Hotter or not? Should we believe model predictions of future climate change?

Why should we believe predictions of climate change over the next century if we cannot predict the weather 3 days ahead? **Reto Knutti** explains why scientists have confidence in climate change models, how statistical methods can help to quantify their uncertainties—and why uncertainty is not an argument for delaying efforts to reduce the damage.

We look at the weather forecast, which indicates a 70% chance of rain, and decide whether to take an umbrella or not. Our decision is based on past experience rather than an understanding of the underlying model that the forecaster used. But, when we look at climate projections for the next century from a similar model, we are torn between believing, questioning and ignoring them. Why is it so difficult to communicate what we know about future climate change? Why are climate model projections uncertain?

The evidence that humans are significantly changing the Earth's climate by fossil fuel emissions is overwhelming and basic physical understanding suggests that the current large-scale warming trends will continue[1]. However, to make decisions for mitigating it, and for local adaptations to it, we need to know how the climate will change locally, and to what extent heavy rainfall events, sea ice, permafrost, heat waves and many other aspects of the climate are likely to change. To predict these detailed changes we inevitably have to rely on climate models—despite the uncertainties they contain.

Uncertainties in climate projections

Climate models consist of a set of equations that are solved numerically on a large computer. Some equations can be derived from first principles—equations of motion, conservation of energy and mass and the like—whereas many other processes have to be described in a simplified form. For example, there is no known equation to describe the effect of a growing tree on the climate, yet trees clearly modify the local climate and water cycle. The overall impacts of trees are there-

There is no known equation to describe the effect of, say, a growing tree—yet such things clearly modify the climate.

fore described—parameterised—in terms of environmental conditions, such as the type of tree, availability of water, light, nutrients and competing plants. Such a parameterisation is always a simplification of the real process and will contain parameters that are not directly measurable. Projections from models are, therefore, inherently uncertain, because a model, by definition, is an imperfect representation of the real world.

Uncertainties in climate models come from uncertainties in initial and boundary conditions and from the fact that we do not fully understand the system or are unable to represent it accurately in a numerical model. Boundary conditions are prescribed externally, e.g. CO_2 concentrations from an economic scenario. A scenario that postulates a flourishing global economy will have more CO_2 than one which supposes a world in deep recession. The initial condition problem is the well-known butterfly effect, where tiny errors in the starting point render the forecast worthless beyond a few days. The disturbance from a butterfly flapping its wings can develop, in theory, into a tornado. Climate projections circumvent this problem by describing the climate as a whole, i.e. the expected statistical distribution of weather rather than the sequence of individual weather situations. Uncertainties about the climate state decades and centuries ahead are thus dominated by uncertainties in the model structure and parameters. For the parts of the model governed by fundamental equations, increased computational capacity and finer resolution will improve the simulation. However, for empirical relationships where there is no fundamental underlying law (like the effect of the tree) even the largest computer may not help much if we are unable to specify the underlying processes fully.

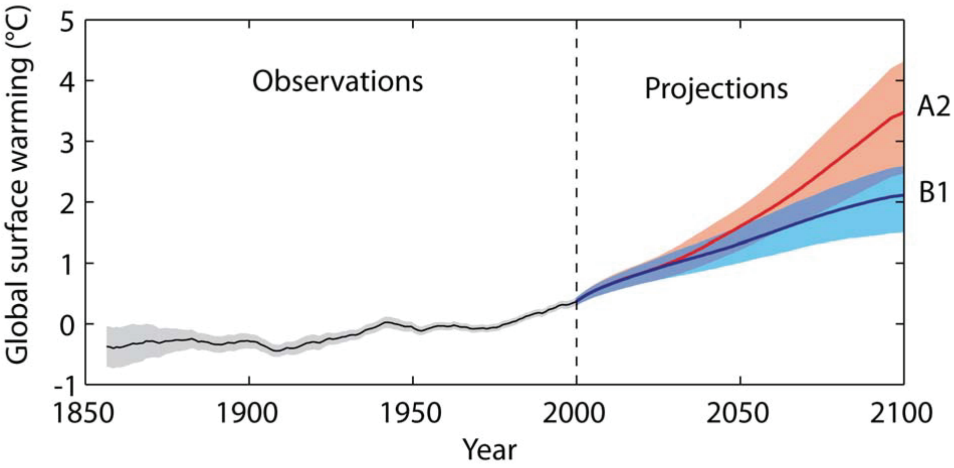

Figure 1. Observed surface warming (black) and its uncertainty (grey) and 5–95% confidence range for simulated future global temperature change for two scenarios (colours) without political intervention. The A2 scenario supposes a world fragmented economically, with continuously increasing population. B1 has a population declining after a mid-century peak, with clean and resource-efficient technology worldwide. A Bayesian method is used to constrain the uncertainty in projections using the observed global surface warming and ocean heat uptake. Modified from Knutti *et al*. 2002.[3]

