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On Non-Propositional Aspects in Modelling Complex Systems

Abstract: This paper aims to show that modeling complex systems inevitably involves non-propositional knowledge and thus the uncertainties associated with the corresponding model predictions cannot be fully quantified. This is exemplified by means of the climate system and climate modeling. The climate system is considered as a paradigm for a complex system, whereby the notion of complexity adopted in this paper is epistemic in nature and does not equate with the technical definition of a complex system as for example used within physics or complexity theory. The epistemic notion of complexity allows to view the climate system as complex with respect to some features, while simple with respect to others. This distinction is of practical significance for political decision making as it allows to treat some climate predictions as (fairly) certain, while acknowledging high uncertainties with others.

1. Introduction

Though it is moral considerations that make us reason about global warming, determining the adequate response to this threat relies on findings from the empirical sciences. Assessing, for example, the adequate greenhouse-gas reduction scheme, the pros and cons of cap and trade or carbon tax, or even the very question as to how much we have to cut down the emissions hinges on empirical prognoses.

Decisions are to be based on the best knowledge available. For climate change just like for many environmental problems the best knowledge available today is provided by science (e.g. Oreskes 2004). This knowledge comprises not only the prognoses themselves—prognoses on, say, the increase of global mean temperature, sea level rise, or the effects all these changes have on the fishing industry. Our best scientific knowledge available today are the prognoses *plus* information on their reliability. Increasing the reliability commonly coincides with reducing the uncertainties of the predictions—an enterprise of major significance within climatology. However, uncertainties remain and will remain. When practical reasoning is based on scientific facts, these uncertainties have to be considered, one way or the other.

Though uncertainty is nothing peculiar to climate modelling or scientific forecasts, uncertainties arising here seem to differ from uncertainties associated with everyday prognoses. We expect science to provide us with quantitative information—even on the uncertainty of its predictions. And indeed, this is particularly what climatology provides us with. The Intergovernmental Panel on Climate Change (IPCC), for example, predicts that a doubling in carbon dioxide concentration "is likely to be in the range 2 degrees Celsius to 4.5 degrees with a best estimate of about 3 degrees, and is very unlikely to be less than 1.5 degrees. Values substantially higher than 4.5 degrees cannot be excluded, [...]" (IPCC 2007, 12). Expressions like *likely* or *very unlikely* are thereby interpreted as probability statements: *Likely* corresponds to probabilities higher than 66%, while *very unlikely* denotes probabilities smaller than 10%.

This paper argues that, despite to all appearance, uncertainties arising in quantitative scientific predications cannot be fully quantified. *Section 2* addresses the question as to what is uncertain about present climate predictions. Not aiming at an exhaustive overview, this section highlights difficulties in modelling the climate system and climatic impacts on humans. On epistemic grounds, two types of uncertainty are distinguished, namely parameter and conceptualization uncertainty. The uncertainties practical decision making has to deal with include, but go well beyond, what climatologists refer to as uncertainty. Shackel's epistemic notion of a complex system is introduced in *section 3*. Problems in predicting the impact of anthropogenic greenhouse gas emissions are related to more general problems concerned with complex systems. In particular it is argued that in this notion the climate system is complex with respect to some features, while simple with respect to others. *Section 4* contends that in modelling complex systems, non-propositional knowledge, i.e. competencies or abilities, become more important than propositional knowledge. Unlike the latter, these competencies may only be learned by practice—by working within a certain scientific field. What is good practice cannot be captured in explicit definitions or in numerical figures assessing the reliability of the practice. Assigning numerical figures, e.g. in the form of probabilities, to the reliability of models and the conceptualization uncertainty associated to their predictions thus is (at least in parts) misleading. Summarizing the findings of this paper in *section 5*, it is stressed that this epistemic feature is of central relevance for practical reasoning as unquantified uncertainties render the applicability of standard decision approaches impossible.

