A note on climate science and climate policy

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Doing the right things

In its fourth Assessment Report (Intergovernmental Panel on Climate Change (IPCC) 2007), the Intergovernmental Panel on Climate Change (IPCC) has pointed out that responding to climate change involves "*an iterative risk management process that includes both mitigation and adaptation, taking into account actual and avoided climate change damages, co-benefits, sustainability, equity and attitudes to risk.*"

Fifteen years later, we have to recognize that humanity is far from having implemented such an "iterative risk management process", that our scientific understanding of the notions involved in this process is less than satisfactory and that solutions towards keeping the earth climate within safe boundaries are difficult to agree upon and implement in practice.

This is not very surprising if one considers that different decision makers, say, countries or coalitions between countries, are due to experience different (negative and positive) impacts from climate change, are in very different cultural, economic and technological situations and, perhaps more importantly, are in competition (if not in war) with each other.

What is perhaps more surprising is that, even within the scientific community, there is little agreement on how to turn the scientific knowledge distilled in the IPCC Assessment Reports into advice to policy makers that is *pragmatic*, *transparent* and, above all, *accountable*.

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Doing the right things rightly

In spite of a strong focus on quantitative analysis and prediction, climate science has been so far embarrassingly incapable of providing advice on matters of climate policy that is *accountable*: decision makers do not precisely know what kind of outcomes and guarantees they can expect from implementing the advice received.

This, too, is not very surprising. Applications of the physical sciences, e.g., to engineering or to public health, heavily rely on *empirical* methods. Where predictions are necessarily uncertain – e.g., because of the lack of well established theories or because of imperfect information – the physicist (chemist, biologist, etc.) can often turn to experiments, either in a laboratory or on the field.

The evidences obtained in such tests and experiments are recorded in formal protocols, analysed and perhaps confirmed (or confuted) by other experiments and finally applied to *pragmatic* decision making.

While formal methods cannot fully replace empirical verification, they can provide very high levels of *transparency* and contribute towards making political decisions more understandable, more transparent and more accountable (Botta et al. 2020).

Differences that matter

However, applying formal methods requires both advisors *and* decision makers to have achieved a shared understanding of the impacts of uncertainties on decision making (Botta, Jansson, and Ionescu 2018), of the differences between decision making under uncertainty and decision making in a deterministic environment and to carefully distinguish between closely related but crucially different notions. In this section, we discuss some of the differences that matter.

Acting vs. planning.

You have had breakfast and are on your way to your office. You drive the car out of the garage, fire up Google Maps on your mobile phone, enter your position and select your office as your goal. You are suggested a route, start driving and follow the suggestions of the routing algorithm. On your way to the office you get re-routed a couple of times, perhaps because of an accident on the original route or because you have made a detour to pick-up a colleague who has called you while you were driving.

In following or rejecting the recommendations of the routing algorithm, you are taking decisions, one after the other. Some of the these decisions entail judgments about uncertain events. Perhaps if you pick-up the colleague you might be caught in a traffic jam and miss an important meeting.

At each decision step, you are concerned with making a *best* decision, one that will get you to the office in the shortest time. Or, perhaps, one that is safest or one that avoids driving through a district you hate.

No matter what your aims are, at each decision step you want to take a decision that best matches your aims. Google Maps is your friend and you have learned how to judge its advice. You start with a route than you trust being the best possible given the information available at the time you drive out of the garage. Perhaps you revise your original plan on your way to the office. For instance, if Google Maps suggests you an alternative route.

In driving and taking decisions on the way to your office, you are *acting*. In doing so, you are exploiting the results of another activity: *planning*.

Planning and acting are closely related but essentially different activities. While driving to the office, driving decisions follow a plan. But the plan evolves in time, following the decisions.

While planning and acting may take place simultaneously, they are *logically distinct* activities. Sometimes, like in the example of driving to the office, planning and acting are concerns of two different agencies: Google Maps is responsible for planning, you – the driver – for acting.

Often, the same agent is involved in planning and acting, typically at different times.

Another example: tomorrow we want to bike to the countryside. We plan a long tour but the weather forecast is uncertain. In the morning it should be sunny but in the afternoon there is a significant chance of thunderstorms. Thunderstorms will come from west and they might align. In that case, we might get heavy hail.

We pack our rain clothes into the bicycle bags but we plan to break the tour if the weather gets really bad by 3pm. We will take a slightly longer route that will allow us to easily reach a train station if we decide to break the tour before 3pm. In this case, we will come back by train. If tomorrow morning the weather forecast worsens, we will make a short tour instead and be back for lunch.

