Abstract

Managing Climate Risks

Roger M. Cooke[1]
Carolyn Kousky[2]

Many Integrated Assessment Models (IAMs) maximize the present value of consumption, equating the marginal benefits of abatement in terms of reduced climate damages with the marginal costs of reducing emissions. Every trader, banker, and investor knows that maximizing expected gain entails a trade-off with risk. According to the theory of rational decision, preferences can always be represented as expected utility, hence from this viewpoint, any aversion to risk could be folded into the rational agent's utility function. This theory, recall, applies to rational *individuals*; groups of rational individuals do not comply the axioms of rational decision theory. The fact is that 'professional risk taking organizations' do manage risk, and not by bending the utility function of a representative consumer. Rather, they employ techniques like value at risk, and optimize expected gain under a risk constraint. Managing risk is a problem of group decision.

Weitzman (2009) has recently called attention to the risks of climate change, arguing that current approaches court probabilities on the order of 0.05~0.01 of consequences that would render life as we know it on the planet impossible. What is the plan to manage this "tail risk"? Risk management shifts the research question from 'how does the optimal abatement level change for different parameter values?' to 'how does our policy choice fare under the range of potential future conditions and how can we buy down the risk of catastrophic outcomes?' As such, it places the quantification of uncertainty in the foreground. Uncertainty quantification is more than a modeler putting distributions on his/her model's parameters. The antecedent question reads: 'is it the right model? What is the model uncertainty?' Failing a definitive answer to that question, *stress testing* our current models for their ability to handle tail risks, and exploring *canonical model variations* are essential steps prior to quantifying uncertainty on parameters. Gone are the days when quantification of the uncertainties was left to the modelers themselves; at the state of the art, quantification is done by *structured expert judgment* in a rigorous and transparent manner.

Stress Testing

Stress testing is preformed to check that models remain realistic and capture the relevant possibilities when their parameters are given extreme values. Many IAMs specify economic damages as a function of temperature change, and model their impact on output and utility. For example, damages at time t induced by temperature change T(t) from pre-industrial mean temperature are represented in DICE as factor that reduces economic output: $1/[1 + 0.0028388T(t)^2]$. The standard Cobb Douglas production function expresses output as a function of total factor productivity, capital stock and labor. Capital depreciates at rate 10%, and is augmented by savings (in the DICE "Base" case the savings rate is optimized with damages set equal to zero, then damages are reinstated). Temperature induced damages and abatement efforts reduce output. Setting damage and abatement equal to zero, an illustrative stress test of the Cobb Douglass model with constant population, constant total factor productivity and DICE values for

[1] Resources for the Future and Dept of Mathematics, Delft University of Technology
[2] Resources for the Future

other parameters is shown in Figure 1. Four output trajectories with initial capital ranging from 10 times the DICE value ($1800 Trill) to $100 ($$1.6\times10^{-8}$ for each inhabitant). The limiting capital value is independent of the starting values – with a vengeance: the four trajectories are effectively identical after 60 years. Such obviously unrealistic consequences underscore the need for circumscribing the empirical domain of application of these simple models. Put the factories and laborers on the Moon and they will produce nothing; other things are involved. Regardless whether the model adequately describes small departures from an equilibrium state, its use for long term projections inevitably entails this sort of behavior and putting uncertainty distributions on the model's parameters will not change that.