2. Climate Science or Climate Fiction?

Prognoses on the future are always uncertain, and so are prognoses on the future climate. So what exactly does uncertainty mean as regards global warming? Before sketching some features of models relevant for the discussion of uncertainties in this paper, let me allow a word of caution. This section does not aim at an exhaustive overview on virtues and vices of present climate modelling, hence the analysis is, willy-nilly, biased. This shall, however, not distract from the fact that, despite all the shortcomings, these are scientific models and the best ones available. Present climate models are readily able to well reproduce the natural climate variability (e.g. Houghton 1995). Moreover, predictions obtained from various models widely agree with one another, the connection between carbon dioxide concentration and global average temperature seems to be well supported not only by numerical simulations, but also by measurements in ice cores (e.g. Roth 1994, 42f.; Wilson/Drury/Chapman 2000).

2.1 Human Influence on the Climate

Not only the emission of greenhouse gases like carbon dioxide, emitted when burning fossils fuels, but various human activities impact, and have always impacted, on the climate: Building development, slash and burn, farming, the regulation of inland waters, etc. change the Earth's surface and thus the amount of radiation backscattered from the Earth's surface as well as the ground-level atmospheric currents. This in turn impinges on the atmospheric mean temperature on a local and, in parts, on a global scale. We know that the settling of man some thousand years ago, for example, and the corresponding crossover from nomadism to farming was accompanied by vast clearings and thus had significant and sustainable impact on the climate.

Already in 1896, S. A. Arrhenius predicted a climatic change due to anthropogenic emissions of carbon dioxide in the wake of the industrial revolution. Today, we know not only that carbon dioxide is a greenhouse gas (i.e. it absorbs and emits radiation within the thermal range), but also that its atmospheric concentration increased from 280 ppm (parts per million) before the industrial revolution to 379 ppm in 2005. What we do not fully understand, however, is as to how the increase in atmospheric greenhouse gas alters the global mean temperature. Due to Feedbacks between various components of the climate system, that comprises not only the atmosphere, but also bio-, hydro-, litho-, and cryosphere, it is not isolated cause-and-effect chains that determine the state of the climate system. An initial warming of the atmosphere caused by an increase in greenhouse-gas concentration may be significantly enhanced or reduced. Higher mean temperature enhances, for example, the growth of oceanic phytoplankton. On dying this phytoplankton[1] produces cloud condensation nuclei. More phytoplankton thus may increase the backscattering ratio of the sky cover and hence counteract the initial temperature rise (e.g. Idso 2001, 325). At the same time, increasing the atmospheric temperature defrosts the permafrost soils in the tundras of Siberia and Canada; huge amounts of the greenhouse gases carbon dioxide and methane that are stored in these permafrost soils are released and thus reinforces the warming of the atmosphere (Lange/Körkel 2003, 10).

The state of the climate system results from a complex interplay between various factors. Due to the feedbacks, the future course of the climate system cannot simply be determined from an extrapolation of its past and present state. Climate models, which aim to represent the major causal mechanisms in the climate system and which are investigated numerically, are the only way today to gain insight into the future climate. Not all feedbacks are known or understood in every detail, the resolution of some feedbacks requires too high spatial and

[1] Compare Mackenzie/Lerman/Ver 2001, 51–82; Wilson/Drury/Chapman 200, 240ff..

temporal resolution to be achieved with today's computational power. Climate predictions, like those reported in the IPCC reports, are commonly based on so-called general circulation models (GCM). Here, only atmosphere and hydrosphere are dynamically simulated, coupled via material and energy exchange; all other spheres of the climate system—bio-, litho-, and cryosphere—are only incorporated as static boundary conditions (cp. Betz 2009a; 2009b). Hence major feedbacks in the climate systems are not fully resolved in the models, for example, the interchange of carbon dioxide between plants and atmosphere. But also purely atmospheric processes may not be adequately represented: Following the IPCC-reports, uncertainty in present climate predictions is mainly due to a lack of understanding of the radiative properties of clouds.

The sketched complexity of the climate system with its numerous components that are linked to each other via feedbacks and the intricate nature of the processes induce that not all causal mechanisms are captured by climate models. This renders their predictions uncertain. I want to refer to this type of uncertainty as *model conceptualization uncertainty*. Note that this terminology does not distinguish between sources of uncertainty and the uncertainty itself; however, the equivocation does not seem troubling.