There is no single best climate model, but rather a pool of models or model components that are combined to study specific questions. A model to study the chemistry in the Antarctic ozone hole may not need a dynamical vegetation component, so the decisions as to what parts of the system are modelled explicitly and what is externally prescribed are guided by the question of what we are interested in as well as practical considerations like computational capacity. But even to study a single question there are multiple models of similar complexity, each of them a credible approximation to the description of the climate system given our limited understanding, the lack of complete observations and the simplifications that need to be made due to computational constraints.

A climate model has dozens of parameters that are not known exactly. If our computers were sufficiently large we could build millions of model versions to explore the uncertainties related to these parameters. The critical step is then to decide whether a model is "credible", "plausible" or consistent with observations (given some known limitations of the model). This is where statisticians can help. Bayesian methods have been developed to produce probabilistic projections for both global and regional climate change by attaching weights to individual models or model versions according to how well they represent the current climate or the observed trends[2,3]. An example of such a probabilistic projection for two future economic scenarios is shown in Figure 1. Both scenarios posit an absence of political intervention to reduce fossil fuel emissions. The projections are based on the Bern 2.5D climate model of intermediate complexity[3]. The figure shows 5–95% confidence ranges for global temperature projections over the next century, constrained by the surface warming and ocean heat uptake that have been observed in the past. Rather than having a scientist tweaking parameters to calibrate a single model based on his or her experience and then run the model once, Bayesian methods provide a whole distribution of future climate trajectories conditional on past observations. But although

this sounds straightforward, the reality is, as always, more complicated.

What is a good model?

In many cases, predictions from numerical models can be evaluated from observed data. For example, we can construct an aircraft with a computer model. Even if we cannot properly simulate turbulence, we consider the project to be successful if the plane flies as predicted. We do not need a perfect model, just one that works. The value of the model in this case is partly based on experience. Similarly, most people have a certain confidence in weather forecasts based on past experience, even if they do not understand the underlying model. For climate projections, the problem is that the life cycle of a model is much shorter than the timescale over which a prediction can be checked against observations[4]. A model lasts a few years; we are asking it to predict the climate decades to centuries ahead—and we need the answers right now, not centuries from now. Because of the lack of direct evaluation on future climate, we need to assume that the equations and parameterisations built into the model can be extrapolated beyond the range of where they are evaluated. This is obvious for parts of the model—such as conservation of mass or energy—but less clear in the case of parameterisations that are empirically derived from observations covering the rather narrow climate regime of the past century. Further complications arise because the data sets used in the model evaluation process are mostly the same as those used for calibrating the model, which may result in circular reasoning. There is a danger that the model–data fit will be artificially inflated, giving a poor indication of how accurate the model will be when it comes to new, out-of-sample predictions. The model calibration is often non-unique, such that different sets of model parameters may reasonably reproduce the observations[3,5]. The obvious idea in Bayesian methods is to throw more data at the problem, hoping that the parameters will be constrained if the amount of data for the evaluation is much larger than the number of adjustable parameters. However, more detailed observations often reveal additional model imperfections and ask for a more complex model, and, the more comprehensive a model, the more difficult it is to evaluate and understand it.

It is difficult to define a unique overall figure of merit, metric or skill score for a climate model. Each model tends to simulate some aspects of the climate system well and some others not so well; climate modellers get nervous when one starts ranking models. The situation is worse because skill has to be defined on the basis of the simulation of processes, the past or the present climate, rather than the quantity we are actually interested in, which is the future, for which no observations exist. Strictly, agreement between model and data therefore does not imply that the modelling assumptions accurately describe the processes producing the observed climate system behaviour; it merely indicates that the model is one (of maybe several) that is plausible, meaning that it is empirically adequate. A lack of disagreement in repeated experiments and applications means that the model is more likely to be adequate and useful to infer some prediction from it, at least within the range of applications or parameters where it has been evaluated.