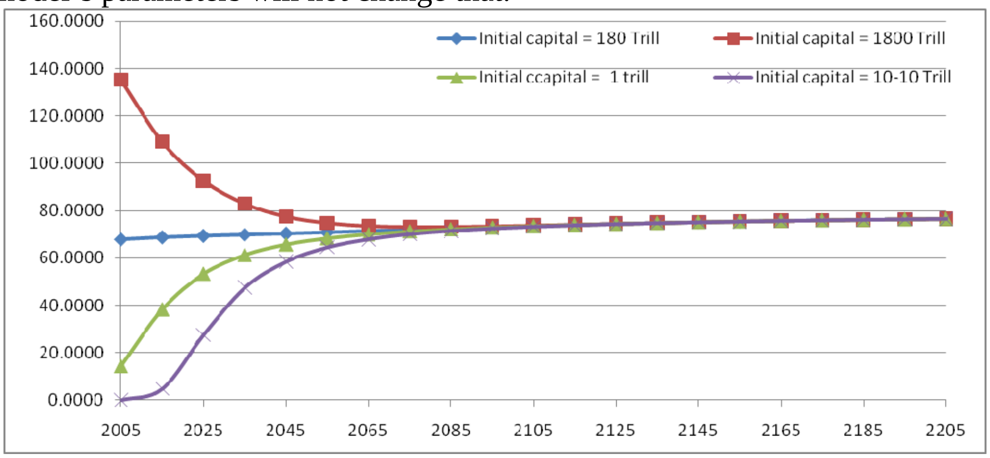


Figure 1. Output gross of abatement cost and climate damage ($trill 2000 USD) Base case, no temperature damage, no abatement, constant population, constant total factor productivity (0.0307951), initial output from production function and DICE defaults for other parameters (DICE 2009 XL version).

A second stress test examines the effect of adding temperature induced economic damages, again without abatement. With $180 Trill initial capital, we assume that temperature increases linearly, leaving other parameters as in the previous case. Figure 2 shows four economic output trajectories, corresponding to temperature increases of 0, 5, 10, and 15 degrees Celsius in 200 years.

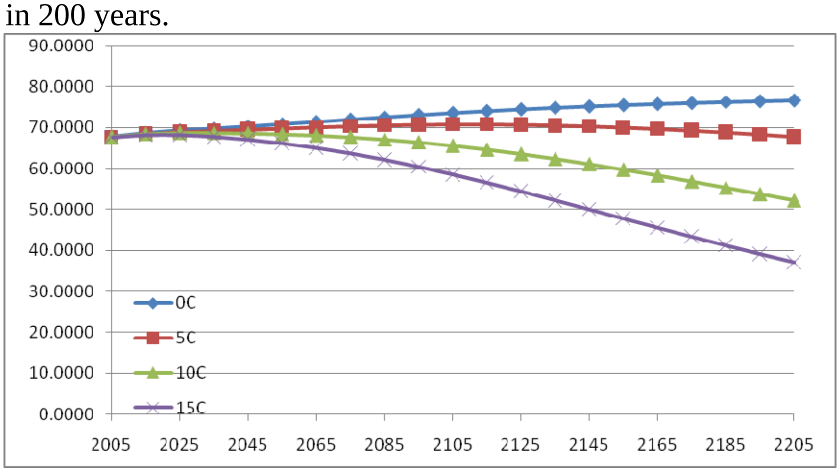


Figure 2Output after damages before abatement, initial capital = 180 $trill, constant population, constant productivity, no abatement, temperature in 200 yr (linear increments)

No scientist claims that life as we know it could exist with 10°C global warming. With a steady temperature rise leading to 10°C above pre-industrial levels in 200 years, this model predicts that output would be reduced to 68.% of its value without temperature rise. Such projections seem a bit sanguine. The essential feature is that climate induced damages hit only economic output; as a result capital can never decrease faster than its natural depreciation rate, and this rate of decrement is reached only for infinite temperature. Again, putting uncertainty on other model parameters may cloud this picture, but will not change this feature.

Canonical Model Variation

It is often noted that simple models like the above cannot explain large differences across time and geography between different economies, pointing to the fact that economic output depends on many factors not present in such simple models. To "save the phenomena" researchers have proposed enhancing the basic model with inter alia social infrastructure, government spending, human capital, knowledge accretion, predation and protection, extortion and expropriation (see Romer (2006), chapter 3). Before proliferating this model, however, it is well to reflect on its fundamental assumptions about damage, capital and output. Could different model types with comparable prime facie plausibility result in macroscopically different behavior?