Next to the model conceptualization there is yet another source of uncertainty, referred to as *parameter uncertainty*: Climate models require input concerning, for example, the future level of greenhouse gas or aerosol concentrations; the numerical value of these quantities hinges on factors like the growth of world population, economic growth, the course of future energy or social policy. So-called energy scenarios assess, amongst others, rates of future anthropogenic release of greenhouse gases and aerosols and thus provide the input for climate models. The relation between the release of gases and political and economic developments is rather intricate. The second largest anthropogenic source of atmospheric carbon dioxide, for example, is land use—an area very sensitive to political and economic decisions (e.g. Houghton 1995). Also of great importance is the efficiency of future energy conversion systems or the energy intensity of industries—factors determined by future technological developments which are hard to predict (e.g. Bourroughs 2001).

The input parameters provided by the energy scenarios are, and remain, highly uncertain. This uncertainty translates to the uncertainty of the climate models which take these parameters as input. The IPCC (and others) react to this uncertainty and invoke the term climate *projections*, instead of *predictions* in order to highlight the dependency of the output on the considered energy scenario.[2]

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[2] Note that 'parameter uncertainty' as defined above is fairly broad, encompassing what, for example Refsgaard et al. 2006 refer to as uncertainty due to *model input* and *model parameters* (more narrowly understood). Apart from our twofold distinction and Refsgaard et al. 2006 threefold distinction, various authors distinguish further uncertainties arising due to *model context*, *model assumptions*, *expert judgment* or *indicator choice* (cp. van der Sluijs 1997; van der Sluijs et al. 2003; Walker et al. 2003). These distinctions proofs very useful for practice, however from a purely epistemic point of view, there is no need to distinguish model parameters and model input any further.

2.2 Impacts of Climate Conditions on Humans

Model conceptualization and parameter uncertainty render it impossible to predict with certainty the exact impact anthropogenic actions have on the future climate. Likewise, the precise effect climatic changes exert on humans can never be predicted with certainty. That these influences may be very severe, however, does not stand to reason. For example, the European revolutions of 1789 and 1848—though a result of the longstanding social, political, and economic disparities— ere initiated after years of bad weather, bad crops and high corn prices (e.g. Flohn 1988, 199). Not only local, but also global weather phenomena had known impact on societies: In the tenth century, worldwide drought may have wiped out the Tang Dynasty in China and that of the Mayan civilization in Mexico (Hopkin 2007; Yancheva et al. 2007). Only minute changes in average climate conditions may significantly impact human wellbeing. A drop of average annual global temperature by, say, only 1°C may shorten the vegetation period near the polar circle, i.e. in Canada, Finland and Island, by three to four weeks (Flohn 1988). Note in particular that, despite the large variations in the atmospheric temperature throughout Earth's history, the prognosticated temperature rise is much faster than all changes currently known within the last 10,000 years. The presently predicted change in global mean temperature leads in most assessments to overall negative consequences, which are most severe in those countries that are already the worst off today.

The impact which changes in mean temperature have on humans hinges on many factors, ranging from the way of farming to the height of landmass above sea level and people's capability to adapt. Major global-warming impacts are expected via rising sea level, or increased frequency and intensity of extreme weather events such as floods, extreme droughts, heavy storms or rainfalls. The expected changes in these factors are commonly provided by climate models. This information then serves as input to so-called *impact models* that estimate the influence of global warming and its geological consequences on human wellbeing.[3] Most often, impact models are welfare economic models estimating the impact of global warming, related changes in weather etc. on a wide range of market and non-market sectors.[4] Note that, unless one assigns an intrinsic value to the climate system (or some of its components), the practical debate on how to react to the threats of global warming must be based on the predictions of these impacts models: Within an anthropo- or pathocentric approach, a mere rise in global atmospheric mean temperature is not *per se* morally wrong or even morally relevant; climate change only becomes a moral problem because of its impact on the wellbeing of human (or other sentient) beings.[5] Hence even if we had perfect understanding of the climate system, we may not know the effects this change has on the wellbeing of future generations which we need to know

[3] Wellbeing is understood broadly, synonymous with welfare or good life, a more detailed understanding is not required here.

