating ourselves in time. This way, we can talk about ‘autumnal weather’, which does not refer to average meteorological variables, but to the idea that the weather is as expected for the meteorological time (Knebusch 2008: 5–6). Hepach (2023: 175–76) argues that we experience climate in its immediacy. He appeals to the phenomenological correlation: subject and object always remain connected and, as conceptualised, this connection should be represented. Hepach compares the climate to a room which influences how the objects and events within the room are experienced. We cannot see the whole room at once, but if the room changes, the experience of what happens inside changes too (correlation). The room, as well as the climate, shape our experiences prior to reflection.

Inquiry into the ‘climate’ according to the phenomenological method, shows us that experience is fundamental to our inferences–whether the climate is experienced prior to reflection or not. Furthermore, it is the target of our descriptions, depictions, and possible understanding. Experience is what we start from and return to. The appropriation of an invisible scientific

[6] It must be noted that climate science has not confirmed that the above-average precipitation in Belgium is a result of climate change. Climate model projections of extreme precipitation events are generally plagued with much uncertainty. This strictly scientific confirmation, however, differs from how extreme weather events are understood against the background of endorsed concepts and claims. This shows clearly how the (scientific) concepts we use and have developed – partially based on experiences – form the background for new experiences.

concept informs our understanding of extreme weather events as climate change. On the other hand, constructing the scientific concept of 'climate' did not happen through immediate experiences alone; it required more than individual experiential 'data'. Scientific concepts are synthesised based on special kinds of (mediated) experiences: a vast amount of empirical data measured in specific ways, modelling outcomes, computer simulations, scientific experiments and so on.

3.4.2. From experience to scientific data

The climate is a scientifically constructed concept–or, at least, a concept that requires more empirical observations than one individual can provide through the senses. Thus, climate models, employing scientific concepts to model a scientific concept, cannot be traced back directly to our experience of the world; the scientific method plays a crucial role. What is the relationship between the phenomenological correlation and the scientific method? what forms the bridge between experience and scientific data?

The phenomenological correlation persists, although objects are experienced as 'out there'. Positing the object of experience goes hand in hand with positing the 'I' as a subject: the experience is divided between object and subject; it is understood as something that emerges in the interaction between the perceiving subject and the world of things surrounding the perceiver.

Why do we divide experiences into a subject and an object? Kant considered space and time to be forms of intuition. We do not decide to conceive of objects in space and time, it is a function engrained in our human nature; it happens unmediated. As we have seen in § 2.1.2 Poincaré refined Kant's forms; according to him, we need engrained concepts of iteration and continuity to discern objects. It follows that experience is split up before any conscious awareness. The moment awareness can enter the scene, there is already an object to be aware of.

The objective perspective, employed in the field of science, does away with the subject-pole of the experience while the object emancipates from its constitution; it becomes a stand-alone object. Is this required or a necessary consequence somehow? In *The View from Nowhere* (1986), Nagel considers this detached view a human ability rather than a well-thought-out approach. Without exploring the benefits of this perspective very deeply, it suffices to allege that it is an approach that 'works well'.

So, for a scientific approach, we employ our ability to create a view from nowhere and dispose of the subject. It might be primarily a matter of making sense of experiences without retaining any variability that is constituted because of the subject's particular features; maybe it is merely easier to derive causal relations between objects and phenomena when abstracting from the subject–when leaving it out of the picture so to speak. Doing away with the variability of individual perspectives results in the perceived 'objectivity' of scientific methods and their outcomes. Nevertheless, it is not legitimate to solidify this: within the context of the scientific method, objectivity is a legitimate assumption, but, once the results are brought to the public–beyond the realm of scientific inquiry–they should be considered as the result of a thought experiment that presupposes the absence of the subject in the existence of the object.

3.4.3. The epistemic value of inferences from supposed stand-alone objects

Making an assumption, to proceed from it and derive interesting, helpful, or–for better and worse–productive insights, does not make the assumption true. An analogy can be made with axioms in mathematics according to the school of mathematical formalism[7]: they are required for 'building' mathematics, but there are no reasons to believe them independently of the reason for their instantiation. Axioms in math, as well as objectivity in science, have a teleological cause. Within the realm of science, where we adopt the view from nowhere and believe–axiomatically–in the existence of the object as a stand-alone object, it seems perfectly warranted to use the adjective 'objective'. In the end, this approach to the world, with the existence of the inferred object taken as an axiom, is the birthplace of objectivity as an idea. Since I am not writing in the capacity of a scientist, I will restrict the use of 'objective' and its derivates to the description of 'reality' as understood through scientific glasses–not mine now.

On the other hand, I want to emphasise the 'realness' of our experience and its impact on our existence. A (theoretical) human being fails to autonomically thermoregulate by sweating when exposed for an extended period to a wet-bulb temperature that exceeds 35°C (Sherwood and Huber 2010, 9552). These are the conditions (the combination of temperature and humidity) at which the average human body overheats: the blood pressure drops, the heart might fail, the kidneys get damaged and so on (Székely, Carletto, and Garami 2015: 452). Between 1999 and 2008, the instantaneous wet bulb temperature never exceeded 31°C, nowhere on earth

[7] Axioms in mathematics are considered teleologically posited and therefore arbitrary to some extent by some (e.g. Quine) and as fundamentally existent by others (e.g. Gödel). The first position is linked to mathematical formalism, and the latter to mathematical Platonism or realism (Horsten 2023).

(Sherwood and Huber 2010: 9553). However, over the past 64 years, the European wet bulb temperatures during summer have, on average, increased by more than 1°C (Ma, Chen, and Ionita 2024: 2059). Furthermore, Powis et al. (2023: 7) show that the geographic range and the frequency of wet bulb temperatures exceeding 35°C rapidly increase with moderately increasing average temperatures. Duhem paid tribute to empiricism by writing "The human mind, presented with the external world in order to know it, first encounters the realm of facts." (my translation)[8] (Duhem 1987: 3:1). In the context of empiricism, 'external' is to be understood as reality as it is experienced and not independent of the subject, as a realist would defend. So, it is compatible with understanding the 'facts' of the external world as posited objects derived from a primordial experience. What is relevant for decision-making, is not whether the object is believed to be a stand-alone object (realism) or whether it retains the connection with how it is experienced and its constitution; what is relevant to manoeuvre in the world, is how an object will affect us. Extended exposure to wet bulb temperature exceeding 35°C is harmful, to say the least; it is a fact that we can be confronted with, independent of our belief in the object's existence. Science may abstract from the human perspective to gain insights we otherwise cannot achieve. We may abandon the subject to inquire into the causal relations between objects in the external world, but, in the end, the fruits of this abstraction are brought back into the realm of experience: the insights gained are meant to help us deal with the facts; they can guide us towards a goal (or away from potential harm).

4. The climate modelling cascade

I have defined a climate model as a representation of a part of the climate system that describes certain climate variables in time based on the underlying processes. I also mentioned that climate models are not weather models; climate models include the processes that are relevant to the variation in the long term and use initial conditions with a different resolution in space and time. The development of a climate model is a unique process. Compared to model development in other fields, a climate model resembles a Frankenstein creation; it couples different models representing separate climate system components. The patchwork lacks significant elegance. As such, it is more complicated and more interesting for an epistemological analysis; for instance, climate model developers must negotiate between the aims of adequate representation and correspondence with empirical data. Intuitively, we might

[8] The original quotation is "L'esprit humaine, mis en presence du monde extérieur pour le connaître, rencontre d'abord le domaine des faits."

expect that a more adequate representation of the climate system results automatically in more accurate projections, but strangely, these two aims can counteract each other.

To illustrate how climate models are developed and which elements and techniques play an essential role in the constitution of their projections, I will refer to one of the models that are included in CMIP6: the Community Earth System Model 2 (CESM2) and a specific component of it: the Community Atmosphere Model (CAM6).

4.1. Modelling one climate-system component

4.1.1. The Community Atmosphere Model 6.0 (CAM6)

The CAM6 model has two main types of components: a dynamical core and a parametrisation suite. The dynamical core of a climate model is the component of the model that numerically solves the set of coupled differential equations for the hydrostatic atmosphere representing the assumed physical processes therein (Ullrich et al. 2017: 4478). There exist different types of dynamical cores depending on the discretisation method and the constraints used to solve the equations (Ullrich et al. 2017: 4480). The parametrisation suite contains equations summarising the excluded processes and the processes occurring at a scale below the grid size of (the ‘subgrid’ processes). They are represented in a simplified way: depending on free parameters and in function of the model’s state vector. The equations in the parametrisation suite provide the input for the processes operating at the resolvable scale of the model (Couvreux et al. 2021: 1,2). Examples of the parametrised processes are cloud microphysics, radiative transfer, aerosols, and deep convection (National Center for Atmospheric Research (NCAR) 2017c). As we will see, each dynamical core has shortcomings; they are addressed by implementing multiple dynamical cores into the same model.

The dynamical cores of CAM6 are fully separated from the parametrisation suite. To obtain a comprehensive solution, the components are ‘coupled’. In CAM6, this coupling is done in a time-split manner or a process-split manner: time-splitting updates the parametrisation suite and the dynamical core sequentially, based on each other’s solutions (equation 3); process-splitting updates both simultaneously, based on the previous solution (equation 4). In the equations provided below, D represents the dynamical core; T, S, R and M represent sets of processes taken up in the parametrisation suite (National Center for Atmospheric Research (NCAR) 2017a).

$$\psi^{n+1} = T\left(S\left(R\left(M\left(D(\psi^{n-1}, 0)\right)\right)\right)\right) \tag{3}$$

$$\psi^{n+1} = D\left(\psi^{n-1}, \frac{T\left(S\left(R\left(M(\psi^{n-1})\right)\right)\right) - \psi^{n-1}}{2\Delta t}\right) \tag{4}$$

Whether the former or latter technique is applied depends on the type of dynamical core, e.g. for spectral transform dynamical cores, process-splitting is most convenient, while for finite-volume dynamical cores, time-splitting is the best option (National Center for Atmospheric Research (NCAR) 2017a). CAM6 comprises four different dynamical cores: the Finite Volume Dynamical Core, the Spectral Element Dynamical Core, the Eulerian Dynamical Core, and the Semi-Langrangian Dynamical Core. The Finite Volume Dynamical Core discretises the governing equations–the hydrostatic balance equations, the conservation of total air mass, the conservation law for tracer species (gases in the atmosphere that occur in small quantities) or water vapour, the first law of thermodynamics, and the momentum equations (Navier-Stokes equations)–horizontally and vertically (National Center for Atmospheric Research (NCAR) 2017b: para. 5.1). The governing equations for the hydrostatic atmosphere are formulated depending on the dynamical core (National Center for Atmospheric Research (NCAR) 2017b).