We have made a plan for two decision steps, one tomorrow morning and one tomorrow afternoon. For each step, we have defined a decision rule: for each possible *state* (in step one, same/worse forecast; in step two, weather stable/really bad) we have planned a corresponding *action*.

Planning under uncertainty

Thus, we have defined two functions, one for each step. Tomorrow morning we will check the weather forecast, apply the first function and decide whether we go for a long or for a short ride.

It is important to realize that, under uncertainty, planning essentially means defining decisions *functions*, one for each decision step. In control theory, these functions are called *policies*. In game theory, they are often called *strategies* or sometimes *contingency plans* (Puterman 2014).

Thus, when we speak of *optimal* plans for a specific decision problem (no matter what optimal means for that specific problem), we speak of optimal *policy sequences*.

This is in contrast to planning for *deterministic* decision problem that is, for decision problems without uncertainty. In this case plans (and, therefore, optimal plans) can be conceived as sequences of actions.

This is because, in absence of uncertainties, a decision at a given step uniquely defines the conditions under which the next decision step takes place.

It goes without saying that, in most realistic situations, planning takes place under uncertainty. Ignoring uncertainties can lead to inefficiencies and fragile planning, as sometimes observed in planned economies.

In *practical* climate decision problems, decisions are taken sequentially and uncertainties are typically unavoidable (Webster 2000), (Webster 2008). They are a consequence of imperfect scientific knowledge but also, and more importantly, of political instability, inertia of legislations and of the intrinsic uncertainty of technological innovation.

Even if we assumed a perfect scientific knowledge of the processes that determine the impacts of GHG emissions on the climate, planning for GHG emission problems would still have to account for these uncertainties.

From this angle, speaking of "emission paths" (in contrast to emission policies or, perhaps more explicitly, of emission decision functions) suggests a fundamental misunderstanding of the problem at stake: no "optimal" emission path can be a meaningful answer to the problem of planning "good" decisions in, e.g. solar radiation management problems (Moreno-Cruz and Keith 2012), (Helwegen et al. 2019), (Nordhaus 2019).

As planning under uncertainty means defining *policies* that is, decisions functions, for each decision step, what are the domains and the codomains of such functions?

For a given decision step, the *domain* of a policy consists of the set of the observations that can be done at that step and that are relevant to decision making.

For tomorrow's morning decision step, we have contemplated only two possible observations: that the weather forecast has worsened or that the weather forecast is unchanged. Perhaps we should also consider the possibility that the weather forecast improves and, in that case, leave our rain clothes at home. We might want to make even more realistic plans and consider the possibility that tomorrow morning we feel very tired or lazy and decide to stay home no matter how the weather will be. No matter how the possible observations looks like, in decision theory, they are called the set of possible *states*.

The *codomain* of a decision function – a *policy* – is typically different in different states. In a given state, it consists of all the actions (options) that can be done in that state.

In our plan for tomorrow, the options are to go for the short tour or to go for the long one in both states. The policy that will guide our decisions is to go for the long tour if the weather forecast is unchanged and for the short ride if it has worsened.

In control theory, the set of actions (options) considered in a given state is called the *controls* set for that state.

Acting under uncertainty: optimality and regret.

We have seen that planning under uncertainty means finding sequences of policies or, in other words, sequences of decision functions.

Sometimes, we can estimate the (uncertain) consequences of acting according to a fixed sequence of decision functions. For instance, we can compute the *possible trajectories* associated with taking decision according to the policy sequence and perhaps even their probabilities.

If we are also able to attach values to possible trajectories, we can often compute so-called *optimal policies*.

The measure of uncertainty accounts for how decision makers aggregate the (uncertain) values associated with the possible trajectories. For example, a risk-neutral decision maker might measure stochastic-uncertainty according to the *expected-value measure*. In the same situation, a risk-averse decision maker might adopt a measure that minimizes the probability of worst outcomes.

What can a decision maker expect from actually taking decisions according to an optimal sequences of decision functions? Can optimality avoid **regret**?