[4] Compare, for example, Tol 2002; Nordhaus/Boyer 2000; Solomon et al. 2007; Stern 2007; Nordhaus 2008.

[5] Compare Hillerbrand 2009; Hillerbrand/Ghil 2008. Note that also non-consequentialists may agree with this claim.

for a moral or political assessment. As impact models consider other sentient beings, if at all, only as of instrumental value, in the following I refer to human wellbeing only.

Model conceptualization uncertainty is unavoidably high for impact models as they model socioeconomic on large temporal and spacial scales (cp. Stern 2007). This welfare-economic modelling is exacerbated as major global warming damage is expected in non-market sectors; the models, however, commonly monetarize all losses.[6] This leaves many losses unconsidered or only partly considered as money has properties that non-monetary losses do not have or have only very rudimentarily (Lumer 2001): money may be lent and exchanged, bear interest etc., monetary losses may be (partially) compensated by investments—not so, say, the loss of habitat, friends, or relatives in extreme weather events. Moreover, in impact models, epistemic and moral values mix which yet adds to the model conceptualization uncertainty.[7] Such a (partial) mixing of impact modelling and normative assessment cannot be avoided: Normative assessment is needed for determining which aspects of human life are worth or necessary to consider. More problematic is the fact that modelling assumptions like the discounting rate for non-monetary losses have to be discussed (also) on moral grounds (cp. Stern 2007). Merging of a normative and a descriptive assessment, though impossible to fully avoid, however blurs many (normative) assumptions and may render the evaluation rather opaque.

3. Predicting of Complex Systems

Feedbacks between various of its subcomponents, which manifest in nonlinear evolution equations of the modeled quantities, are characteristic for the climate and socioeconomic systems. In the language of the mathematical sciences such systems are referred to as *complex systems*.[8] These may exhibit chaotic behaviour and thus, though deterministic in principle, cannot be predicted in every detail: Very similar causes may not lead to similar effects.

Though the climate and socioeconomic systems are complex in the mathematical sense, I do not want to adopt this notion. This paper is on epistemic issues, therefore I want to follow Shackel's epistemic definition of a complex system—a non-technical one given purely in epistemic terms.[9] In this notion, a complex system is defined as a non-simple one. For simple systems knowing one or reasonably many features gives reliable information of another feature (or some other features), such as the one you are interested in. For complex systems, this relation does not hold. A system therefore may be complex either because (i) only knowing of many features gives reliable knowledge about the feature of

[6] For a notable exception see Lumer 2001 and 2002.

[7] Despite its relevance in climate ethics, moral uncertainty is not addressed in this paper. Note moreover that often impact and climate models mix, e.g. Nordhaus 2008.

[8] To be more precise, a complex system is one with more than three interacting degrees of freedom.

[9] Private communication June 2008.

interest, or because (ii) the relation between the feature of interest and others is unclear.[10]

As regards information about future global warming and its impacts, the climate and socioeconomic systems are complex in the epistemic sense: Only knowledge of many features gives insight into the features of interest, and the interdependence of various features is unclear. Note that only one reason for this is that the system is complex in the mathematical sense. The two ways in which a system may be complex directly link to the (sources of) uncertainties that were introduced in *section 2*, parameter and conceptualization uncertainty. Firstly, not all of the numerous parameters in the models may be known with the required precision. Secondly, as only a complicated interplay between its numerous features determines the state of the climate system of interest here, not all relevant causal mechanisms may be adequately incorporated into the model. This may be due to a lack of knowledge or due to contingent limitations like finite computational power.

Complexity and simplicity are, in the definition adopted here, purely epistemic features. They not only depend on the modeled system, but also on which feature of the system one is actually interested in, the desired accuracy of the feature of interest, the available background knowledge, etc. Unlike the mathematical one, the epistemic notion of a complex system is neutral with respect to whether a mathematical or less rigorous description of the system is pursued. It also encompasses a less strict usage of the term that follows its demotic meaning (e.g. Parker 2006). The adopted definition of a complex system is vague, both as regards to what counts as *reasonably many* and *reliable*; there are borderline cases. It is an epistemic notion and systems which are complex as regards one feature, may be simple as regards another. Hence the very same (ontological) system may be (epistemically) complex or simple depending on the feature of interest or the required reliability. Strictly speaking, the model may represent some (real) target system as complex or simple; however, like for the mathematical use of the term, complexity is applied to systems, keeping in mind the problems associated with models and representation (e.g. Giere 2004). Note that likewise the classification of parameter and conceptualization uncertainty is always relative to some model focusing on certain features of interest.