Discretisation on a grid of a certain size implies that some of the information presented by the continuous differential equations is lost; there is only one solution for a certain period and a certain finite region in space. Equations are discretised horizontally and vertically. First, integrating over a finite volume preserves the exactitude of the equation–at least for the determined volume. To solve the integral, however, a difference operator is introduced for decomposition in time and space, resulting in an approximate solution (National Center for Atmospheric Research (NCAR) 2017b: para. 5.1). The accuracy of the integration methods is enhanced with increasing degrees of freedom available for the subgrid solutions (zero degrees of freedom result in a constant subgrid distribution, one degree of freedom results in a slope, two or more degrees of freedom allow for a second- or higher-order polynomial describing subgrid dynamics). The Finite Volume Dynamical Core of CAM6 allows for a second-order polynomial through the Piecewise Parabolic Method, striking a good balance between accuracy and calculation efficiency (National Center for Atmospheric Research (NCAR) 2017b: 5.1).

To ensure the solutions at grid size are sufficiently accurate, the discretisation should comply with three conditions. In the case of the Finite-Volume Dynamical Core, firstly, the system solution should be conservative over time. This can be guaranteed by ensuring that the flux leaving through a certain face of the finite volume over which is integrated is equal to the flux entering through that face in the neighbouring finite volume cell. A second condition is called ‘constancy’: a scalar that is initially homogenous should remain so everywhere in the subsequent time-steps of the solution. Lastly, the solution should be shape-preserving: local extrema should not be exaggerated, nor underestimated. Satisfying these three conditions simultaneously is challenging, especially for a multi-dimensional flow. When, for example, the algorithm fails to consider the transversal contributions to the face-normal flow–that is the only flow considered in the one-dimensional case–so-called ‘splitting errors’ are introduced during the calculation of subsequent system solutions such that the solutions will satisfy the conservation condition but not the constancy condition (Leonard, Lock, and MacVean 1996: 2588–89).

For CAM6 splitting error is reduced by first applying one-dimensional flux-form operators that ensure conservative solutions, and replacing them by derived advective-form operators, preserving shape and ensuring constancy. This way a two-dimensional solution is obtained. Using a vertical Lagrangian coordinate system reduces the three-dimensional differential equations to their two-dimensional forms (the Lagrangian coordinate system moves vertically with the fluid). In the horizontal direction, an Eulerian coordinate system is used. The scalars (i.e. pressure) defined in the horizontal coordinate system determine the ‘position’ of the vertical coordinate system. This way, vertical advection errors are eliminated. However, due to the diabatic warming and cooling processes simulated, the Lagrangian surfaces deform. To omit consequential errors, the surfaces are mapped back to the Eulerian coordinate space by a conservative algorithm with a reference coordinate (National Center for Atmospheric Research (NCAR) 2017b: para. 5.1.).

4.1.2. Sources of uncertainty in the modelling of one climate-system component

To represent climate phenomena, the reality that brings them about is understood as a system of several interacting elements. Within the boundaries of this system, we can describe the movement of matter and energy. External influences, related to processes not represented by the system equations, can be accounted for by ‘boundary conditions’; we condition the internal description of the system on what the situation should look like at its boundaries. Already at this point, uncertainty comes into play: we understand the phenomena we perceive by positing a system of causal relations. This system is not part of the ‘real’ or ‘objective’ world, it is a conceptual representation. A discrepancy exists between what the world ‘is’, independently of our human conception, our perception of it, and our understanding of it.

The conceptual system by which we understand the perceived phenomena can be transcribed into a mathematical form: the system is represented by a set of coupled differential equations that describe the evolution of the physical, chemical, and biological climate processes in time (IPCC 2023: 181). Different authors have described different stages in the translation from reality to a model: they mention mind-internal, cognitive, conceptual, mathematical, physical, and computer models. Hestens (2006: 10) distinguishes mental and conceptual models: the former as subjective and personal knowledge, the latter as objective and scientific knowledge, already formalised. Lian and Zeng (2023: 805) distinguish the physical model from the mathematical model, both counting as ‘objective’ and ‘scientific’, with the latter referring to the dynamic framework of models. Sargent (2010: 168) focuses on the distinction between the conceptual model and the computer model, the former a result of analysis and modelling, while the latter results from implementing the conceptual model by computer programming. The correspondence between the two models is tested by ‘computerized model verification’ whereas comparing the conceptual and the computer model to the real world is called validation. Since the qualities highlighted by these different model stages, and how they relate to each other, may clarify the climate modelling process, I will tailor the concepts to develop a framework that conceives of the genesis of a climate model in four stages: the phenomenon, the mind-internal model, the conceptual model, and the computer-simulated model.

The ‘facts’: phenomena against objects and concepts

As we have seen in § 3.4.2, models are derived from the empirical world. This happens partially through experience in a ‘natural’ way, with the subject- and object-pole present. For another part, the scientific method–adopting the ‘view from nowhere’ and abolishing the subject–plays a crucial role in the constitution of scientific concepts. With ‘object’, I refer to things in the world that can immediately be posited prior to reflection. Concepts are the things that mediate between the experiences and the understanding of them. They are posited to make sense of the variability in the pattern of experience that was first met with frustration instead of fulfilment. The constitution of an apt concept can transform frustration in the face of variability into fulfilment.

The mind-internal model

Individually–but often inspired by the intersubjective 'trend'[9]–we understand the phenomenon as something with a cause (and maybe an impact). I will call the causal understanding, going beyond the phenomenon as it presents itself, the 'mind-internal model'. This is a subjective model; it has not been formalised to be communicable and understandable yet. It is merely an individual interpretation of what presents itself. Note that, also here, the contribution of the scientific approach and its methods with vast amounts of measured empirical data is crucial.

Formalisation and conceptual models

To share our subjective insights, we must formalise them so they would be communicable and understandable to others. I will call the variants of formalised models instances of a 'conceptual model'. Formalisation can rely on conventions that were developed in more (or less) organic ways, over shorter or longer periods, and more (or less) strict, or ambiguous. The use of language allows for substantial ambiguity, whereas logic and mathematics leave less room for interpretation, but are also less flexible suitors. If we want the phenomenon to be understood as precisely[10] as possible, mathematical formalisation seems fit for purpose.

In the case of climate models, there is a mathematical instance of the conceptual model, but as Lian and Zeng (2023: 805) distinguish physical and mathematical models, it becomes clear that another instance of the conceptual model, at a lower level of abstraction, is also relevant. I understand this physical model as a conceptual model that employs physical theories to

[9] With 'intersubjectively inspired', I mean that making sense of a phenomenon, even before the insights are formalised and shared, depends on how the individual has learned to think about experiences by its community and the tradition. Thunderstorms were once understood by appealing to the Gods, while now, when hearing the rumbling of an approaching thunderstorm, the average Danish person would only think about Thor riding the clouds while swinging a hammer by pure association–not in a causal sense. In a causal sense, this average Danish human being would think about something with friction between masses of air and electricity.

[10] I will not claim that a mathematical formalisation often leads to the highest accuracy. This judgement would only be defendable within the scientific realm, where accuracy is a measure of the degree of overlap between the results from our theories and the objective world as measured empirically. Understanding accuracy as approaching the phenomenon of experience as closely as possible – what we ought to do outside of the scientific realm, poetics arguably performs better than math. In Poetics of Space, Bachelard inquires into the ontology (the entity and dynamism) that is referred to through the poetic image: "The poet does not confer the past of his image upon me, and yet his image immediately takes root in me. The communicability of an unusual image is a fact of great ontological significance." (Bachelard 1964: xvii).

understand bits and pieces of the causal relations underlying the phenomenon's emergence, but, without a coherent mathematical integration of these multiple physical theories. Therefore, having the relevant theories in mind, mathematisation will lead to a conceptual model at a higher level of abstraction that must be fully coherent (unlike the physical understanding). Some aspects are only 'vaguely' present in the physical model: they are not (yet) sufficiently understood to be described mathematically, or it is too complicated to integrate their mathematical description into the existing governing equations.

In short: the well-posedness of the physical model in a mathematical sense–thus the configuration of the dynamical cores–is crucial to the reasonability of the model outcome (Lian and Zeng 2023: 805). Processes that are not well understood can be represented by parametrisation (IPCC 2023: 181). It is known, however, that there must be a more adequate representation than the parametrised one that we do not have access to for now.

The computer-simulated model

In the case of CAM6, the mathematical conceptual model exists of the continuous differential equations that describe the flow over the sphere of the Earth. A fourth stage comes into the picture as the conceptual model should provide certain information: concrete solutions in time and space. However, the conceptual model comprises a set of coupled, non-linear, partial differential equations. Often, we do not have a well-studied solution for them–our insight into the nature of the equations is poor–and it is said that 'there is no analytic solution for the equation'. We fail to unravel how the mathematical representation of the system behaves exactly at every point of its 'state-space'. However, we can find approximate solutions by specifying conditions and iteratively testing whether a specific solution complies with the equations. 'Fortunately,' numerical methods allow us to obtain a discrete solution. Given the computational capacity needed to solve the coupled equations numerically, this is done by a computer program. I will call the form in which the mathematical conceptual model is implemented by computer programming script, the computer-simulated model. Clearly, the fit between the conceptual model and its numerical implementation is far from exact (Oberkampf, Trucano, and Hirsch 2004: 26).

Finding solutions for the mathematical expression of the climate-system components requires discretisation. The simple fact that the solution will only be available at specific instances in time and space implies a loss of information. The various algorithms to obtain the discrete solutions constrain the differential equations that can be included in the dynamical core. Hence, not the equations most adequately describing the system are chosen, but the equations that describe the system as adequately as possible while complying with the constraints of the algorithm of choice. Furthermore, no algorithm satisfies the three conditions for an accurate solution (conservation in time, constancy, and shape preservation) simultaneously, so, inaccuracies, such as splitting errors and deformations, are introduced. Although techniques (e.g. applying operators ensuring conservative solutions and others ensuring consistency and shape preservation sequentially) are applied to minimise these errors, they in turn have undesirable consequences (e.g. deformation of the Lagrangian surface).

Other sources of constraints is that each dynamical core comes with its specific type of grid–that can be implemented at different resolutions–and its specific type of physics-dynamics coupling. This is yet another reason why employing different dynamical cores can lead to significant differences between the model outcomes (Jun, Choi, and Kim 2018: 2811; Herrington et al. 2022: 23–25).

At last, it speaks for itself that the employment of parametrisations–not directly representing any physical process, but merely simulating subgrid phenomena and phenomena that are not well understood–is a source of uncertainty as well. Figure 1 depicts the constitution of a model component.