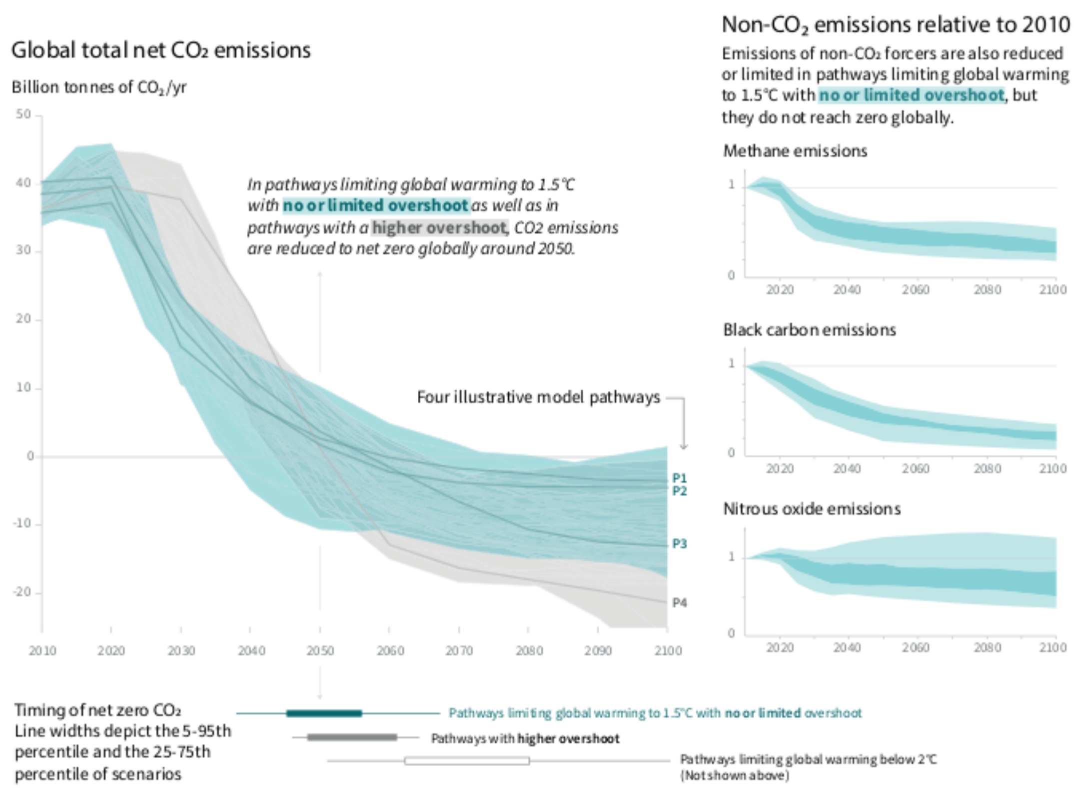
Unfortunately, this is not the case. Even if we follow provably optimal decision rules, we can always have bad luck and take a decision that in hindsight we might regret: avoiding smoking and regularly go biking does not guarantee one not to die from lung cancer. Still, it's a better policy than chain smoking and sitting the whole day in front of a computer.

This is another important difference between decision making under uncertainty and decision making in a deterministic environment: in the deterministic case optimal decisions do indeed guarantee regret-free decision making.

What to do and how to do it.

Another difference that must be kept in mind when considering the problem of applying climate science to policy making is that between what to do and how to do it.

Consider, for example, the guideline on global GHG emissions at page 19 of the summary for policy makers of the IPCC special report on global warming of 1.5 °C (Intergovernmental Panel on Climate Change (IPCC) 2018):



The blue corridor entails emission paths that, according to the knowledge available at the point in time in which the summary was prepared, limit global warming to 1.5 °C with no or limited overshooting.

The summary and, specifically, the corridor provides crucial information to decision makers. However it does not attempt at answering the question of how to actually implement an emission path that is consistent with the "safe" emission corridor. Answering this question has very different dimensions that can hardly be covered within climate science.

Along one such dimensions we have the problem of finding sequences of policies (or decision rules, see section Planning under uncertainty) that support pragmatic decisions (e.g., on GHG abatement targets at a given point in time and in a given state) that are likely to yield global GHG emissions within the "safe" corridor. The focus here is on *likely*: global decision are necessarily uncertain (Rougier and Crucifix 2018) and every attempt at finding realistic policy sequences has to account for such uncertainties. Tackling the problem of finding policy sequences under uncertainty requires contributions from, among others, control theory, expert elicitation, computer science and of course climate science (Webster 2000), (Botta, Jansson, and Ionescu 2017), (Webster 2008), (Helwegen et al. 2019), (Heitzig et al. 2016), (Botta, Jansson, and Ionescu 2018).

Another obvious dimension of the problem of applying global guidelines to policy making entails the question of how to actually get decision makers (countries) that are likely to experience different (negative and positive) impacts from climate change and that are in competition with each other to actually coordinate and cooperate to achieve global goals. The question is at the border between moral philosophy (Hardin 1968), (Ockenfels, Werner, and Edenhofer 2020), game theory (Heitzig 2012) and economics. Recently formal methods have been proposed as a means of improving the accountability of mechanism (rules) that are designed to fulfill well defined specifications (Caminati et al. 2015), (Rowat, Kerber, and Lange-Bever 2016).