Many aspects of the observed climate do not relate very clearly to the changes in the future: a model that simulates temperature over the UK well today may not necessarily do so in the future. Several models simulate the present well, yet disagree in the magnitude of the future changes they predict[5]. An example is given in Figure 2, which shows how four global coupled climate models from the recent Intergovernmental Panel on Climate Change (IPCC) assessment report[1] simulate northern

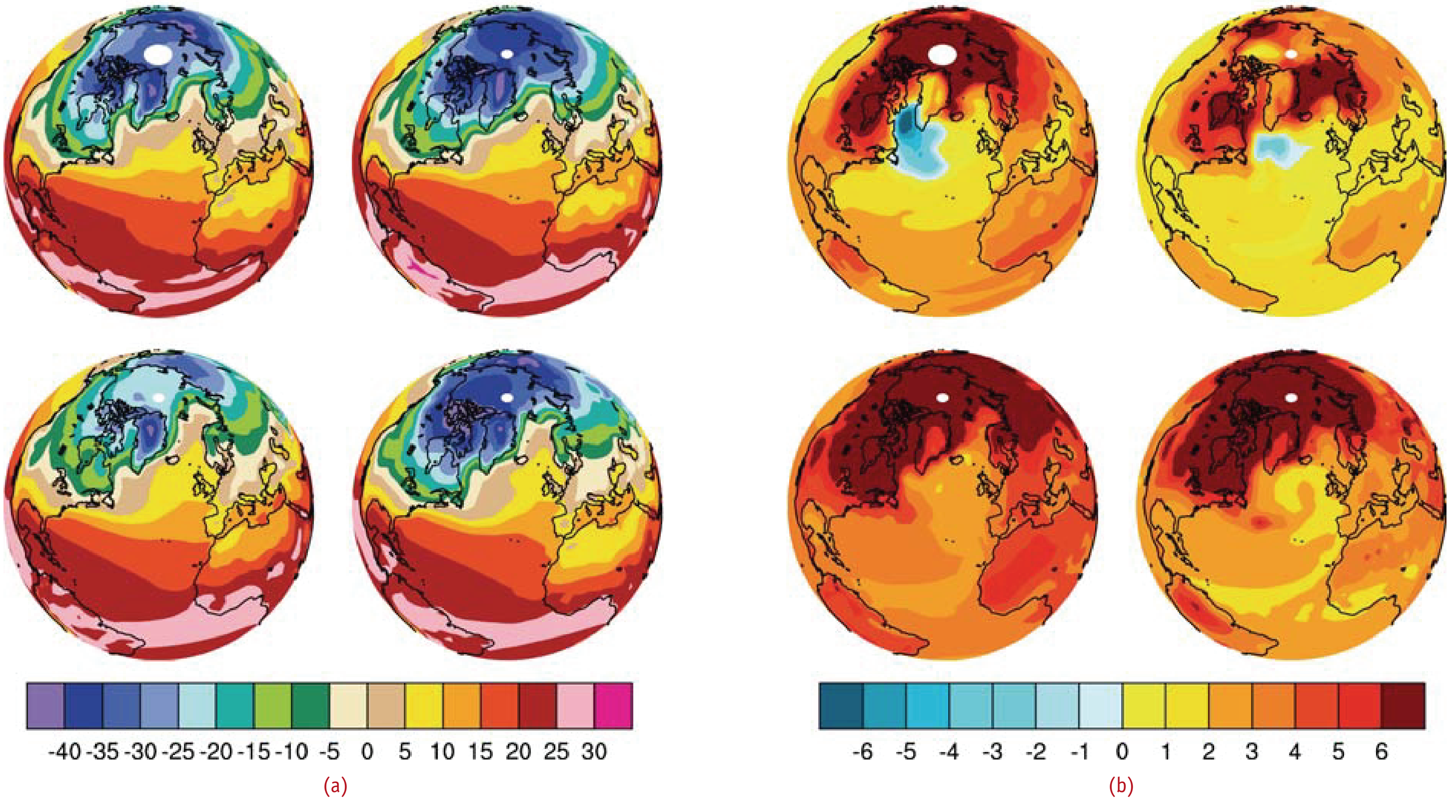

Figure 2. (a) Simulated “present day” December to February surface temperature and (b) the projected warming between 2080 and 2099 relative to 1980–1999 for the IPCC’s Special Report on Emissions A1B scenario for four climate models (°C). There is no obvious connection between the present day temperature pattern and the simulated warming that the models predict. Modified from Knutti (2008)[6]

winter temperature for the current climate. The agreement with observations today is similar for all models, but the models differ widely in their predictions of the future. Their bias patterns do not clearly relate to the warming patterns they predict for the end of the century. Indeed, the current generation of model tends to converge in simulating what we observe, but not in their future response.