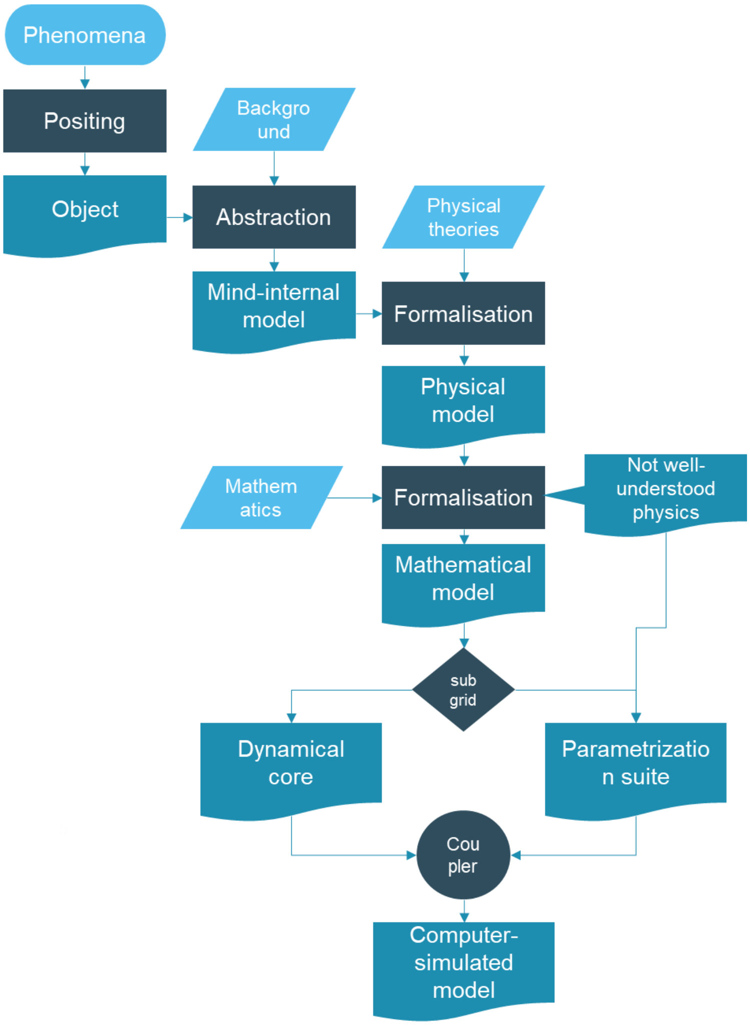

Figure 1: Flowchart depicting the modelling process for one model component. The light blue blocks depict input, the dark blue blocks depict processes, and the turquoise blocks depict outcomes (that can be used as input afterwards). Note that the scientific input for the constitution of the concept is missing here.

4.2. Modelling the climate system or the earth system

4.2.1. The Community Earth System Model 2 (CESM2)

The CAM6 model is the submodel representing the atmospheric processes in the Community Earth System Model 2 (CESM2). CESM2 is a coupled Earth system model released in June 2018 by the NCAR–this modelling group also delivered a model for the first IPCC assessment in 1990. The predecessors of the CESMs (1 and 2) were the community climate system models (CCSMs). Because of the inclusion of processes such as global dynamical vegetation changes, land use changes due to anthropogenic activities, and processes of aerosol effects among others, what was first called a climate system model is now called an earth system model, it includes processes that are not comprised in the climate system but play an important role as external drivers and forcings. CESM2 simulations are executed as a contribution to CMIP6. The model participates in twenty Model Intercomparison Projects (MIPs) including ScenarioMIP (Danabasoglu et al. 2020: 2).

CESM2 is a coupled earth system model: it exists of several coupled component models that represent parts of the climate system, among which CAM6–described in § 4.1.1–represents the atmosphere. Other components models included in CESM2 are a land model, a sea-ice model a land-ice model, an ocean model, a surface waves model, and a river runoff model (see Figure 2: Component models of the CESM2 model. (Danabasoglu et al. 2020: 3).Figure 2) (Danabasoglu et al. 2020, 3). The model can operate with two versions for the atmospheric component: a low-top variant (CAM6) and a high-top variant: the Whole Atmosphere Community Climate Model (WACCM)). CAM6 represents the atmosphere up to a pressure of 2.26 hPa, or about 40 km above the sea level with 32 vertical levels; WACCM6 represents up to a pressure of 4.5×10^{-6} hPa, or about 130 km above the sea level earth with 70 vertical levels. The high-top variant better represents the stratosphere and includes upper atmospheric processes that are not included in the low-top variant (Danabasoglu et al. 2020: 3,4). However, running the high-top variant on the Cheyenne supercomputer costs about seven times more than running the low-top variant on the same device, since the former simulates four years per day, while the latter simulates thirty years per day (Danabasoglu et al. 2020: 7). Here it becomes clear how financial concerns are relevant to modelling decisions.

The coordinated functioning of the five model components is enabled by the Common Infrastructure for Modelling the Earth (CIME) software. This software controls, among other things, the intercomponent exchange of fluxes and information about the component state between the atmospheric, land, wave, and sea-ice components. The fluxes between the atmospheric and ocean components are calculated by the compiler and exchanged every timestep of one hour towards the ocean component and every timestep of thirty minutes towards the atmospheric component. Furthermore, CIME is equipped with additional software–the Case Control System–to configure, compile, and execute complex earth system model experiments (Danabasoglu et al. 2020: 7).

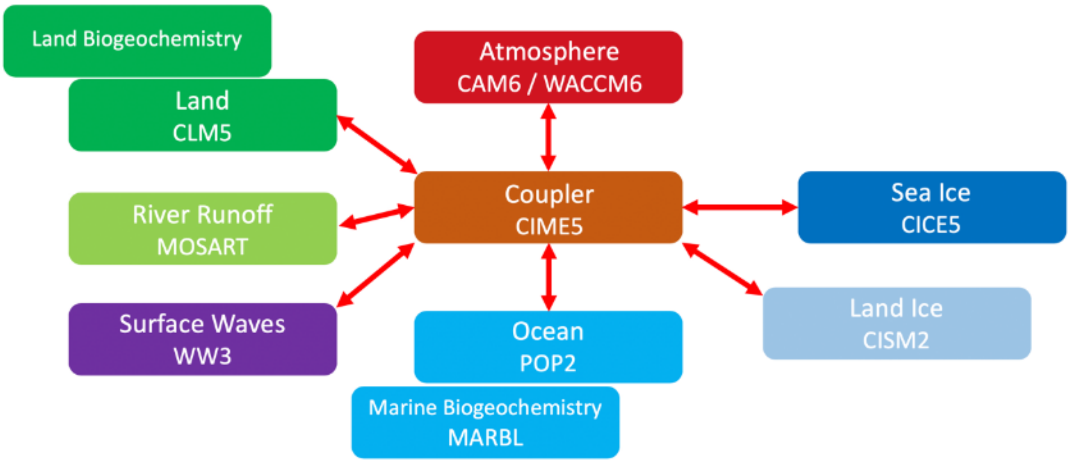

Figure 2: Component models of the CESM2 model. (Danabasoglu et al. 2020: 3).

4.2.2. Sources of uncertainty in the modelling process of a climate model or earth system model

In § 4.1.2, I discussed the sources of uncertainty that can be found in the modelling of one component of the climate system: the conceptualization of reality (the idea of a complex dynamic system), the mathematical formalization of this system, the discretization as such, the constraints on the equations, grid, and dynamics-physics coupling imposed by specific discretization algorithms, as well as the errors introduced by those, and the parametrization of sub-grid and processes that are not sufficiently understood. These sources of uncertainty remain present in complete climate system or earth system models given their composition of multiple single climate components.

In the following paragraph, I will focus on the estimation of the parameters included in the parametrization suite. Parameter estimation is relevant to the models for individual components as well, so I could have included this already in the § 4.1.2. However, estimation happens throughout different stages of the modelling process: first at the process level, then as a set of parameters representing processes comprised by a specific component (such as CAM6), and ultimately, at the level of the coupled model–the integrated climate model comprising all components and their processes (Hourdin et al. 2017: 591).

Lack-of-fit and trade-offs

In § 4.1.2, I mentioned the lack of fit between the computer-simulated model and the conceptual system: a climate or earth system model does not represent the climate system fully adequately. It can represent certain components or processes more adequately than others, and often there exists a trade-off between the adequacy of the representation of distinct parts: enhancing the adequacy of one part, implies a cost regarding the adequacy of representation of another part. There exist trade-offs between the adequate simulation of different target processes, e.g., tuning the parametrisation representing cumulus clouds to improve the simulation of the Madden-Julian Oscillation (MJO)–a mode of tropical interseasonal variability–goes hand in hand with an increased bias in the mean state of the variables (Kim et al. 2012; 2011). Another kind of trade-off exists between adequate simulation of target systems and adequate representation of the physics of the climate system by tuning the parametrisations, e.g., the parameterisation for cloud microphysics that results in the best simulations of temperature, is at the same time a suboptimal configuration compared to what is known about cloud microphysics based on satellite data. Process-based tuning–the bottom-up approach attempting to represent the physical processes adequately–results in a different optimal parametrisation than top-down, tuning, constrained by a target outcome (e.g. the temperature trend or radiation balance) (Suzuki, Golaz, and Stephens 2013: 4468).

Calibration and ‘tuning’ for adequacy for purpose

The prioritisation of some parts over others depends on the model’s purpose; what is enhanced is the model’s ‘adequacy for purpose’ (Oberkampf, Trucano, and Hirsch 2004: 26). Adequacy for purpose can be enhanced through the process called ‘tuning’ which was already mentioned in the previous paragraph. Tuning partially has the same goal as calibration: the estimation (calculation) of the parameters of a hypothetical population based on a sample of the population (Fisher 1922: 311–12). In a technical sense, it concerns optimising a cost function that minimises the distance between the estimated values for the variables and the observed data. Calibration, however, is a purely heuristic procedure; the parameter values are determined by nothing more than the algorithm and the empirical calibration data. Calibration can provide satisfying results for very ‘basic’ models–e.g. linear combinations of variables of which the coefficients should be estimated. However, in the case of a climate model, the parameter values are part of the simplified representation of processes that cannot be included in the dynamic core of the model. If they ought to adequately represent these processes, they cannot just take any value that works well with the others for overall model fit. Many parameters are up for estimation and when looking for combinations of their values that fit the calibration data, often, multiple combinations are performing equally well. When calibration is applied to estimate the parameters of a climate model, given the complex configuration of such a model and the many structural insufficiencies it might contain, enhancing overall adequacy will often lead to the choice of parameter values that are suboptimally representing their target process (Hourdin et al. 2017: 591). For example, for CAM6, one of the statistical methods applied is a Perturbed Parameter Ensemble (PPE) method, tuning 45 parameters simultaneously to avoid ‘getting stuck’ at local extrema for a subset of parameters. Experiments show that multiple sets of parameter values can lead to equally adequate simulations. This observation underlines the need for expert opinion to pick out the sets of values that approach the assumed physical basis best (Eidhammer et al. 2024: 23).

So, a procedure that welcomes expert judgment offers benefits; this is an essential difference relative to the calibration process and therefore, it merits another title: ‘tuning’. Hourdin (2017: 590) draws an analogy with reaching ‘harmony’ in music: to produce a beautiful symphony, the musicians should (1) individually practice their lines, *and* (2) literally ‘attune’ to one another. Furthermore, the musicianship is not purely a technical endeavour: musicians play according to what the composer wrote on the staff, but additionally, they perform their interpretation of the written music. Music emerges where the static signs on the staff coincide with a musician who interacts with them. This dialogue also happens at the level of the integrated piece of music, produced by the whole orchestra playing together: the conductor ensures the tempo and attenuation are achieved as it is meant to be according to the sheet music, but also brings some interpretation into play.

