Predictability and Understanding of Our Climate Risk: Approximations, Bugs and Insight

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Sometimes we are forced to do science in the dark. Progress across the sciences, both pure and applied, is often achieved by the light of our failures. Weather forecasters, for example, have watched their simulations go wrong, sometimes daily, for decades. Today the uncertainty in a 4 day weather forecast is comparable to the uncertainty in two-day forecasts of the past. Guidelines for statistical good practice given out-of-sample results are well developed in fields with similar “weather-like” tasks. Climate forecasting differs fundamentally. By the nature of the questions addressed, relevant out-of-sample evaluation is impossible. Simplifications (known to be inadequate if interpreted as approximations) are made in order to ensure the code runs faster than real-time. These are neither Known Unknowns nor Unknown Unknowns, nor are they Unknown Knowns (insights known within the science, but not to those formulating the model). Rather, these intentional omissions are “Suppressed Knowns”: engineering fixes without which there are no simulations to guide decision making and policy at all. And the impact of such simplifications cannot be evaluated in practice, unlike engineering fixes informed by having seen earlier buildings and bridges fall down. Science in the dark can inform policy and aid decision making, but its insights, its analysis, and its criticism must be distinguished from the products of science informed by empirical evaluation.

The risk posed by greenhouse gases has been well documented by climate science for decades; the natural desire for detailed impacts, and the “reduction in the uncertainty” of those details has deepened the decision support niche for climate models. Yet while both the science and the models yield insight into the risks we face, approximations, simplifications, bugs and our ignorance prevent climate models from quantifying the uncertainty in our future. There are bugs of the sort that make changing the compiler painful, while a change of hardware can kill a climate model - its basic structure then being lost or evolving if the code is rewritten. There are other shortcomings, not traditional “bugs” like dividing by zero, but shortcomings of simulation due to the failure to represent mountains (or clouds) with sufficient accuracy. These constraints may be imposed by our technology as much as by the limits of our understanding. In weather-like tasks their implications can be noted and the models ignored (if run) where they tend to be misinformative; but not in climate-like tasks. Of course “Science in the Dark” is not done in-sample on purpose: it can only be done in-sample due to the nature of the questions asked. While it is unfair to criticise the science for accepting the nature of the problem as posed, it is naïve to treat the outputs of that science with the same confidence given the outputs of tried and tested weather-like sciences. Approaches for using scientific simulations in climate-like tasks include the provision of a “Minority Opinion” in conjunction with each large projection report, reporting the likelihood of specific impacts via non-probability odds on and against, and completing each model-based probability forecast by including the “Probability of a Big Surprise” as a function of lead time, thereby quantifying second-order uncertainty. Alternative approaches are welcome.