Consider the example of the orbital motion of the Earth around the Sun. This is a simple system as regards its approximate period, it is complex when one is interested in more precise information, the deviation from the ellipsoidal motion, etc. Likewise the climate system is simple with respect to some features, and complex with respect to others. It is simple as regards the question as to whether human activity impacts the climate, but also simple with respect to the question which countries will be most harmed by climate change. Determining that it is the less and the least developed countries that, on average, will suffer most from climate change, does not invoke running nonlinear models; a close

[10] Note that the two ways in which systems be complex distinguished above comprise Kuhlman's (2009) distinction between compositionally and dynamically complex systems, respectively. However, the terminology above is broader than Kuhlman's as he follows the mathematical modelling.

inspection of, for example, the sensitive behaviour of crop yield on aridity and the limited means of adapting to such changes suffices. Following the epistemic notion of complex systems introduced above, answering the very question as to why climate change is of moral significance thus does not invoke predicting complex systems. The question, however, as to how exactly we have to react (if at all) to the global warming threat, is a question that relies heavily on more detailed information of atmospheric temperature, say, and thus on information obtained from the analysis of a complex system.

4. Knowing-How in Scientific Modelling

By specifying a range for the uncertain parameters and assigning corresponding likelihoods, the uncertainty in the modeled quantity may be expressed by the width of the corresponding probability distribution and thus by a numerical figure. This procedure is known within nonlinear science as sensitivity analysis. If the range of the height of future emissions, say, is varied within a certain interval, one may specify a parameter range for the mean atmospheric temperature. When climatologist refer to 'reducing uncertainties', they aim at curtailing the width of the probability distribution.

Model conceptualization uncertainty is often treated in a similar fashion to parameter uncertainty: By varying not only the input parameters, but at the same time also varying the underlying model, the IPCC, for example, is able to specify an interval for, say, the expected range of temperature increase (e.g. 2007, 12). However, I want to argue in the following, that model conceptualization uncertainty may not satisfactorily be treated in the same way parameter uncertainty is and thus uncertainties cannot be fully quantified.[11]

Scientific predictions are derived from some model representing the target system of interest.[12] Uncertainties capture the reliability of model predictions and are thus related to the reliability of the models, i.e. their structure and the numerical values of their parameters. I want to argue in the following that as regards complex systems, the reliability scientists may assign to their models is only apprehended within the community of scientists working in the field under consideration. When communicating to outsiders, essential information gets lost; hence capturing the reliability in quantitative figures is highly misleading.

The argument, builds on two premises, that are argued in more detail below: (i) Just like any model, climate or impact models cannot be derived from theories[13] in a straightforward way. (ii) There is no exhaustive propositional account of this derivation. For complex systems deriving a model involves less what, with reference to G. Ryle, is referred to as *knowledge-that*, a relation between some

[11] There have been several attempts recently to quantify conceptualization uncertainties (e.g. Moss/Schneider 2000), but these all remain rather fragmentary (see below).

[12] Particularly in climatology, these models are implemented numerically which may cause additional complications which are, however, not considered in this paper.

[13] The term theory as it is used here refers not only to well developed theoretical bodies like Newtonian mechanics, but also to theoretical backgrounds assumptions that form common beliefs within a field, e.g. the efficient market hypotheses.

thinker and a (true) proposition, but *knowledge-how*, an ability and complex of dispositions.

Before defending the two premises, let me briefly dilate on the usage of the term model and theory in this paper. In the semantic interpretation of theories, the relation between model and theory is well-defined; its notion of model, however, is a great distance away from the usage of the term *model* within climatology or economy. Deriving a model from a theory invokes more than merely setting numerical values for some free parameters. I thus follow the more recent accounts of models used by Cartwright, Giere, Morrison and others. One unifying theme in the different terminology of these authors is that while theories are related with general propositions (often in the form of laws of nature), models are less general, but closer to the phenomena (or data). For the purpose of this paper, this vague intuitive understanding of models and theories suffices.