Back to tuning in climate models, where this also happens (broadly speaking), at two levels and includes subjective judgement: first the parameters are brought within their observational range by running an estimation for the corresponding processes; then, the estimation is further refined against the constraints of the fully integrated system–often against the radiation balance at the top of the atmosphere (Lguensat et al. 2023: 2). These steps rely partially on technique and ‘knowledge’ about the specific process. Nevertheless, an important contribution is the expert judgement of the modelling team and the choices they make to prioritise the representation of certain processes over others with adequacy for purpose in mind.

The legitimacy of tuning

By tuning, modelling groups address the problems with mere calibration: a model fit without representational adequacy. However, they can also decide to deliberately 'impurify' the representation of a process and enhance the accuracy of the model projections. Whether compensation for model error by tuning is legitimate, is a topic of debate (Hourdin et al. 2017: 590). In any case, it is never legitimate over the whole line: even if it seems better to sacrifice the representational adequacy regarding specific processes for the accuracy of the envisaged model projections (its purpose), there will always remain processes that are vital to this purpose and should be represented as adequately as possible. We want a model to make accurate predictions–approaching observational data–for the right reasons, namely, that the representation of the system is (sufficiently) adequate (Knutti 2018: 349). If accuracy were a result of a combination of parameter values that are merely working well together (the combination that corresponds to a (local) minimum of the cost function), but in themselves have little to do with the processes they represent, it can be argued that the model solutions are obtained by sheer luck. I admit that 'sheer luck' is a dramatic way of putting it: as Baumberger et al. defend, "it is far from trivial that a model can be successfully calibrated." (Baumberger, Knutti, and Hirsch Hadorn 2017: 8). The parameter values are not the only focal point of adequate representation; so, at least partially, the accuracy of the predictions relies on the well-posedness of the model configuration that exists besides the parameter values. Otherwise, no sufficiently good solutions for the parameter values would exist in the first place; it would not be possible to make the model fit the observational data.

We could believe that the reason for the accuracy of the projections is irrelevant: if the projections are accurate, and the purpose of the model is to make accurate projections regarding a certain variable, then why would we bother any longer about how these predictions are obtained? The reason is that the projections should be accurate beyond the space made up by the tuning data. For predicting phenomena that have not manifested yet, we rely on the idea that we understand the principles by which they emerge. The epistemic value of the projections beyond the tuning dataset is warranted by the adequate representation a climate model offers of the climate system (Baumberger, Knutti, and Hirsch Hadorn 2017: 12). The (increased) belief that the representation of the climate system is sufficiently adequate to allow meaningful projections beyond the tuning dataset is warranted by evaluating the model after it has been tuned with 'use-novel' data: data that were not included in the tuning dataset, and therefore indicate the model performance beyond the space made up by the tuning data (Frisch 2019, 997–98; Oberkampf and Barone 2006: 9). It should be noted that applying the model to a domain that is larger than the domain covered by the empirical data it has been tuned and evaluated on, brings additional uncertainty, the validation procedure with use-novel data notwithstanding. Oberkampf and Barone acknowledge that "how this extrapolation should be accomplished is a complex, and unresolved, issue." (Oberkampf and Barone 2006: 13). Figure 3 depicts the process from model components to a coupled model.

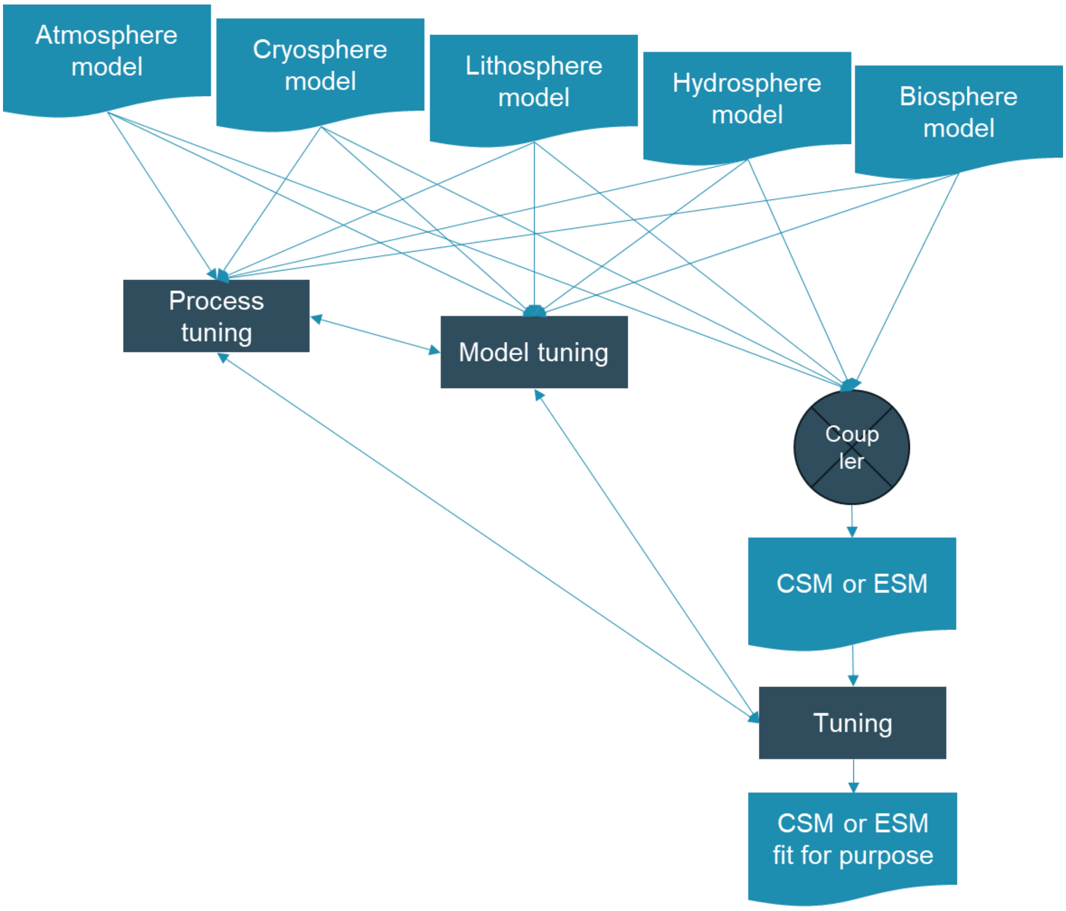

Figure 3: Flowchart depicting the modelling process for a coupled earth system model. The light blue blocks depict input, the dark blue blocks depict processes, and the turquoise blocks depict outcomes (that can be used as input afterwards). CSM stands for climate system model, ESM stands for earth system model.

4.3. Multi-model ensemble projections and experiments

4.3.1. The Coupled Model Intercomparison Project (CMIP)

Before climate models had seen daylight, weather models were already the subject of philosophical reflection: from 1963 on, Sanders (1963; 1973) inquired into the subjective aspect of meteorological forecasting. He assessed the accuracy of forecasters' statements about the likelihood of weather events with the climatologically expected values as a benchmark–expressed in values for temperature and precipitation, the occurrence of thunder, and wind direction among others (1963: 194). He found that the group-mean probability forecast is more accurate than the most accurate forecast of an individual forecaster (1963: 201; 1973: 1176). Gyakum (1986) and Wobus et al. (1995) confirmed these findings. From a literature review over a wide variety of fields–weather forecasting, psychology, and econometrics among others–Clemen (1989) concludes that ensemble forecasts provide higher accuracy predictions compared to the best of the individual ones in the subjective, as well as for more objective–in the sense that no human judgement directly produces the prediction statement–statistical ensemble forecasts. Thompson (1977) developed the mathematical side of the phenomenon and showed that the optimal–and thus weighted–combination of two independent forecasts can reduce the error variance by about twenty per cent. It is important however to keep in mind that this error reduction only takes place for model ensembles that perform at similar accuracies. If some models perform significantly worse than others, they will drag the accuracy level of the mean down (Fritsch et al. 2000: 578).

Ensemble forecasts can be created in multiple ways. One way that has been proven to improve the accuracy is the employment of differing 'units'–human beings or models–that generate the forecast based on the initial conditions although the practice causes the ensemble spread to increase significantly (Stensrud et al. 1999; Hamill and Colucci 1997). Alternatively, varying the initial conditions for a single forecast-generating unit also provides an ensemble spread of which the mean will be more accurate than the individual predictions (Molteni et al. 1996; Toth and Kalnay 1993; Stensrud et al. 1999; Hamill and Colucci 1997).

Besides the insight into the advantages of pooling several predictions to obtain a more accurate result, it was not clear what the sources of the differences in projections of independent models were. In 1989, the Atmospheric Model Intercomparison Project–an effort to compare the atmospheric climate models of several modelling groups and inquire into the representation of the physical processes, the corresponding error and performance–was founded (Gates 1992, 1963). This project is the predecessor of the Coupled Model Intercomparison Project (CMIP). In 1990 the first IPCC assessment report was published; an updated version in 1992 (IPCC 1992: vii). The findings for the 1990 report were informed by global coupled general circulation models from the National Centre for Atmospheric Research (NCAR) and the National Fluid Dynamics Laboratory, both located in the US. For the 1992 update, model results from the Max-Planck-Institute for Meteorology in Germany and the Hadley Centre of the UK Meteorological Office were included. These results accounted for a transient response to increasing CO_2 levels (IPCC 1992: 103–4). In the years after the publication of the first assessment report, many more modelling groups dedicated themselves to the development of coupled climate models (Meehl 1995: 951). The report of a workshop, organised in 1994 by the World Climate Research Programme Steering Group on Global Coupled Modelling, states the following:

> It was suggested that WCRP continue to facilitate the international coordination of global coupled modeling and that an update to an earlier "level1" model intercomparison undertaken […] for the four global coupled models that were referenced in the 1992 IPCC report be performed for the larger set of models now in use. (Meehl 1995: 957)

The proposal to undertake coupled model intercomparison activities was widely supported and CMIP was born (Meehl et al. 2000a, 313) to "better understand past, present, and future climate change arising from natural, unforced variability or in response to changes in radiative forcings in a multi-model context." (Eyring et al. 2016: 1938).

CMIP provides climate researchers with a database of the inter-comparable output from a set of global coupled general circulation models evaluated under standardised boundary conditions. The effect of anthropogenic activity on the historical climate record can be detected from these simulations, and the future climatic impact of anthropogenic emissions can be projected. Meanwhile, the CMIP researchers inquire into the model architecture to elicit sources of consensus and divergence in the output of different models (Covey et al. 2003: 104). Hagedorn et al. (2005) inferred from the literature that ensemble models perform better and show that this is a result of error compensation, as well as increased consistency. It was mentioned earlier that lower-performing models drag down the overall performance of the ensemble; this could be addressed by ensemble weighting (and ascribing lower weights to lower-performing models) (Hagedorn et al. 2005: 231).

