EGU21-15363
https://doi.org/10.5194/egusphere-egu21-15363
EGU General Assembly 2021

A Bayesian-inferred physical module to estimate robust mitigation pathways with cost-benefit IAMs

Thomas Gasser[1], Artem Baklanov[1,2], Armon Rezai[1,3], Côme Chéritel[1,4], and Michael Obersteiner[1,5]
[1]International Institute for Applied Systems Analysis, Laxenburg, Austria (gasser@iiasa.ac.at)
[2]Higher School of Economics University, Saint-Petersburg, Russia
[3]Department of Socio-Economics, University of Economics and Business, Vienna, Austria
[4]Ecole Polytechnique, Palaiseau, France
[5]Environmental Change Institute, University of Oxford, Oxford, UK

Cost-benefit integrated assessment models (IAMs) include a simplified representation of both the anthropogenic and natural components of the Earth system, and of the interactions and feedbacks between them. As such, they embed economic- and physics-based equations, and the uncertainty in one domain will inevitably affect the other. Most often, however, the physical uncertainty is explored by testing the sensitivity of the optimal mitigation pathway to a few key physical parameters; but for robust decision-making, the optimal pathway itself should ideally embed the uncertainty.

Here, we present a new physical module for cost-benefit IAMs that is based on state-of-the-art climate sciences. The module follows well-established formulations that were deemed a good trade-off between simplicity and accuracy. Therefore, its overall complexity remains low, as is necessary to be used with optimisation algorithms, but able to reproduce the behaviour of more complex CMIP models. It is made of four components that all exhibit a degree of non-linearity: global climate response, ocean carbon cycle, land carbon cycle, and permafrost carbon system. (Two impact components were also developed: surface ocean acidification, and sea-level rise response.)

The calibration of this new module is done through Bayesian inference. Prior distributions of the module's parameters are taken from CMIP multi-model ensembles, and prior distributions of historical constraints are taken from observational datasets (such as global mean surface temperature) and other synthesis exercises (such as IPCC reports or the global carbon budget). The Bayesian calibration itself is done with a full-rank automatic differentiation variational inference (ADVI) algorithm, which leads to posterior distributions of parameters that are consistent with observations. Additionally, the full-rank ADVI algorithm also finds correlations between parameters (i.e. co-distributions) that tend to further reduce the uncertainty in projected climate change.

We then implement this new module within the DICE model (that is likely the most widely used cost-benefit IAM), and we demonstrate a significant improvement of the physical modelling, and thus of the IAM's results. We run a Monte Carlo ensemble of 4000 elements taken from the Bayesian calibration, to properly sample the physical uncertainty in the optimal mitigation pathway simulated by DICE. Notably, our new module leads to a social cost of carbon (SCC) of 26 USD / tCO2 (90% range: 13–43), which is lower than 37 USD / tCO2 in the original model.

This Monte Carlo approach is not a robust one, however, and a final simulation is run to estimate one *unique* mitigation pathway shared across all 4000 states of the world (by maximizing the total welfare). This *robust* mitigation pathway is therefore a unique solution that embeds the physical uncertainty, and it is different from the average pathway of the Monte Carlo ensemble. The unicity of the solution (and its lack of explicit uncertainty) makes it very attractive for decision-making and communication purposes. We posit this robust approach could be applied with the cost-optimal IAMs that are used by the IPCC to create and investigate climate change scenarios.