Let us first consider the simple model of the Earth's orbital motion around the Sun. This model is derived from Newton's theory of gravitation and Newton's second law. Deriving the model invokes neglecting the internal structure of the two bodies, neglecting other planets or comets, and approximating the motion as a two-body problem with only point masses. As argued by Bailer-Jones (2001), the adequacy of the assumptions made in deriving the model of the Earth's motion around the Sun are not captured in their propositional content alone. The assumptions are simply wrong, transcribing the 'message' of the model solely into propositions would yield to a false model. This, however, does not do justice to scientific practice. Nonetheless the statement made above reaches further than the observation that the content of a model cannot be equated with its propositions; rather it was claimed that in deriving models it is less knowledge, but abilities that are involved. As stated in *section 3* the system of the Earth' movement around the Sun as considered here is not complex. The message of the model may not be translatable into propositions, but the derivation seems not to involve much skill either.[14] This is different for complex systems. As outlined in *section 2*, important feedbacks are neglected between various components of the climate system when deriving climate models from more fundamental theories like atmospheric chemistry or hydrodynamics. Our present understanding of the climate system does not allow us to 'prove' the correctness or adequacy of these assumptions. Making the right assumptions is an ability, a skill that has to be trained rather than a knowledge of facts (broadly understood) that can be learned from text books.[15]

The argument that not only knowledge, but also skill is involved in deriving models representing complex target systems seems easy to buy; however, it has wide-ranging consequences. The assumptions involved in deriving a model may

[14] This may not have been so in the past. Though today we know why the assumptions in deriving the Earth-Sun model work, i.e. why the derived predictions on period etc. are reliable; but this was not known at the time. The perturbation theory involved in showing the adequacy of the assumptions made, i.e. showing that the two body problem gives a first approximation to the real motion of Earth and Sun and all other factors may be treated in a perturbation expansion was only shown more recently.

[15] Note that this feature of climate modelling is associated with the complexity (in Shackel's sense) of the modeled system and thus holds also for models of other complex systems.

not be correct, but as they are propositions one may assess the deviations of what is currently perceived as true. For example, one may assess the wrongness of the assumption that Earth and Sun both are point masses considering the distance between both bodies. When abilities are centrally involved in deriving a model and these abilities cannot be reduced to propositions, this seems out of reach. Not only can the abilities be interpreted as part of an intricate web of background knowledge; rather these abilities involve knowledge how to pursue the specific experimental paradigm, the accepted practice, and the general research experience within the field. These factors cannot be defined explicitly, but must be learned by working in the field. In this respect, a scientific community can be seen as an instance of a Wittgensteinian language community:

> "[T]he term 'language game' is meant to bring into prominence the fact that the speaking of a language is part of an activity." (Wittgenstein 2001, 10)

As an example of a language-game, Wittgenstein himself refers to "presenting the results of an experiment in tables and diagrams" (ibid.). Likewise, assessing the reliability of climate models is, at least to some extent, something that is learnt by the practice of carrying out and verifying such predictions.

As there are borderline cases which are neither clearly complex nor simple, it may remain unclear whether the reliability of some models may be quantified. Nonetheless, there are clear cases for which they can or cannot be quantified; regarding the impacts of the greenhouse effect on humans the climate system is an example of a complex system and thus the reliability of the models cannot be communicated outside the scientific community.

5. Reducing Uncertainty

As argued above, due to model conceptualization uncertainty the reliability of complex models cannot entirely be communicated to outside the scientific community. Estimating as to how well a model represents the relevant causal mechanisms if these are yet unknown, has not much prospect of success. Quantitative figures aiming to capture this reliability are misleading and miss central points. Hence a model pluralistic approach as pursued by the IPCC is also unable to capture all uncertainties because it cannot reflect different reliability of different models.