In the past two decades, the CMIP experiments have expanded: from including fifteen models (Lambert and Boer 2001: 83), to more than a hundred models from 49 modelling centres (Durack 2024a; 2024b); from considering a constant level of CO_2 forcing (Lambert and Boer 2001: 87), to a transient response arising because of a linear increase in CO_2 with one per cent a year (Meehl et al. 2000b: 315), to projections considering complex socio-economic pathways bringing about the forcings that the climate system could undergo (van Vuuren et al. 2011: 5).

The Coupled Model Intercomparison Project Phase Six (CMIP6)

The details of the most recent project phase of CMIP: CMIP6, were published in 2016. The structure of CMIP6 consists of three main aspects: (1) a set of common experiments comprising CMIP historical simulations and what is referred to as 'DECK' (Diagnostic, Evaluation and Characterization of Klima), (2) common standards, coordination, infrastructure, and documentation, and (3) a set of 21 Model Intercomparison Projects (MIPs) that address questions specific to CMIP6 (see Figure 4) (Eyring et al. 2016: 1937). DECK comprises a preindustrial (PI)–before 1850–control simulation, an atmospheric model intercomparison project simulation, a simulation with a forcing of an abrupt quadrupling of CO_2 concentration, and a simulation with a forcing of a linear increase in CO_2 concentration of one per cent a year. These experiments make it possible to compare the performance of CMIP6 models and the models of future CMIP phases. The historical simulation simulates the climate from 1850 to 2014 (Eyring et al. 2016: 1940–41). CESM2, described in § 4.2.1, contributes to CMIP6 with datasets arising from preindustrial climate simulations (before 1850) and simulations for the historical period from 1850 to 2014.

Using forcing datasets corresponding to specific models for executing the DECK experiments and the historical simulation might be beneficial to assessing uncertainty in the model output. However, it would be difficult to distinguish the uncertainty in the outcomes from the uncertainty in the forcing dataset. Therefore, these experiments preferably get executed with the same standardised forcing datasets for all participating models. Additionally, how the forcing dataset is used exactly for the experiments should be well documented and the uncertainty should be assessed (Eyring et al. 2016: 1941).

The Model Intercomparison Projects (MIPs)

MIPs are experiments aiming to answer specific questions and therefore often specific for their corresponding CMIP phase. In the case of CMIP6, 21 MIPs have been selected with the World

Climate Research Programme's Grand Science Challenges[11] in mind (Eyring et al. 2016: 1944). The overarching questions that should be addressed by the MIPs are "How does the Earth system respond to forcing?", "What are the origins and consequences of systematic model biases?", and "How can we assess future climate change given internal climate variability, climate predictability, and uncertainties in scenarios?" (Eyring et al. 2016: 1945). Examples of MIPs are the Decadal Climate Prediction Project which aims to predict and understand forced climate change and internal variability for projections up to ten years into the future; the Land-Use MIP focussing on the influence of land-use changes on climate change and exploring mitigation strategies based on these feedbacks, and ScenarioMIP focussing on the impact of certain plausible future scenarios, including adaptation and mitigation strategies, as well as exploring the uncertainties that come with such projections. (Eyring et al. 2016: 1946–47). CESM2, discussed in § 4.2.1 takes part in twenty MIPs, including ScenarioMIP (Danabasoglu et al. 2020: 2).

I will restrict my focus to ScenarioMIP since this MIP produces future climate projections I focus on in this thesis.

[11] The Grand Challenges of the World Climate Research Programme are areas of research, modelling, analysis, and observations that are focused on during the decade from 2012 to 2022 (World Climate Research Programme (WRCP) 2023). The topics require continued research since there is still a lot of uncertainty concerned (Beniston 2013: 1). The identified challenges were (1) Melting Ice and Global Consequences, (2) Clouds, Circulation and Climate Sensitivity, (3) Carbon Feedbacks in the Climate System, (4) Weather and Climate Extremes, (5) Water for the Food Baskets of the World, (6) Regional Sea-Level Change and Coastal Impacts, and (7) Near-term Climate Prediction (World Climate Research Programme (WRCP) 2023).

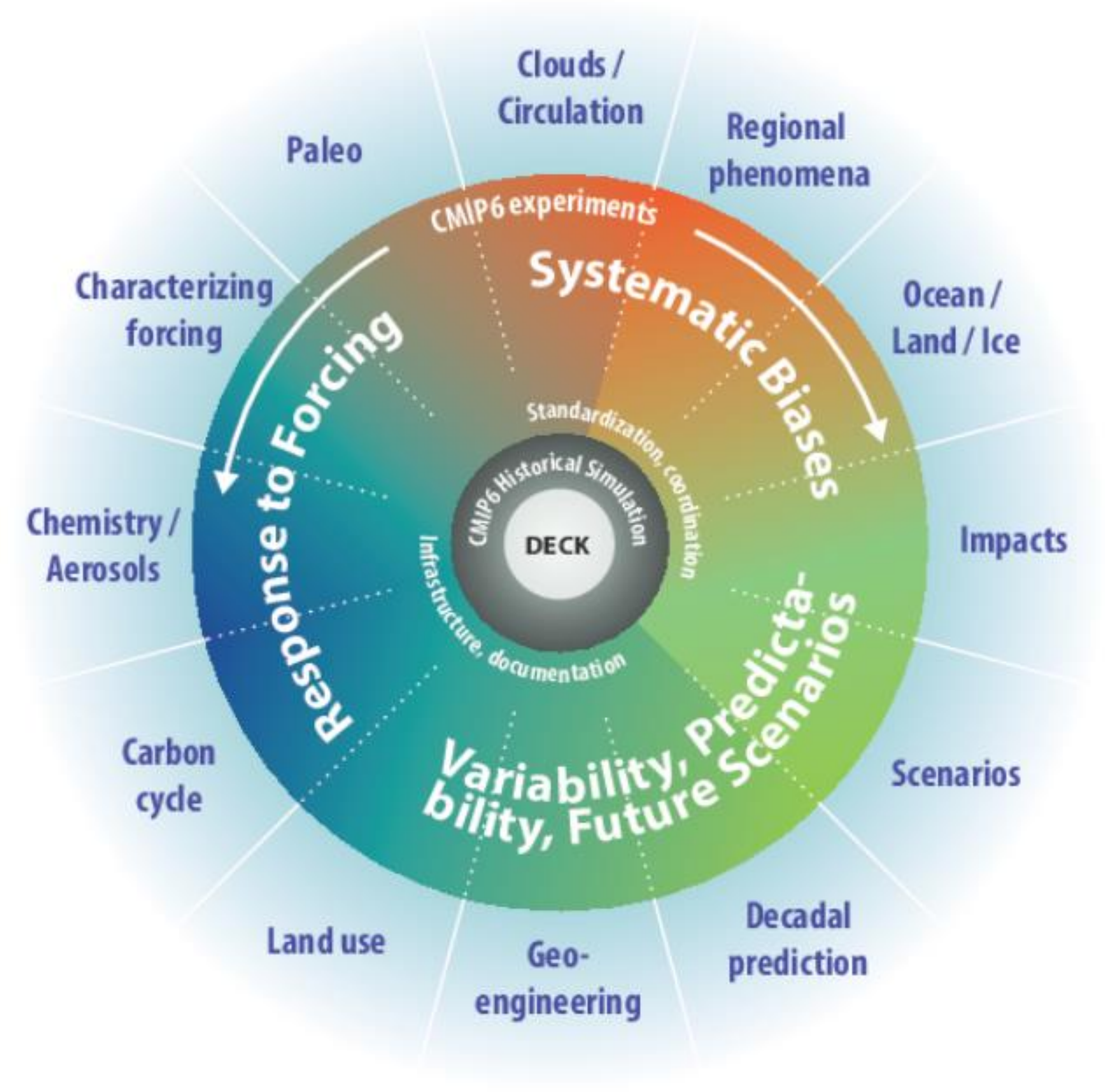

Figure 4: Overview of the components and experiments of CMIP6 (Eyring et al. 2016: 1944)

The Scenario Model Intercomparison Project (ScenarioMIP)

Around 2010, the interest in the impact of climate policies and adaptation measures more generally grew while the then scenarios–the Special Report on Emission Scenarios (SRES)– only included non-climate policy conditions. On the technical side, the SRES scenarios did not meet the input requirements of the new generation of climate models (van Vuuren et al. 2011: 6); therefore, developing a corresponding generation of scenarios, as requested by the IPCC in 2008, was unavoidable (Pachauri 2008: 2). The scenarios, updated and expanded relative to the SRES are the Representative Concentration Pathways (RCPs), presented radiative forcing ranging from 2.6 W/m² to 8.5 W/m² including two intermediate scenarios of 4.5 W/m² and 6

W/m². They covered the range of forcings and corresponding scenarios discussed in the scientific literature and were thus called 'representative'. The scenarios in the literature were many more than the four RCPs developed, implying that one RCP represents multiple specific scenarios. The RCPs were combinable with climate models as well as integrated assessment models[12]. Moreover, they have been created based on the results of IAMs to ensure plausibility and consistency: first, a set of conditions for the year 2100 was specified, then the different pathways leading up to these conditions were explored, considering trends in energy use, GHG emissions, and land use. The result of this development process was a set of four different time series of GHGs and air pollutant concentrations and land-use change, ranging from the year 1850 to the year 2100, with extensions to the year 2300 (van Vuuren et al. 2011: 7–9).

The RCPs were used for CMIP5 experiments; with the advent of CMIP6, new emission scenarios have been developed again: on the one hand, the four RCPs updated based on the Shared Socioeconomic Pathways (SSPs), on the other hand, four additional so-called 'gap-scenarios', corresponding to average forcing levels that are of interest but were not considered by the previous set of RCPs yet[13] (O'Neill et al. 2016: 3468). The SSPs are based on five internally consistent narratives–developed by experts–describing possible future socio-economic developments without explicit additional climate policies for climate change mitigation or adaptation (Riahi et al. 2016: 155). From these narratives, quantitative models develop demographic and economic drivers (education, population, urbanisation, and GDP projections), and a set of IAMs determine the emission, land-use, and energy trajectories emerging from the narratives between 2015 and 2100, or, in the extended version from 2015 to 2300 (Eyring et al. 2016: 1941). A depiction of this process can be found in Figure 5.