Finally, a crucial dimension of the *how to do it* problem is technological: is it meaningful to complement unavoidable GHG emissions reductions with solar radiation management measures? Will nuclear fusion and GHG sequestration arrive in time to mitigate the impacts of fossil fuel economies?

The bottom line

At the interface between climate science and climate policy there is plenty of opportunities for confusion and misunderstandings. We have flagged differences that matter and that is worth keeping in mind when discussing how to turn scientific knowledge into advice to policy makers.

References

Botta, Nicola, Nuria Brede, Michel Crucifix, Cezar Ionescu, Patrik Jansson, and Marina Martínez. 2020. "Climate Science and Verified Programming." TiPES WP6 internal note.

Botta, Nicola, Patrik Jansson, and Cezar Ionescu. 2017. "Contributions to a Computational Theory of Policy Advice and Avoidability." *J. Funct. Program.*, nos. 27, e23.

———. 2018. "The Impact of Uncertainty on Optimal Emission Policies." *Earth System Dynamics* 9 (2): 525–42. https://doi.org/10.5194/esd-9-525-2018.

Caminati, Marco B., Manfred Kerber, Christoph Lange-Bever, and Colin Rowat. 2015. "Sound Auction Specification and Implementation." In *EC '15 Proceedings of the 16th ACM Conference on Economics and Computation*, edited by Tim Roughgarden, Michal Feldman, and Michael Schwarz, 547–64. Association for Computing Machinery. https://doi.org/10.1145/2764468.2764511.

Hardin, Garrett. 1968. "The Tragedy of the Commons." *Science* 162 (3859): 1243–8. http://www.sciencemag.org/cgi/content/full/162/3859/1243.

Heitzig, Jobst. 2012. "Bottom-Up Strategic Linking of Carbon Markets: Which Climate Coalitions Would Farsighted Players Form?" *SSRN Environmental Economics eJournal*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2119219.

Heitzig, Jobst, Tim Kittel, Jonathan F. Donges, and Nora Molkenthin. 2016. "Topology of Sustainable Management of Dynamical Systems with Desirable States: From Defining Planetary Boundaries to Safe Operating Spaces in the Earth System." *Earth System Dynamics* 7: 21–50.

Helwegen, Koen G., Claudia E. Wieners, Jason E. Frank, and Henk A. Dijkstra. 2019. "Complementing CO_2 Emission Reduction by Solar Radiation Management Might Strongly Enhance Future Welfare." *Earth System Dynamics* 10 (3): 453–72. https://doi.org/10.5194/esd-10-453-2019.

Intergovernmental Panel on Climate Change (IPCC). 2007. "Climate Change 2007: Synthesis Report. Contributions of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change."

———. 2018. "IPCC, 2018: Summary for Policymakers." Edited by V. Masson-Delmotte, P. Zhai, H. O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, et al. https://www.ipcc.ch/site/assets/uploads/2018/10/SR15_SPM_version_stand_alone_LR.pdf; Intergovernmental Panel on Climate Change (IPCC).

Moreno-Cruz, Juan, and David Keith. 2012. "Climate Policy Under Uncertainty: A Case for Geoengineering." *Climatic Change*. https://doi.org/10.1007/s10584-012-0487-4.

Nordhaus, William. 2019. "Economics of the Disintegration of the Greenland Ice Sheet." *Proceedings of the National Academy of Sciences* 116 (25): 12261–9. https://doi.org/10.1073/pnas.1814990116.

Ockenfels, Axel, Peter Werner, and Ottmar Edenhofer. 2020. "Pricing Externalities and Moral Behaviour." *Nature Sustainability*, 361–80. https://doi.org/10.1038/s41893-020-0554-1.

Puterman, Martin L. 2014. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons.

Rougier, Jonathan, and Michel Crucifix. 2018. "Uncertainly in Climate Science and Climate Policy." *arXiv: Physics and Society*, 361–80.

Rowat, Colin, Manfred Kerber, and Christoph Lange-Bever. 2016. "An Introduction to Mechanized Reasoning." *Journal of Mathematical Economics* 66 (October): 26–39. https://doi.org/10.1016/j.jmateco.2016.06.005.

Webster, Mort D. 2000. "The Curious Role of "Learning" in Climate Policy: Should We Wait for More Data?" MIT Joint Program on the Science; Policy of Global Change, Report No. 67.

———. 2008. "Incorporating Path Dependency into Decision-Analytic Methods: An Application to Global Climate-Change Policy." *Decision Analysis* 5 (2): 60–75.