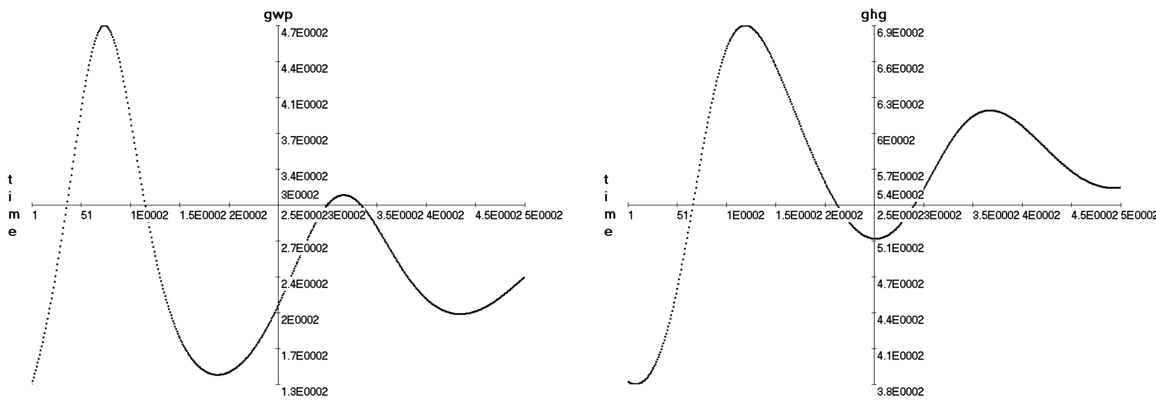
We illustrate with one variation based on the following simple idea: Gross World Production (GWP[trillion USD 2005]) produces pollution in the form of greenhouse gases; pollution, if unchecked, will ultimately destroy necessary conditions for production. This simple observation suggests that Lotka Volterra type models might provide a perspective which an uncertainty analysis ought not rule out. The quantity of anthropogenic greenhouse gases in the atmosphere at year t, GHG(t) [ppm CO_2], is the amount in the previous year, less what has decayed at a rate, say, 0.0083, plus any new emissions in time period t. Assume that new emissions are a fixed fraction, say, 0.024 of GWP (Kelly and Kohlstadt 2001). Different values can be found in the literature, but these are representative. Real GWP has grown at an annual rate of 3% over the last 48 years (this includes population growth); assume that this growth is decreased by a damage function D of temperature T, and ultimately of GHG, this gives the following system:

(1) $\mathrm{GHG}(t+1) = (1-0.0083)\mathrm{GHG}(t) + 0.024\times\mathrm{GWP}(t).$

(2) $\mathrm{GWP}(t+1) = [1+ 0.03 - D(T(\mathrm{GHG}(t)))]\mathrm{GWP}(t).$

If D were linear in GHG, this would be a simple Lotka Volterra type system. With *cs* as the climate sensitivity and 280 ppm the pre-industrial level of greenhouse gases, equilibrium temperature follows $T(\mathrm{GHG}(t)) = cs\times \ln(\mathrm{GHG}(t)/280)/\ln(2)$. Adopting Weitzman's (2010) notion of a "death temperature" of 18°C we write damages as $D(\mathrm{GHG})(t) = (T/18)^2$. Anthropogenic greenhouse gases increase with production; if GWP(t) were constant, they would increase to a constant 0.024×GWP/0.0083 However, as GWP increases, GHGs and temperature keep rising as well, lowering the growth rate of GWP. When $D > 0.03$, GWP starts decreasing. Eventually 0.024×GWP < 0.0083, and then greenhouse gases start decreasing, reducing damages to a point where production can start growing again. Figure 2 shows GWP and GHG as functions of time out to 500 yrs, with all variables at their nominal values. GWP collapses. Greenhouse gases also collapse, but not to their initial level; hence the next upswing in GWP is attenuated. A steady state is eventually reached after some 1,500 years. This is not offered as a plausible model, its role is to spotlight the fundamental modeling assumptions. Evidently, different ways of modeling the impact of climate change damages give qualitatively different predictions, and steady state values may not be relevant for current policy choices. Neither theoretical nor empirical evidence exclude the Lotka Volterra type of interaction between damages and production presented here. A credible uncertainty analysis should fold in this and other possibilities, which brings us to the next point of examining a range of future conditions for a given policy choice.

Figure 3: The impact of climate damages on GWP (left) and greenhouse gases (right)