Multiple IAMs were used to assess the robustness of the resulting scenarios and the uncertainty corresponding to each SSP (Riahi et al. 2016: 156). The resulting quantitative trajectories are consistent with the literature about plausible forcing scenarios. SSP mitigation scenarios are developed based on the baseline SSPs and with the RCP forcing levels as the target values for 2100. Using the previous RCP forcing levels ensures continuity with foregoing assessments and facilitates integrated research (Riahi et al. 2016: 156). Since the success rate of policies

[12] An integrated assessment model (IAM) combines the exploration of human systems (society and economy) and natural systems to support decision-making (Weyant et al. 1995: 371).
[13] The average forcing levels reached by 2100 considered in these additional forcing pathways are (1) below 2,6 W/m² (corresponding to the aim of the Paris Agreement to stay 'well below 2°C', considered in this scenarios as below 1,5°C global mean temperature rise above pre-industrial levels), (2) 3,4 W/m² (a new mitigation scenario), (3) a variant of the 3,4W/m² pathway with an overshoot in radiative forcing during the 21st century still, and 7,0 W/m², a baseline pathway corresponding to a scenario without mitigation efforts.

depends on the societal circumstances, the stringency of the policies and the policy instruments used for implementation, and when and where they are implemented, 'shared policy assumptions', corresponding to each of the narratives, have been formulated as well (Kriegler et al. 2014: 404). The development of the SSPs happened through the cooperation of climate modelling, integrated assessment, and impact adaptation and vulnerability communities. With CMIP6, the scenario experiments are not part of the core experiments but are included with a dedicated MIP: ScenarioMIP. (O'Neill et al. 2016: 3462).

> The Scenario Model Intercomparison Project (ScenarioMIP) is the primary activity within Phase 6 of the Coupled Model Intercomparison Project (CMIP6) that will provide multi-model climate projections based on alternative scenarios of future emissions and land use changes produced with integrated assessment models. (O'Neill et al. 2016: 3461)

The objectives of this MIP are to (1) provide climate model simulations that support integrated research (by climate modelling, integrated assessment, and impact, adaptation and vulnerability communities) and enhance the understanding of the physical climate system and its impact on societies, (2) provide a basis for specific scientific questions from ScenarioMIP, but also other MIPs that need scenario-based research, and (3) provide a basis for inquiry in projection uncertainty quantification (O'Neill et al. 2016: 3463). The first objective, to support integrated research, has priority; an overarching research question corresponding to this objective is: "What are the mitigation efforts, climate outcomes, impacts, and adaptation options that would be associated with a range of radiative forcing pathways?" (O'Neill et al. 2016: 3465)

A subset of the resulting data from the sixth phase of the CMIP experiments (CMIP6) has been used for the development of the sixth cycle of the IPCC report (IPCC 2023: 215–17).

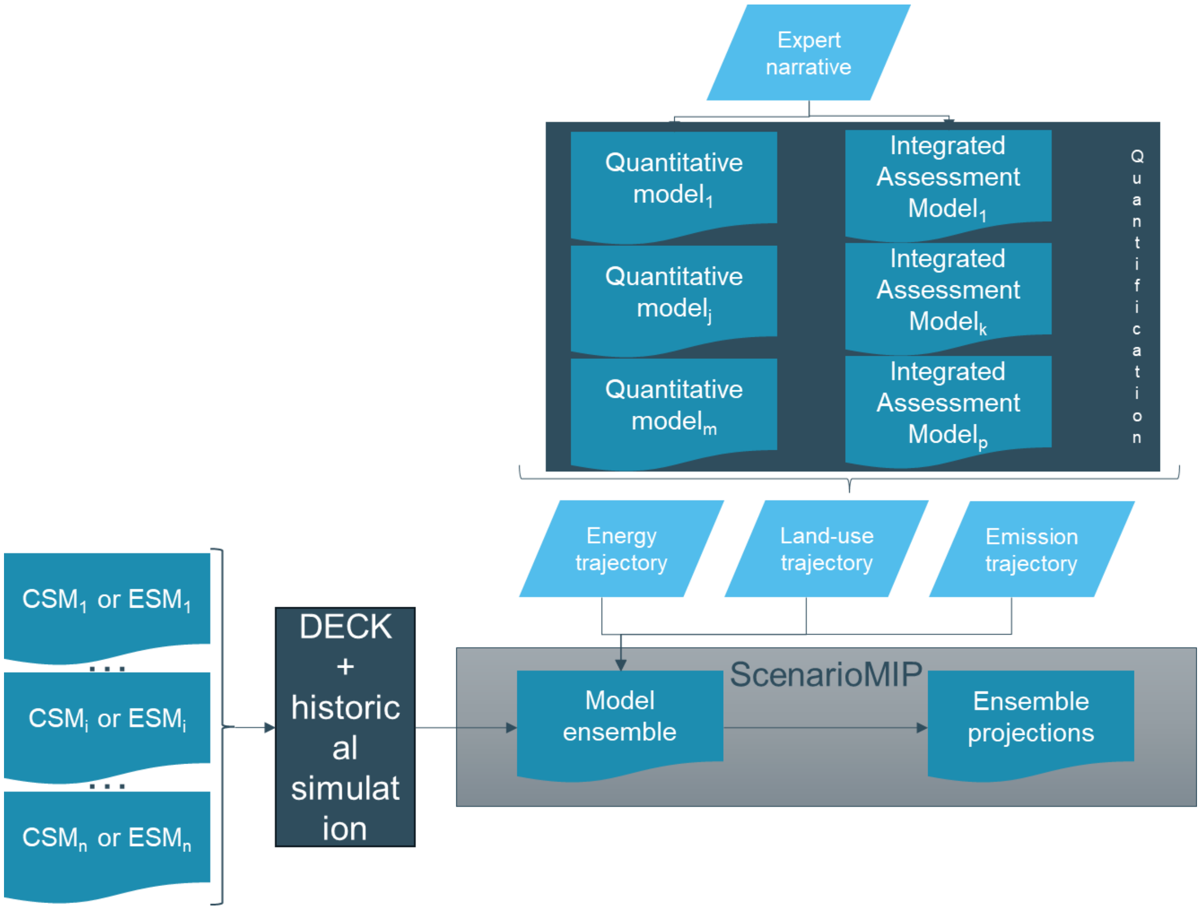

Figure 5: Flowchart depicting the pathway from individual climate models to a model ensemble and the ScenarioMIP experiment that leads to the ensemble projections. The input for ScenarioMIP are trajectories constituted by quantification of expert narratives. The light blue blocks depict input, the dark blue blocks depict processes, and the turquoise blocks depict outcomes.

4.3.2. Uncertainties in the ScenarioMIP projections

Uncertainty in the projections of the general climate variables

In general–focussing on geophysical outcomes such as global averages and spatial patterns for the variables surface atmospheric temperature and precipitation–some CMIP6 models have a higher climate sensitivity than their predecessors in CMIP5. Moreover, the shared socioeconomic pathways (SSPs), used for ScenarioMIP6, consider a wider range of radiative forcings than the representative concentration pathways (RCPs) applied to ScenarioMIP5. These features have consequences for the outcomes of the simulations: especially towards the end of the 21st century (2081-2100) CMIP6 outcomes span a wider range than CMIP5 outcomes (Tebaldi et al. 2021). Model uncertainty is found to be the main reason for this. Concretely, it concerns the structural differences between the included models and the differences between models regarding the size and evolution of the internal variability–generally decreasing–in time (Tebaldi et al. 2021). Hence, for some simulations, the CMIP6 projections are more uncertain than the projections their predecessor CMIP5 made. Zhang and Chen (2021) calculate that the total uncertainty in CMIP6 projections is 1.20 to 1.93 times higher than in the CMIP5 projections. Scenario uncertainty–the variation among outputs based on different scenarios–is smaller for CMIP6 projections than for CMIP5 projections. It is more of a hassle to connect the outcomes of CMIP5 projections to their respective mitigation actions: the RCPs pool multiple mitigation actions per scenario. This conflation impaired the cost-benefit analysis for individual actions based on the model outputs (Stouffer et al. 2017: 100). Planton et al. (2021) report that CMIP6 models perform significantly better for eight out of twenty-four climate variables relevant to climate dynamics. Only for the coupling between the ocean surface and subsurface temperature anomalies, the CMIP6 models perform significantly worse than the CMIP5 models.

So, model uncertainty and the uncertainty due to internal variability–here referring to the noise–are shown to be larger for CMIP6 projections than CMIP5 projections, with model uncertainty as the dominant contributor (at least when assessing for global geophysical outcomes). The contribution of scenario uncertainty is smaller for CMIP6 than it used to be for CMIP5 projections. Model uncertainty and internal variability dominate short-term projections while scenario uncertainty overtakes the former sources of uncertainty in the projections for 2060-2070 onwards (Zhang and Chen 2021).

Uncertainty in the projections of extreme events

More specific outcomes of interest are the impact of the SSPs on trends in extreme events (extreme droughts, extreme precipitation events etc.). Monerie et al. (2020) show that model uncertainty is the main source of uncertainty in the precipitation projections for the Sahel. The decomposition of the precipitation rate in dynamic and thermodynamic aspects shows that the former (the response of atmospheric circulation to climate change), is the main contributor to the uncertainty in the projections. The uncertainty and its sources are the same for CMIP5 and CMIP6 models. Also, John et al. (2022) find large uncertainties regarding CMIP6 projections of extreme precipitation events at a regional scale; according to their assessment, internal variability is the main contributor since most of the included models project the same trend. Wu et al. (2024) investigated the uncertainty in CMIP6 projections of hydrological variables–runoff, precipitation, evapotranspiration, and soil moisture. For the 21st century, more than seventy per cent of the overall uncertainty for these variables can be attributed to model uncertainty. The further in the future the projections are made, the more the contribution of internal variability decreases, while the contribution of scenario uncertainty increases.

Besides extreme precipitation, drought is of interest too: Ji et al. (2024) decomposed the uncertainty in drought projections of CMIP6 models over the three commonly used sources of uncertainty: internal variability of the climate system, model uncertainty, and scenario uncertainty. They found that model uncertainty, on average, accounts for about seventy per cent of the uncertainty in the projections and is the dominant source in projections for tropical regions, whereas, in North America, Eastern South America, the Mediterranean, and southern Australia, scenario uncertainty is the most important contributor to the overall uncertainty.

Uncertainties in the projections of El Niño Southern Oscillation

Another particular interest is the impact of climate change on climate processes of internal variability such as El Niño Southern Oscillation (ENSO)–the ‘dominant mode of interannual climate variability’ with a significant impact on, among others, agriculture. Brown et al. (2020) find biases in sea surface temperature that cause the intertropical convergence zone to shift northward. These biases are slightly smaller for CMIP6 than for CMIP5 models. In general, the ENSO pattern, temperatures and precipitation are well simulated, but highly model-dependent: both CMIP5 and CMIP6 project an increased ensemble mean for ENSO amplitude in the future. Beobide-Arsuaga et al. (2021) quantified the uncertainty in ENSO projections for CMIP6 models and decomposed this uncertainty over the model uncertainty, the scenario uncertainty, and the internal variability. Uncertainty in the projected ENSO amplitude increases over time. During the first three decades of the twenty-first century, internal variability is the main source of this uncertainty, later, inter-model differences play the biggest role.

Uncertainty in the projections due to empirical data bias

Another source of uncertainty that comes to the fore is the empirical data used for model building: You et al. (2021) find that the CMIP6 models consistently underestimate the mean surface temperatures over the territory of China–called a ‘cold bias’. Model uncertainty is responsible for the uncertainty in the short term, while scenario uncertainty gains importance in the long term. They infer that the difficulties of CMIP5 models in representing the atmospheric processes over complex geography persist in the CMIP6 models. Besides the complex topography, they suppose data biases due to sparsely placed stations, the inadequate representation of the snow-albedo feedback and low-level cloud cover, and the deficient inclusion of atmospheric pollution lay at the basis of the cold bias.