Should we trust the models?

The issues and *caveats* discussed above should not imply that the current models are useless; rather they demonstrate that uncertainties are difficult to quantify and to reduce and that the definition of model performance is vague. Despite some limitations, climate models have reached a level of maturity that is remarkable. Confidence in climate models is based on different lines of evidence. Models are based on physical principles like conservation of energy, mass and angular momentum. They reproduce the mean state and variability in many variables reasonably well and continue to improve in simulating smaller scale features. Progress has been made in understanding climate feedbacks and intermodel differences. Model calibration from observations is unavoidable for certain subcomponents of the models, but the amount of data is large and the number of model parameters is small, so the calibration is not a statistical curve fitting exercise. Models reproduce observed global trends and patterns in many variables. They are tested on more distant past climate states, which provide a useful and relatively independent evaluation, although uncertainties in evidence of the distant past are larger and proxy data may not be used directly to test the model. Multiple models agree on large scales, which is implicitly or explicitly interpreted as increasing our confidence. Projections from newer models are consistent with older ones, indicating a certain robustness. Finally, confidence comes from the fact that we can understand results in terms of processes. The model results we trust most are those that we can understand the best, and which we can relate to simpler models, conceptual or theoretical frameworks[7].

How can we go forward?

One may see the evolution of climate models like the natural selection of organisms. Successful components or pieces of models are kept and less effective ones are replaced. But how large and diverse should the zoo of models be? There are at least two competing ways to allocate resources. Model diversity helps to quantify uncertainty and may increase the chances to discover something new or very different, whereas steady model improvement of a few existing models helps to improve the fitness for a particular purpose but may be less likely to change things dramatically. With few exceptions, climate modelling has traditionally taken the latter approach, in which a single model in each institution is made as complex as can be afforded. This may be useful for a best-guess prediction, but methods to quantify uncertainty by using statistical methods are likely to benefit more from a large number of models[5]. These Bayesian methods are still in their infancy and few methods have been proposed to combine results from multiple models beyond simple averaging. Doing so requires metrics of model performance: a thorny but unavoidable step[2]. Additionally, progress is needed in statistical methods that can handle very large data sets and can take into account the discrepancy between models and data, in particular the fact that many models are imperfect in a similar way.

However, uncertainty in climate projections may still not decrease quickly, both because the present provides only a weak constraint on the future, and because models continue to include more processes and feedbacks interactively, giving rise to new sources of uncertainty and possibilities for model spread. Some uncertainties are even intrinsic and irreducible. Volcanic eruptions in the future fall into this category. The chaotic nature of short-term changes are also inherently unpredictable; so also, potentially, are some tipping points. Scientists need to specify all possible outcomes, rather than trying to reduce spread where it cannot be reduced.

Conclusions

Some may argue that long-term forecasts are useless because they cannot be evaluated properly. Little can be learnt, they say, from a prediction without verification. Indeed the climate change problem is peculiar in that the past offers no direct well-observed analogy to learn from. Yet the ability of the models to reproduce the current climate, the recent observed trends as well as the more distant past, the fact that they are based on physical principles and the fact that we can understand and interpret many of the results from known processes provide support for their credibility.

Finally, as a thought experiment, let us assume that we had a perfect model to make a prediction with no uncertainty. Would the world be any different? Would we fight the climate change problem more effectively? Accurate information on the expected trends is critical for local adaptation, and uncertainties in climate model projections are admittedly an issue. But they are unlikely to be the limiting factor that prevents us from making a decision and from acting on, rather than talking about, the climate change problem. It is already well known that fossil fuel emissions need to be reduced dramatically and soon to prevent dangerous impacts from climate change; it has long been clear that mitigation is more cost effective than letting future generations pay for the damage we are causing today. Uncertainty does not prevent us from making decisions in our daily life; that should also apply to the steps we need to take to solve the climate change problem.

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