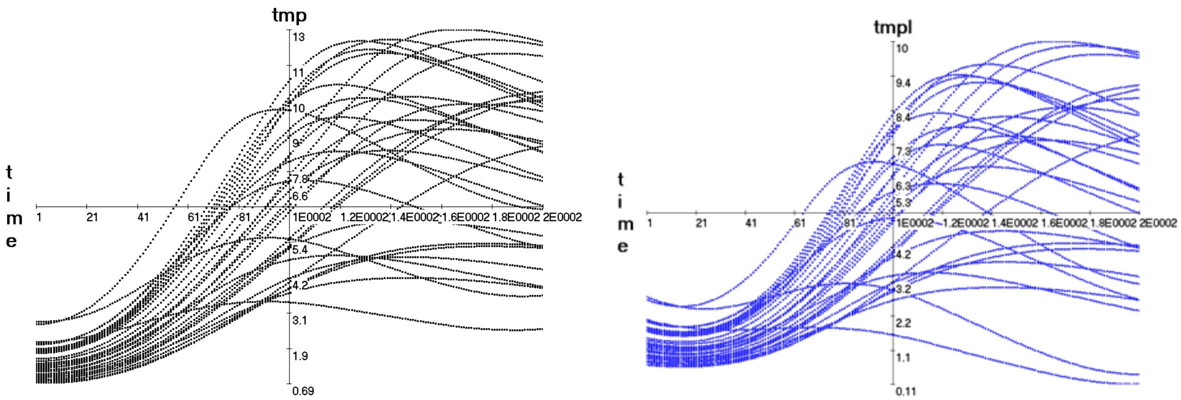


Structured Expert Judgment for Quantifying Uncertainties

Uncertainty analysis with climate models must be informed by the broad community of climate experts - not simply the intuitions or proclivities of modelers - through a process of structured expert judgment. Experience teaches that independent experts will not necessarily buy into the models whose parameter uncertainties they are asked to quantify. Hence, experts must be queried about observable phenomena, results of thought-experiments if you will, and their uncertainty over these phenomena must be 'pulled back' onto the parameters of the model in question. This process is analogous to the process by which model parameters would be estimated from data, if there were data. The new wrinkle is that data are replaced by experts' uncertainty distributions on the results of possible, but not actual, measurements. The 'pull back' process is called probabilistic inversion, and has been developed and applied extensively in uncertainty analysis over the last two decades (see Cooke and Kelly 2010 and references therein). In general, an exact probabilistic inverse does not exist, and the degree to which a model enables a good approximation to the original distributions on observables forms an important aspect of model evaluation. Four features of the structured expert judgment approach deserve mention: (i) Experts are regarded as statistical hypotheses, and their statistical likelihood and informativeness are assessed by their performance on calibration questions from their field whose true values are known post hoc. (ii) Experts' ability to give statistically accurate and informative assessments is found to vary considerably. (iii) Experts' uncertainty assessments are combined using performance based weights. (iv) Dependence, either assessed directly by experts or induced by the probabilistic inversion operation, is a significant feature of an uncertainty analysis.

When uncertainty has been quantified in a traceable and defensible manner, an ensemble of possible futures for each policy choice may be generated. Figure 4 shows 30 Lotka Volterra temperature trajectories out to 200 years, with BAU emissions at 2.4% GWP (left) and stringent emissions at 1.5% of GWP (right); and using representative distributions for uncertain variables. Employing a value at risk management strategy, we would search for an emissions path optimizing consumption while holding the probability of exceeding a stipulated temperature threshold below a tolerable threshold.

Figure 4: Possible temperature trajectories under (left) emissions at 2.4%GWP and (right) emissions at 1.8% GWP (right)



These reflections challenge us to deploy risk management strategies on a global scale. We suggest this begin with (i) stress testing models, (ii) exploring alternative models, and (iii) quantifying uncertainty in such models via structured expert judgment. We are condemned to choose a climate policy without knowing all the relevant parameters, but we are not condemned to ignore the downside risks of our choices.

References

Cooke, R. M. and G. N. Kelly (2010). Climate Change Uncertainty Quantification: Lessons Learned from the Joint EU-USNRC Project on Uncertainty Analysis of Probabilistic Accident Consequence Code. Resources for the Future Discussion Paper 10-29. Washington, D.C., Resources for the Future,

Kelly, D.L. and Kohlstadt C.D. (2001) “Malthus and climate chantge: betting on a stable population” J. of Environmental Economics and Management 41, 135-161.

Romer, D. (2006) Advanced Macroeconomics McGraw Hill Irwin, Boston.

Weitzman, M. (2010). GHG Targets as Insurance Against Catastrophc Climate Damages. Cambridge, MA, Harvard University.

Weitzman, M. L. (2009). "On Modeling and Interpreting the Economics of Catastrophic Climate Change." Review of Economics and Statistics **91**(1): 1-19.