Uncertainty in the downstream projections: impact modelling

Further downstream, the climate model projections are used as an input to model specific impacts of climate change. The projections of these models contain even more uncertainty since the uncertainty of the climate projections propagates while more model uncertainty is added by the impact model used. Müller et al. (2021) make an uncertainty assessment for crop model projections and find that further in the future–projections for the end of the 21st century– the climate-model-induced variance is the main contributor to the overall uncertainty. The crop model-induced uncertainty is the main contributor to the overall uncertainty for short-term and medium-term projections.

4.3.3. Sources of uncertainty in ScenarioMIP projections

In the scientific papers about the uncertainties in the CMIP6 projections summarised in § 4.3.2, five main loci of uncertainty came back: internal variability, model uncertainty, scenario uncertainty, climate dataset uncertainty, and uncertainties downstream. I will proceed with an overview of these types of uncertainty and derive their meaning and place in the total uncertainty related to climate models.

Model uncertainty

When models with a different configuration are run on the same input data, they produce different outcomes. The uncertainty derived from that is called ‘structural model uncertainty’. It comes down to the idea that, either no model configuration adequately represents its target system, or under the assumption that there would be a model that does so, we do not know which one it would be. Wu et al. (2022: 4) consider model uncertainty corresponding to a certain input scenario. The model uncertainty is quantified as the variance among the outcomes for different models running on a certain scenario:

$$M = \frac{1}{\#S} * \sum_S var_m\left(x_{m,s,t}\right) \qquad (5)$$

With #S the number of scenarios, $x_{m,s,t}$ the outcome of a model m for a scenario s at time t, and var_m the variance of a certain model.

Assessing the spread of the outcomes of a model ensemble–several models run in the same input data–is a common way to estimate model uncertainty. Winsberg (2012: 119) elucidates four problems with this approach: it assumes that (1) all models are equally performant and that (2) the models included in the ensemble are representative of the space with all possible models. Furthermore, (3) climate models are not independent of one another and (4) climate modellers tend to tune the models to fit previous average outcomes better.

Because of these reasons, using ensemble spread to estimate model structural uncertainty is not a reliable approach. Especially, the idea that the models would represent the space with all models is problematic. Winsberg argues that it should not comprise 'all possible models', only these models that adequately represent the target system. We would have to assume then that they can be found in a normal distribution around the 'ideal model'; an assumption that is not complied with (Winsberg 2012: 122).

Internal variability

The IPCC glossary defines climate variability as "Deviations of climate variables from a given mean state (including the occurrence of extremes, etc.) at all spatial and temporal scales beyond that of individual weather events." (IPCC 2023: 2224). One kind of climate variability is so-called 'natural variability' resulting from processes other than anthropogenic influence. On the one hand, natural variability can occur due to processes external to the climate system, such as volcanic eruptions, on the other hand, this variability is considered internal or intrinsic to the system when it occurs due to internal fluctuations of processes; the fluctuations observed when the system is "subject to a constant or periodic external forcing (such as the annual cycle)." (IPCC 2023: 2224).

Wu et al. (2022: 4) quantify the internal variability of a model as the variance of the residuals of the fits across all scenarios. Calculating this over all models, they obtain what would correspond to the internal variability of the climate system itself:

$$V = \frac{1}{\#M} * \sum_M var_{s,t}(\epsilon_{m,s,t}) \qquad (6)$$

With $var_{s,t}(\epsilon_{m,s,t})$ the variance of the model m across all scenarios at all times.

Lehner et al. (2020: 491–92) connect internal variability to the chaotic nature of the climate system: at a certain point in time, the precision of the initial conditions is not sufficient anymore to predict the system's evolution. So, internal variability comprises the influence of the initial conditions on the projections. Since the aim of these projections is understanding the impact of a forcing scenario on the evolution of the climate variables–that are summarising statistics of particular states and aim to average out internal variability–the influence of the weather conditions that contingently but inevitably provide the starting point of the evolution, should ideally be reduced to zero (Winsberg 2018: 42–43). Winsberg explains that internal variability contributes to uncertainty in the projections in an indirect way; it is not clear from only a few runs of a model what variability in the outcome is a change of the climate variables and what is due to the sensitive dependence of the system on the initial conditions. A higher number of model runs (ideally, but impossibly one for each possible set of initial conditions to strictly exclude conflation) is needed to distinguish between the two sources of variability and disregard the former (2018: 93).

Scenario uncertainty

Wu et al. (2022: 4) quantify scenario uncertainty as the variance of a multi-model average under the different considered scenarios.

$$S = var_s\left(\frac{1}{\#M} * \sum_M x_{m,s,t}\right) \tag{7}$$

However, Winsberg (2018: 95) does not consider this type of uncertainty as a real source of uncertainty in the projections: these projections are, in fact, transparently dependent on the proposed scenario. The scenario as such is uncertain, there is no uncertainty emerging during the process resulting in the projections.

Winsberg’s sources of uncertainty in climate projections

As mentioned in the previous sections, Winsberg reclassifies the main sources of uncertainty based on philosophical reflections regarding their nature and their relations. He divides model uncertainty into two independent sources: the model configuration comprising the initial equations, the discretisation scheme, and the parametrisation scheme on the one hand and the chosen values for the parameters on the other hand. Furthermore, he includes climate dataset uncertainty, which is sometimes mentioned as a fourth main source of uncertainty, in the uncertainty due to the parameter values since it is an inseparable part thereof. Finally, scenario uncertainty is not exactly a source of uncertainty for what is found in the climate model projections since these projections are either conditional on the scenarios or independent of them.

4.3.4. Interpreting increasing and decreasing uncertainty between CMIP phases

Model uncertainty and internal variability are larger for CMIP6 than for CMIP5 projections. Is this a disappointing fact? Before drawing conclusions, we should investigate the reasons for this evolution. First of all, modelling groups are, besides reducing uncertainty in the outcomes per se, hopefully also working on a sound representation of the climate system. The reason that model uncertainty grows can be interpreted as the consequence of experimentation with methods to include a better representation of the physics of the system into the model instead of focusing excessively on the adequacy of the eventual outcomes with observations. The increase in model uncertainty could indicate a growing awareness regarding the variety of options to represent the climate system, without a certain representation being singled out as the 'best' one for all applications. Furthermore, CMIP6 elaborates on a higher number of climate-related questions for which the outcomes of the models form the basis of inquiry. Assuming no dramatic increase in the ability to represent the physics of the system between the fifth and sixth CMIP phase, the models included in CMIP6 experiments should cover a broader range of 'fitness for purpose' and a wider span of corresponding model configurations.

Internal variability as understood by Winsberg can only indirectly result in more uncertainty in the projections. This happens if we do not include enough model runs to distinguish between what share of the variability is due to the influence of the initial conditions (over which a climate model should average) and what is a more consistent change independent of which initial conditions the model runs on.

Scenario uncertainty is smaller for CMIP6 projections than for CMIP5 projections. The emission and mitigation pathways of CMIP6 are developed more rigorously and disentangle different mitigation strategies that were conflated in the RCPs used in CMIP5. The scenarios must consider a reasonable range of possibilities regarding the course of human action while minimising the conflation of different mitigation actions. Winsberg teaches us that the projection outcomes are conditional on the input scenario and therefore scenarios are no source of uncertainty to the projections although they are uncertain. The scenario uncertainty in the CMIP6 projections quantified as the variance of a multi-model average under the different considered scenarios is nothing more than the different outcomes conditioned on different scenarios. When considering this variance uncertainty, we are losing sight of the problem this outcome must address. Collingwood elucidates this error in the chapter "Question and Answer" in *An Autobiography* for interpreting a written text: we cannot adequately interpret 'the answer' a piece of writing presents without having the question it is answering in mind (Collingwood 1939). The same applies to (climate) model projections: the MIPs aim to answer specific questions in the light of which the model outcomes should be interpreted. A diverging range of outcomes across multiple scenarios can only be problematic if we look for convergence. As we saw in § 4.3.1 ScenarioMIP aims to answer the question "What are the mitigation efforts, climate outcomes, impacts, and adaptation options that would be associated with a range of radiative forcing pathways?". This indicates convergence is not what we are looking for; on the contrary, hopefully, the outcome values show dependency on our specific course of action. If there were no variance in that sense, it would mean that factors beyond our sphere of influence would determine the evolution of the climate system and implementing explicit climate policies would be completely in vain. Fortunately, different emission and mitigation scenarios result in different model projections.

It remains, however, desirable to obtain convergence of the outcomes of different models based on the same scenario. If all modelling groups would represent the physical processes of the climate system as adequately as possible, convergence would indicate that we are getting closer to an adequate representation of the overall system. This seems not to be the case yet; thus, there remains plenty of room for improvement in model configuration.

5. Conclusions

This thesis was supposed to be concerning 'uncertainty in climate models'. More specifically, I answered the question "What constitutive elements lay at the basis of climate model projection uncertainties?". To answer this question, I have explored climate models from various perspectives.

First (§ 2), I investigated modelling in science in its historical context and conducted a conceptual analysis of the concept of 'system' since it is the climate *system* that is modelled. In § 3, I turned to the central concept of this thesis: the climate. I introduced the necessary and relevant definitions, meanings, and features and linked them with the characteristics that something understood as a system can exhibit (non-linearity, chaotic and dynamic nature etc.). I explored how climate models were constituted and their relationship with the weather and the models thereof. Then, I applied the phenomenological method to understand the ideation of the climate. Finally (§ 4), I looked at the technical side of climate modelling. I studied the methods used in the several phases of the modelling process–from a single model component to model ensembles and their projections–and identified the loci of uncertainty generation connected to them. In this concluding chapter, I will highlight the noteworthy findings of the undertaken discourse.

Conceptual analysis in a historical context

First, I investigated modelling in science as the broader context in which climate modelling is encountered. I adopted a historical perspective by delving into the historical milieu where the modelling attitude in its modern form emerged: Western Europe in the early twentieth century. At that time, Maxwell developed a model that combined heuristic analogies with supposed true representations of the real world; it was met with serious criticism. Eventually, this hybrid model form, combining elements of established theories with heuristic ones, was embraced in a vast range of scientific fields. The modelling attitude dethroned theory and took its role as the prime tool of scientific inquiry.

Questions about the relationship between theory and model, the epistemic value of models, and the nature of models intrigued philosophers of science from the second half of the twentieth century, until today. Among many other views on the relation between models and theory, models can be considered instances of theories in a more specific domain, theories may be inferred from models, or models are considered to mediate between theory and empirical data. The latter view is commonly ascribed to the role of climate models in climate science.

In a second instance, I turned to the target of climate models, namely, the 'climate system'. This brought us to explore the meaning of 'a system' and how to model it. The concept of a system emphasises the crucial role of the interactions between different components in bringing about the phenomena of interest. Systems can be complex, non-linear, and chaotic. These three characteristics apply to the climate system.