However, there are other ways of assessing the reliability and thus the uncertainty of forecast that do not take the circuit via the model's reliability. One may, for example, fall back to a Bayesian account:[16] Via subjective probabilities, the reliability of scientific outcomes are quantified directly. But it is firstly impossible to choose a meaningful prior probability due to the large time scales on

[16] Note that when scientists refer to Bayesian approaches, they quite often estimate *a priori* probabilities via frequencies and thus by conditional probabilities (conditioned on the models used to determine the respective frequency). These type of Bayesian approaches are, however, model-dependent. For further criticisms of the Bayesian approaches as discussed in the main body of the text, see, for example, Sober 2005.

which the climate system reacts to changes. Secondly there is insufficient data for updating these probabilities. The Bayesian method thus fails for climate change. Another way as to how to assign subjective probabilities follows Laplace's principle of insufficient reason: All possible effects are taken as equally probable. This approach was put forward, for example, by Harsanyi (1975; 1982). But there is no logical superiority of Harsanyi's assumption of equiprobability over Rawls' focus on the worst outcome as per se there is no logical need to assign subjective probabilities to uncertain decision outcomes based on Harsanyi's equiprobability assumption or other. We do have information on the likelihood of certain effects of climate change—albeit these are hard to communicate outside one's own narrow scientific community.

Though this paper is on epistemic issues and thus I do not want to dwell on the interpretation of probabilities in detail here, note that a weak objective interpretation of probability is adopted here: Our most successful method for tackling uncertainty has been to regiment situations of uncertainty by the use of probabilistic propositions. But unless one is a certain kind of subjectivist about probability, one wishes that one's probabilistic beliefs be constrained by objective facts so that they approximate objective variables. The term probability in its every day use captures something real in the sense that the probability that it rains tomorrow is somehow linked to the real world, in this case the likelihood that it will rain tomorrow. Note that even a modest subjective interpretation of probabilities, that takes probabilities to be belief functions that obey certain restraints, may be consistent with this weak objective interpretation.

As argued above and elsewhere (cp. Frame et al. 2007), there is no reliable basis for assigning probabilities in the above sense to the empirical input needed for a practical assessment. However, there is good practice of how to deal with uncertainties. When the conditions of Bayesianism are not met like in the case of climate change, dealing with uncertainties always invokes the reliability of the model's representation of the considered target system. There is no distinct science of how to deal with uncertainty; good practice of dealing with uncertainty is always sensitive to the context. It must be learnt by doing and unlike propositional knowledge, it cannot be simply acquired, but the competence may be trained to reach a higher grade. It is beyond the scope of this paper to address these rather technical issues; the reader is referred to Moss/Schneider 2000 and van der Sluijs et al. 2005 and references therein.

Summarizing, in the terminology of technology assessment, how to react to global warming is a genuine decision under uncertainty because we lack probability estimates on (at least some of) the possible outcomes. This is distinguished from decision under risk in which we do have some reliable probability estimate. It was argued that presupposing a weak realistic understanding of probability, it is not possible to reduce the global-warming issue to a risk problem. This was linked to the fact that predicting the exact impacts of greenhouse gas emissions involves modelling of complex systems. In deriving such models, abilities are more important than propositional knowledge. The former can only be learned by doing, by working in the field. Assessing the 'reliability' of certain steps in deriving complex models cannot entirely be communicated to outside the scientific community. A distinction between conceptualization and parameter uncertainty was introduced that may provide the ground for practical decision making to incorporate the uncertainties: While the former is related to the non-propositional content of a model and thus may not be satisfactorily be reflected in a quantitative figure, for the latter quantitative estimates may be given. Let me allow a final word of caution. Arguing that not all aspects of scientific uncertainties may be captured in numerical figures and that they may be misunderstood outside the scientific community is not to be mistaken as putting the case for a dictatorship of experts. It is rather up to the scientists to provide standards of good practice. If anything, the paper aimed to invoke not to trust any numerical figure only because its predictions and uncertainties are captured in quantitative terms—its prognoses may not be better or more scientific than qualitative ones. In addressing the uncertainty of climate predictions from an epistemic view this paper aimed to provide a basis for incorporating all the scientific findings into the practical debate, i.e. climate or impact model predictions plus the associated uncertainty including those that may not be quantified.

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