I then investigated the history of the development of climate models specifically. They were developed based on weather models in the second half of the twentieth century. By then, the modelling approach was not as controversial anymore in the scientific realm. However, the philosophical considerations complementing the advances in the modelling attitude were still scarce. The rapid evolutions and expansions regarding science forced a high degree of specialisation. Whereas in Maxwell's times, scientists were also philosophers of science, due to the specialisation a division occurred: scientific and philosophical inquiry were not conducted by the same person anymore. Nowadays, philosophers of science must keep pace with the novelties in the scientific realm; their endeavours are complicated by the high level of sophistication and complexity of the models to simulate the climate system.

Phenomenological analysis of the climate

I attempted to interpret the concept of 'climate' by conducting a phenomenological analysis. This appeared more cumbersome than expected: the climate is (1) something that requires time-consciousness to be experienced and therefore processes such as memory and expectation to fit into the intentional act, and (2) it is a scientifically constructed concept so it is not straightforward in what sense it would be an object of experience. During this inquiry, it became clear that the relation between a supposed experience of the climate and the scientific concept at least exists in the appropriation of the latter that becomes a part of the background against which phenomena are interpreted: suddenly, an extreme precipitation event is understood because of 'climate change', while this has not been predicted nor confirmed scientifically.

The construction of the concept of climate does not rely solely (if at all) on subjective experience; scientific inquiry plays a crucial role. The relationship between the individual experience and the scientific inquiry consists of a shift from the division between subject and object where both remain present to the abolishment of the subject. In the scientific realm, we assume a stand-alone object. The apparent virtue of this assumption within the practice of science notwithstanding, it is not legitimate to solidify the absence of the subject when the outcomes of scientific procedures are brought into the world. On the other hand, restoring the phenomenological correlation does not render the scientific results meaningless.

The technicalities of climate modelling

The technical phases of model building commence with experience in the presence of the subject-pole. To conceptualise the climate, experience is completed with information from the scientific approach and a mind-internal model is constituted. This model is conceptualised, formalised, and implemented. Each conversion comes with adjustments that add adequacy (e.g. when aligning with well-established physical theories) or sacrifice adequacy (e.g. when trading adequacy for compliance with what is mathematically feasible). Without access to the real world, adequacy of the model with this real world is a myth; adequacy with the conceptual system we have constituted, on the other hand, is attainable.

The core feature of the model is the set of continuous differential equations. Due to their complexity, their solutions rely on numerical instead of analytical calculation methods. This conversion implies a loss of information too: instead of information at all points of the state space, we obtain solutions at discrete points only. The model configuration–the inclusion of equations in the dynamical core and how they are formulated–depends heavily on the features of the discretisation algorithm, its grid and the physics-dynamics coupling. Errors arising from the calculation method (splitting errors) can be compensated for, but the employed measures do not come without consequences. Climate models comprise multiple dynamical cores compensating for each other's constraints. The parametrisation suite forms an even bigger source of uncertainties and errors. Ideally, all physical processes would be represented as adequately as possible after tuning (at the level of the process, of individual model components, and the coupled model); however, the adequacy of the representation of several processes stands in trade-off with others, and with the accuracy of the model outcomes. In tuning, choices must be made again; introducing subjective uncertainty is unavoidable. Model builders should strike the right balance between bottom-up and top-down tuning; however, one can doubt whether trusting the outcomes of a model that performs well because of top-down tuning, lacking physical adequacy, is warranted.

The choices made form a source of subjective uncertainty, while the technical constraints of the chosen approach introduce errors. The concept of 'adequacy-for-purpose' (or fitness-for-purpose) is introduced: a model is never adequate relative to the entire climate system. By making choices during the modelling process, the model becomes more apt to answer some questions and less apt to answer others.

Individual coupled models are pooled into multi-model ensembles. Ensemble modelling is supposed to provide more accurate and consistent outputs based on the idea that the individual model errors will average each other. Furthermore, ensemble projections can be used to gain insight into the projection uncertainties, decomposing and quantifying them. ScenarioMIP is an ensemble model experiment that projects climate trajectories with scenarios as input. The model input is a set of quantitative emission, land-use, and energy trajectories constructed based on expert-developed narratives converted by quantitative models and IAMs.

Sources of uncertainty in climate model projections

The ensemble model projections carry all the uncertainty gathered along the path to their constitution. Conversions between model phases, discretisation errors, parametrisation choices, the uncertainty in the tuning and evaluation datasets, the uncertainties in the input scenarios, the choices about the ensemble weights etc. In the literature, projection uncertainty is traced back to three main sources: internal variability, model uncertainty, and scenario uncertainty; a fourth source mentioned is dataset uncertainty. Winsberg, however, retains only model uncertainty as the main source, since internal variability is merely the noise due to the sensitive dependence on the initial conditions, that should have been averaged out, and scenario uncertainty is rather a condition to the model outcomes they can or cannot be dependent on. Dataset uncertainty is considered a constitutive element of model uncertainty.

Interpreting climate model projection uncertainty

We have seen how the development of climate models comprises various sources of uncertainty; the question remains how these should be interpreted. Overall, there are three important elements to remember: first, a climate model is built to gain insight into the climate system that explains climate phenomena. The climate phenomena are highly uncertain when we rely on experience alone, the system we conceptualise to explain the phenomena is too complex to be analysed without the help of simulation techniques. A climate model, with all its uncertainty, reduces the original uncertainty that is many times more voluminous. Secondly, climate models cannot be adequate as such, they are intended for a specific purpose. It is not warranted to use the climate model outcomes for answering questions they were not built for; this will result in a meaningless response. Lastly, the previous reasoning can be applied to the uncertainty quantification and decomposition. The uncertainty in the outcomes should be evaluated considering the question asked: including more models and more scenarios (that are plausible) results in a higher model spread, but also in a more accurate model spread. High precision does not mean high accuracy; we are looking for accuracy rather than inaccurate precision.

6. Outlook

In this thesis, I made an overview of the uncertainties that enter during the modelling process: from individual experience, via the development of scientific concepts, the algorithms for numerical discretisation and parametrisation, the various phases of model configuration–formalisation, implementation, tuning, evaluation–and the coupling of model components, to the intercomparison experiments compiling model ensembles and ensemble projections. I made an overview of the projection uncertainties at the end of the modelling process and explored how they relate to so-called ‘sources of uncertainty’.

There are many relevant aspects I did not explore. To begin with, in climate modelling, many choices are made. Exploring the levels at which ‘subjective uncertainty’ enters the model would be interesting. How could this be accounted for (maybe even quantified)? To continue, the scenarios used as input for future projections in the context of ScenarioMIP are developed in multiple phases relying on various scientific communities, narratives, impact assessment models and more, as I touched upon in § 4.3.1. They probably carry a significant level of uncertainty beyond the scenario uncertainty as it is quantified based on the climate model outputs (see equation 7). An ongoing controversy regarding multi-model ensembles is whether all models included should have the same ‘weight’ in the calculations. As we have seen in § 4.3.1, there are well-justified reasons for preferring weighted model ensembles. Some models are known to perform better than others, so it seems logical that these models have more impact on the outcomes of the ensemble. However, O’Loughlin (2024) argues that lower-performing models help scientists gain knowledge they otherwise would not obtain and therefore we should not discard them.

Furthermore, I wrote ‘the end of the modelling process’, but climate model projections are far from the final outcomes. Often, the model projections form the input data for simulations with regional impact models, such as the crop model that was briefly mentioned in § 4.3.2. Bias correction and downscaling methods adjust and warp the climate model projections to align them with the input format of the impact model; these procedures may be the major source of uncertainty in the impact model projections (Lafferty and Sriver 2023). Finally, the outcomes produced by the climate and impact models require interpretation and are communicated to policymakers and other users. In communicating an outcome, the uncertainty of this outcome ought to be communicated too. The IPCC’s ‘calibrated uncertainty language’, developed for this purpose, is received with controversy (Dethier 2023). However, there are not many viable alternatives on the market (yet); to inform model and model outcome users about the uncertainty in the outcomes and the limits of the model, without evoking inadequate scepticism remains an unresolved balancing exercise. Winsberg (2024) emphasises the importance of making disclaimers about models for scientific and policy-making communities that will use the model outcomes. Reminding the enormous complexity of these ‘Frankenstein creations’ built by plenty of experts in different fields, we could ask how conferring information to ensure users know the domain in which the model is fit for purpose, would be effective.

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ABSTRACT

Few fields in human life benefit from what we call ‘climate change’. The consequences of climate change become apparent and are obstructing–sometimes taking–our lives. This is reason enough to anticipate them and implement mitigation and adaptation strategies through policymaking. However, climate model outputs are plagued with uncertainty; this fact evokes controversy about how they should be interpreted, communicated, and used in decision-making. What do these models tell us and should we base any policy decisions on their outcomes if these are highly uncertain? To warrant our trust in the model outcomes regarding decision-making, the sources of and reasons for the uncertainty should be well-understood.

In this thesis, I investigate the emergence of uncertainty in climate model projections. More precisely, I examine what elements throughout the modelling process are the reason for the uncertainty in the outcomes and how this should be interpreted. Is trust in the outcomes warranted? I evaluate this question as a philosopher of science, conducting a philosophical analysis of the climate modelling process and the concepts related to it.

I cast light on the question by analysing climate modelling in three main ways: through a conceptual analysis of ‘model’, ‘climate’, and ‘system’, through an analysis of the experience of ‘climate’, and from a technical perspective by examining the construction of single-model components, coupled global earth system models, and model ensembles.

When considering how the climate is experienced, I find that it is not clear how it could be experienced since it is a scientifically constructed concept. On the other hand, knowledge of this scientific concept may influence our interpretation of weather phenomena. Furthermore, there are many phases in the model-building process; each phase introduces errors and therefore uncertainty that is carried along to the subsequent phases. Observational data is used to estimate some free values in the model. Choosing which values to align with the data on the one hand and with the physical theory on the other hand requires expert opinion. It is a matter of debate whether the outcomes are trustworthy when they result from alignment with observational data, at the expense of adequate representation of the physical processes. The choices made form a source of subjective uncertainty, while the technical constraints of the chosen approach introduce errors. The concept of ‘adequacy-for-purpose’ means that a model is never adequate relative to the entire climate system, but more apt to answer some questions and less apt to answer others.

Overall, there are three important elements to remember: first, a climate model is built to gain insight into climate phenomena that are highly uncertain. Although the model includes uncertainty too, it reduces the uncertainty in the climate phenomena per se. Secondly, climate models are never ‘true’, but can be adequate for their intended purpose. Using climate model outcomes for answering questions they were not built for will result in meaningless responses. Lastly, including more models and more plausible scenarios will result in more different outcomes; if these outcomes are, on average, closer to the ‘truth’, this should not be a problem. Converging outcomes does not necessarily mean they are more correct. Obtaining more correct average answers, by evaluating more models and more scenarios, is a good practice.

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